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A Multi-Industry Analysis of Human-Machine Systems: The Connection to Truck Automation

Todd Pascoe, Shirley McGough and Janis Jansz*
Curtin University, Western Australia

KEYWORDS

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Mining
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Human-machine systems
Driverless trucks

ABSTRACT

This research is a critical review of safety-related themes in human-machine systems across multiple industries. The aim is to explore the lessons of engineering human-machine systems and the residual consequences of introducing driverless trucks on a Western Australian (WA) mine site. The method involved the identifying key words, phrases and contributing factors leading to driverless truck events to-date. An eligibility criterion aided the selection of relevant human factors research in the field of artificial intelligence, automated systems and augmentation. Literature is categorised into 9 publication types, with 11 separate industries associated within 182 pieces of material. Three broad categories were synthesised to include: (i) technology; (ii) processes; and (iii) human factors, with three research questions answering how this research applies to truck automation. Within those categories, 23 research themes were found under the human-machine system domain. The findings highlight the Mining Industry's knowledge gaps and informs the design of driverless technology, formation of work processes and the accommodation of local human adaption. Conclusions provide a way forward for the industry and pass on lessons learnt to avoid automation pitfalls.

1. INTRODUCTION

More than a decade ago, Rio Tinto trialed the first driverless haul truck in Western Australia (WA). Driverless haul trucks do not need a safety driver and operate independently via machine algorithms (Hamada & Saito, 2018). An algorithm is responsible for controlling the actions of the haul truck, with every truck operating within the same operating parameters. The only difference is that Mine Control gives individual truck assignments in order to deliver the daily plan. In addition, system-based roles and ancillary equipment operators are given residual tasks to help the driverless trucks through non-designed situations (Caterpillar, 2013). Therefore, the haul trucks are semi-automated and interact frequently with humans in performing operational tasks.

Driverless haul trucks introduced a new set of hazards and risks, which appeared to be transforming the risk profile of mine sites who were deploying automated technology (Department of Mines and Petroleum, 2014b). The inherent nature of automated system design and architecture introduce properties like complexity, reductionism, literalism, and brittleness (Billings, 2018; Dekker, 2014b; Ito

* *Corresponding Author*: j.jansz@curtin.edu.au

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& Howe, 2016). An engineered human-machine system can be considered a 'joint' system, where both agents are required to collaborate as a team (Christofferson & Woods, 2002). It is evident that the Aviation Industry has learnt the most on how to cooperate human and machine in one system. This way, beyond isolation, the two agents can work collaboratively to become more resilient in times of disruption. Mining companies invest in driverless technology based on the potential of making their supply chains a lot safer and more productive (Palmer, 2019). However, despite the hype around removing 'driving errors', the technology has simply removed human exposure to driving trucks and transformed what remained (Department of Mines and Petroleum, 2015a).

The number of significant driverless truck incidents illustrates the importance of human factors research, currently six publicly reported since 2014 in WA alone illustrates the importance of human factors research (Department of Mines and Petroleum, 2014b; Jamasmie, 2019; McKinnon, 2019). Such an emergence could hinder the deployment of driverless technology due to the complex nature of unconventional incidents. Moreover, the landscape in mining operations is swiftly evolving as more products and vendors enter the market, with human factors playing a vital role. Human factors in this digital age is argued to be "people in systems, rather than people versus systems" (Dekker, 2019, p. xix). Such a view will allow the Western Australian (WA) Mining Industry to become more human-centered when designing and deploying driverless technology (Giacomin, 2015). Therefore, as a joint human and machine system, despite being two completely different agents, they should complement one another. Thus, within the context of human-machine systems, human factors study the design of technology to suite the attention, memory and perceptions of humans. More specifically, taking the study of human cognition into the 'real world' and understanding the interactions people have in complex systems (Rankin et al., 2016).

As a consequence, cognitive systems engineering has progressively become popular with the expansion of computerised systems (de Vries, 2017; Hew, 2016; Woods & Hollnagel, 2006). Researchers are already aware of the reverberations of automated technology and the human-machine breakdowns that have occurred across various industries. Waves of automation and technological disruption can be identified in: Aviation, which included automated flight capabilities (Sarter, 2008); Manufacturing, comprised of product assembly and machining (Frohm et al., 2006); Healthcare involving ICU devices and monitoring equipment (Dominiczak & Khansa, 2018), Nuclear encompassing plant status and real-time decision making assistance (Schmitt, 2012); Maritime including advances in communication and navigation equipment (de Vries, 2017); Mining equipment that comprises of haul trucks and production drills (Department of Mines and Petroleum, 2015a), and Transportation that deploys driverless cars, trains, trucks and buses (Fridman et al., 2018; Gschwandtner et al., 2010).

Despite there being various perspectives concerning automated mining equipment (Bellamy & Pravica, 2011), it is argued that driverless haul truck safety has not been given enough attention. The full extent of the human factors that apply in driverless haul truck systems are yet to be explored. There are in fact perspectives that concentrate on designing remote operating equipment that is user centered (Horberry, 2012; Horberry et al., 2011), and the benefits of removing human exposure through remote control (Fisher & Schnittger, 2012). Further perspectives argue the need for more human factors research given safety outcomes are unknown (Lynas & Horberry, 2010), while others claim automation reduces 'human error' (Hamada & Saito, 2018) and increases safety through obstacle detection (Brundrett, 2014). Furthermore, there are interviews such as Lynas and Horberry (2010) that concentrate on developers and users of technology, which explore the cognitive capacities required to operate equipment remotely.

Undoubtedly, the literature is yet to understand how human factors research applies to haul truck automation, an opportunity that underpinned the reason for undertaking this research. More

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specifically, the review attempts to address the following questions: (1) How are the theoretical viewpoints of human-machine systems influencing the approach to haul truck automation? (2) What processes are designed to support automation, and do they equip human supervisors to improvise in non-designed situations? (3) Does human adaptive behavior manage unanticipated machine performances and the decisions to intervene or not during beyond design performances? This review draws on human factors research from other industries that have adopted and deployed automated technology, applying the concepts and lessons learnt to fast-forward the WA Mining Industry's thinking to equip them for this digital revolution.

2. METHODOLOGY

2.1 Introduction

To outline the process for identifying and organizing the research on the topic, the steps proposed by Creswell and Creswell (2017) were embraced. The methodological process encompassed the following steps:

1. Identify studies and key words, search databases and websites
2. Collect at least 50 research studies, prioritise them and validate the abstracts, chapters and conclusions
3. Design a literature map to visually represent the groupings
4. Summarise and organize the literature into themes and concepts to identify opportunities

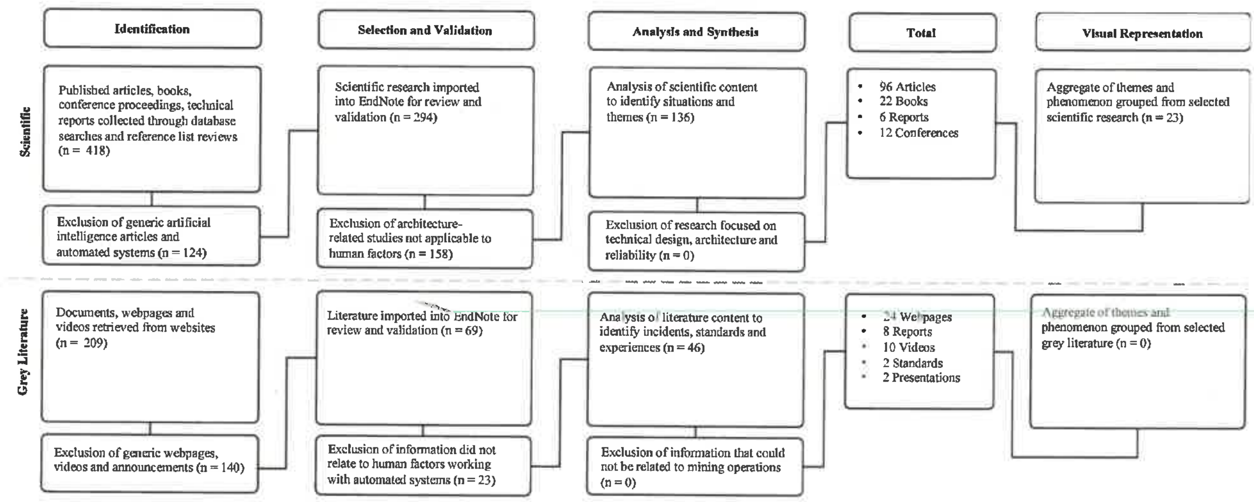

Figure 1. Process flowchart for reviewing the literature

2.2 Study and Literature Identification

The literature review originally began by evaluating the two driverless incidents reports (Department of Mines and Petroleum, 2014b; 2015c). Both reports were analysed to identify key words, phrases and contributing factors that led to the event. The first report (Department of Mines and Petroleum, 2014b, pp. 1-2) provided a summary of the hazards. Through seeking the safe use of mobile autonomous equipment, the safety bulletin identified "detection systems" and "remotely overriding" as a factor of design in driverless haulage. Human factors included responding to "system information and warnings", misinterpreting "system information", "lack of knowledge and understanding" and "not adhering to clearance zones". Secondly, Department of Mines and Petroleum (2015c, pp. 1-2) summarised an incident between a manually watercart and a driverless haul truck. The report noted that

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"assigning roads in the control system were inadequate". In addition, the watercart driver was not aware of the autonomous truck's direction despite an in-cab awareness system to "monitor the autonomous truck's path". These key words and phrases used in this report provided the basis for searching for research studies associated with human-machine systems.

2.3 Selection and Validation

The selection of literature was based on an eligibility criterion. To be selected the literature (scientific or grey) needed to be relevant in the fields of artificial intelligence, automated systems, or augmentation. In addition, the literature needed to be applicable to human factors, which could then allow similarities to be drawn in how people work with artificial agents. More importantly, the situations where humans are successful and sometimes fail, ultimately leading or avoiding undesired situations. Firstly, the abstracts of the research papers and introductions were evaluated based on their intent. For example, if the literature was not designed to understand how humans and machines work together, then it was excluded. The excluded writings were arranged into their reasons for exclusion. Secondly, the content of the literature was evaluated for substance and relevance, excluding those that could not be impactful in a mining context. Thirdly, the writings that were more centered around human adaption, cognition and response were included, while technical architecture of the automated system were removed. Despite this, a majority of scientific papers focused on the human element working with a machine. Lastly, the literature found to be unsuitable for inclusion were used in the introduction for context setting.

Table 1. Criteria for inclusion and exclusion

Selection	Component	Scientific Literature	Grey Literature
		Conference proceedings, peer-reviewed articles, books and chapters, interviews.	*Government reports and standards, publicly released incidents, YouTube videos, announcements, Company tutorials and public engagements*
Inclusion	Title	Key words: automation, driverless, autonomous haul trucks, human factors, augmentation, artificial intelligence	Key words: haul truck automation, driverless, autonomous haulage, haul truck incident.
	Abstract	Articles relating to the human factors in automated systems	
	Content	Human factors research orientated towards understanding situations, experiences and adaptions of humans while working with artificial systems.	Details of reports and situations, code of practices highlighting risks and hazards, issues with application, workplace incidents and anecdotal experiences
Exclusion	Title	Generic artificial intelligence and automated system articles	Generic webpages, videos and announcements with no correlations with driverless/ automated haulage
	Abstract	Design and architecture-related studies that did not explore associated human factors	
	Content	Research focused on technical design, architecture and network reliability	Writings paraphrasing the intent and purpose of driverless haulage, no specific relation to how the technology works practically

2.4 Analysis and Synthesis

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The selected literature was categorised into their associated publication type. The purpose of analysing associated publication types helps frame where the research was publicised. This was necessarily given that the technology is relatively new to the WA Mining Industry and academic research is yet to explore. Moreover, it also highlights the magnitude of research that can be drawn from other industries who have already deployed automated systems. As Figure 1 illustrates, a majority of literature included in the research were scientific papers. This can be explained by the volume of research that has been undertaken in the Aviation Industry shown in Figure 2. The significance of grey literature (i.e. web pages, online videos) highlights the methods currently being used to understand the topic. Once innovation tapers and competitive advantages plateau, perhaps more academic research in the field of human-machine systems can be undertaken in the Mining Industry.

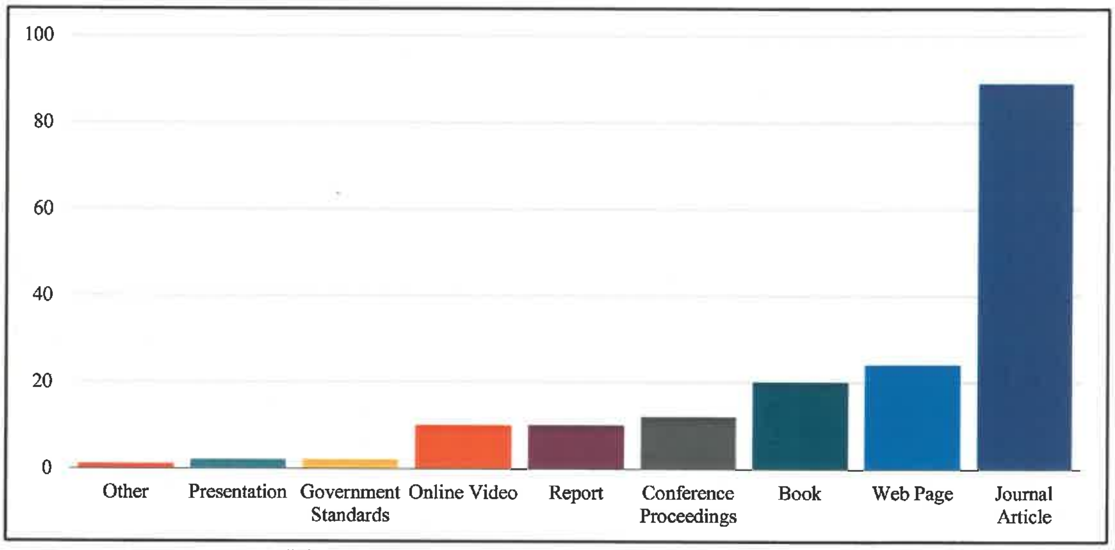

Figure 2. Analysis of literature by type

The timeframe and industry of focus of research were considered in Figure 3. There were 11 industries identified within the 182 pieces of literature included in the research. By including the industry where the research was undertaken, readers are given an indication of where automated systems have been deployed in industry. More specifically, where research has been able to take place and explore the consequences of replacing human work. Figure 2 illustrates how the Aviation Industry was the first industry to explore associated human factors. From there, healthcare, manufacturing, maritime and other associated industries have been able to leverage from those insights. The whole purpose of this literature review is to do exactly that for the WA Mining Industry. Therefore, the industry can avoid the pitfalls of automation, leveraging the lessons learnt from existing research and optimise their current designs and systems of work.

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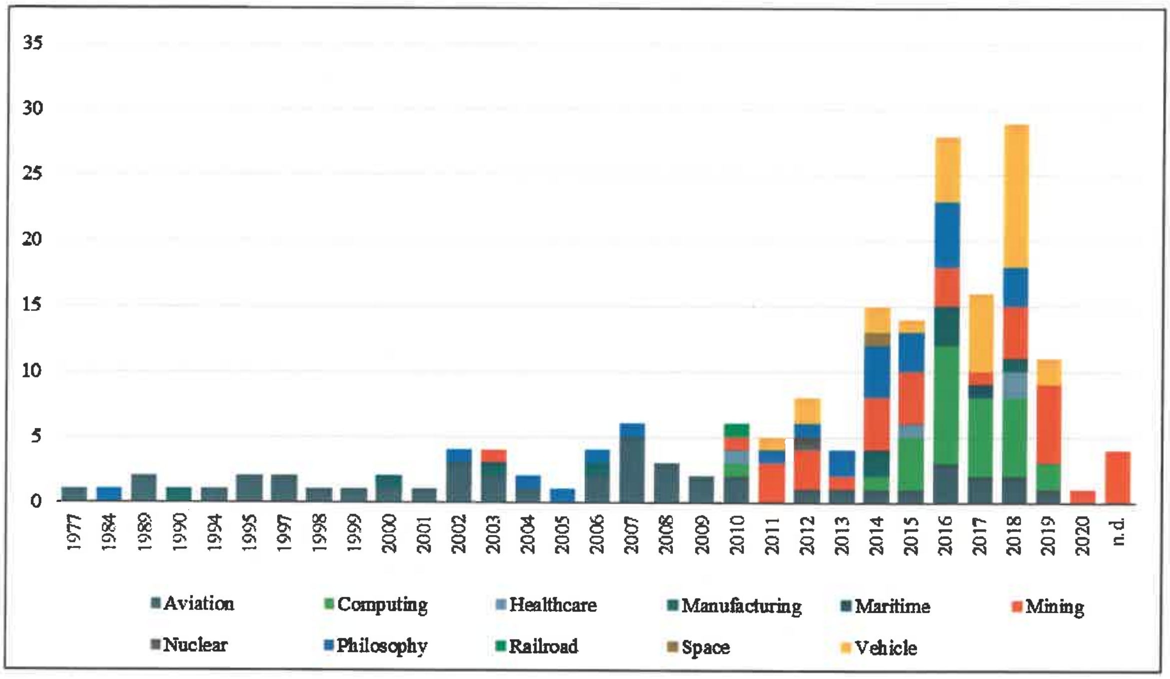

Figure 3. Analysis of publication timeframe by industry type

There were three broad categories that were identified in the literature:

(i) Technology;
(ii) Processes; and
(iii) Human Factors.

These categories also contained sub-themes that provided additional context to the category. For example, machine modes formed a part of technology, which was reinforcing how the technology presented in the workplace. In addition, mode awareness was how well people were being made aware of the machine modes and the complexities behind it.

By providing themes, readers are able to clearly understand the phenomenon that research has identified thus far. Therefore, the illustration of a mind map in Figure 4 provides a visual representation of human-machine system topics. The identified topics and associated findings can then be used for academics, mining operators and regulators to further explore individual topics further.

Figure 4. Mind map abstraction of research themes associated with human-machine systems

3. RESULTS

3.1 Engineering Human-Machine Systems

Reductionism and Complexity

Reductionism simplifies haulage systems into their most basic parts (Dekker, 2010). The parts are made up of driving to a load source, awaiting to be loaded by an excavator, driving to a destination and then dumping (Caterpillar, 2013). When this process is complete, it is then repeated. Systems are simplified in this way to enable technology to change out human tasks that it can perform (Lake et al., 2016). Often, the replacement is dependent on what technological advancements make it viable (Panetta, 2019). That means that driverless trucks must achieve or exceed human level performance. Although, human level performance is evaluated in isolation, the study is only a constituent part in a complex whole. That constituent part is then reverse engineered into a machine, following a narrow set of instructions (Fridman et al., 2018). On the surface, the restructured haulage system can appear to operate as intended. However, it is the reverberations along the fringes where the consequences take place (Department of Mines and Petroluem, 2015c). A driverless truck, for instance, may be unable to achieve its dump destination due to material being placed in the way. A human is now required to remove that material or redirect the truck to a new dump location. This example highlights the characteristics of the system, complex interactions between components. Therefore, the properties of the system arise after drivers have been replaced, which can be difficult to predict (Department of Mines and Petroluem, 2014b). Complex systems create their own individual structures, which can be defiant of the product designer. In response to the introduction, the environment modifies and restructures the entire system (Dekker, 2014b).

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Complex systems cannot be understood through the analysis of independent tasks. Complexity evolves through the interactions of the systems' components (Cilliers, 2002a). Furthermore, automation creates interdependencies that generate non-linear relationships. Therefore, systems are not linear input-output devices as metaphorically described (McCarthy et al., 2000). Humans will not simply undertake one task, while an automated system uninterruptedly perform another (Mitchell, 2018). A system is a complex web of component dependencies, transformations, trade-offs and influences (Dekker, 2019). Although automation has freed trucks drivers to perform 'more important' tasks, the reality is that the truck fleet becomes silent, awkward and difficult to instruct (Christoffersen & Woods, 2002). What used to be a mine site filled with radio calls, now quietly and independently executes the task. The difficult and clumsy part, however, is that the apparent simplicities turn into actual complexities (Woods, 2018). The automation of sub-driving tasks, which asks Engineers to focus on the components. This is quite appealing when attempting to seek ways to produce and optimise at a lower cost (Caterpillar, n.d.-a). Inefficiencies are targeted, ironing out the variability and increasing the predictability (Hamada & Saito, 2018). However, the simplification can be achieved from what is excluded. Complex systems are ignorant of local control and external influences that leave the system vulnerable beyond engineering predictions (Chandler, 2014). For example, a design engineer who is located internationally, can simply change a filter that can impact the vendors entire fleet across Western Australia. Hence, the reason why haulage systems are now becoming more complex. The connections are becoming wider, closely connected to a socio-technical system that cannot be isolated (Bellamy & Pravica, 2011).

The analysis of what a system contains will not explain what it will do. The components will react differently, depending on the type and number of influential factors (Dekker et al., 2012). The properties will emerge once they interact in the workplace. For example, a truck is unable to identify a wet road, therefore the interaction will require traction controls to avoid losing control (Jamasmie, 2019). Upon realising the trucks' limitations, system supervisors will install speed restrictions on haul routes to avoid truck slides (Department of Mines and Petroluem, 2015a). This is why the reconstruction of systems with machine agents sometimes fail; the non-linearity of the consequences does not represent the entire system. Despite the neat allocation of functions (de Winter & Dodou, 2011), the activities are derived from arbitrary views of human-machine strengths and weaknesses (Dekker & Woods, 2002b). The problem is that they are never fixed, the capabilities and limitations evolve as people learn and technological systems are upgraded (Lake et al., 2016; Woodward & Finn, 2016). Moreover, automation systems can only operate within the confines of the data they were programmed upon (Earley, 2016). This often leaves users waiting for upgrades before new capabilities start to emerge. At best, the system will be upgraded with the designer's imagination on how the system will work (Hamada & Saito, 2018). Therefore, it is the human helping driverless trucks to adapt, while understanding how the technology works. Once it is understood, automation is opportunity to improve how safely and efficiently trucks are driven. It could, however, just make haulage just as high-risk as it is today, or worse (Department of Mines and Petroluem, 2014b).

Data Outputs and Insights

Data produced by a machine has typically outweighed the ability of humans to remain in-the-loop (Wiener, 1989). Being out-of-loop is driven by automated system that combines labels, numbers and colors that contain various levels of meaning (Endsley & Kiris, 1995). Supervisors of automated systems need to adapt to new data languages often cloaked as machine insights (Sarter et al., 1997). People follow recommendations given by a machine, with little insight into how it arrived at its conclusion (Hurley & Adebayo, 2016). Automated systems are marginally transparent, given that their algorithms are considered Intellectual Property of the designer (World Intellectual Property Organization, 2019). Therefore, automated systems operate independently from their users, limiting the

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decision-making process to enable user's ability to solve their own problems (Brantingham et al., 2018). While the automated systems gather performance data, the information is fed back to the vendor for optimisation (Hurley & Adebayo, 2016). Optimising the system without educating the end-user to truly understand what is happening, limits the overall human-centered improvement cycle (Giacomin, 2015). Transferring driving tasks to a machine, redistributes all the tactical information previously communicated by truck drivers (Caterpillar, 2013). Where a simple discussion could be held with a truck driver, now needs to be carefully extracted from filtered information or collected by observing truck movements (Caterpillar Global Mining, 2019).

Driverless technology appears to have skipped ahead of the research theories that try to explain data ontology. The WA Mining Industry automated trucks whose agency they previously understood and actively controlled (Department of Mines and Petroluem, 2015b). However, as haulage systems were engineered, the interaction and dependencies on others change, yielding a more complex by-product (Department of Mines and Petroluem, 2015a). Vehicle interactions evolved from complex situations (Department of Mines and Petroluem, 2015c); requiring equipment operators to use data to navigate and foresee situations. Understanding system data is unique to that person and cannot be reconstructed by any other person (Sieck et al., 2007). As more driving tasks are automated, the further people are removed from the immediate process (Wessel et al., 2019). Therefore, data outputs can become more mysterious than they were previously (Rankin et al., 2016). Although the developer designs the system, it is the user who is responsible for working out what the data trying to explain (Endsley, 2016). The problem is that interconnections form to quickly distribute data across the system, informing and directing people on what automated equipment will do next (Christoffersen & Woods, 2002).

The lack of transparency in automation has not stopped designers from attempting to 'augment' human work (Araujo, 2018). Augmentation is to enable people to be more creative and thoughtful by computing data insights (Hebbar, 2017). Big data does all the heavy lifting, while a human simply actions the recommendations from the machine (Hurley & Adebayo, 2016). However, a solution-driven approach is argued to deskill the human, rather than increase their knowledge and understanding (Bravo Orellana, 2015; Ito & Howe, 2016). As people are promoted to higher levels of supervisory control, the less they learn about the operation (Sarter & Woods, 1995). Whether data informs people on what to execute, or simply supervise a machine to perform a task, people must identify situations that are beyond the machine's data set (Skeem & Lowenkamp, 2016). This activity is often under-specified and requires people to improvise, reintroducing them into non-designed situations (de Visser et al., 2018). The data presented can appear more confusing than it did before, making it difficult to return the system to a safe state (Stensson & Jansson, 2014). Although display functions may list rules that decided an outcome, the literal representation during peak periods may be cognitively restrictive (Cummings et al., 2016). Nonetheless, providing users with access to computations and partial decision-making are more useful than solutions (Zittrain et al., 2018). Furthermore, if the aim of using data to is to augment human work, then the human must be creative with that data. While the ontology is biased (Bolukbasi et al., 2016), opaque (Buolamwini & Gebrum, 2018), solutionist (Ross & Swetlitz, 2018) and specialised (Skeem & Lowenkamp, 2016), data will continue to reinforce old habits and underpin the optimisation problems that led them to automation.

Literalism and Parameterisation

Driverless haul trucks give the impression they are safer by projecting their haul route. A truck displays its travel pathway via an in-cab display in manually operated equipment (Caterpillar Global Mining, 2019). This level of transparency in travel routes can also increase the level of trust people have for automated systems (Botsman, 2017). Providing travel pathways increase the certainty around what the machine will do next. However, despite this level of transparency, a manually operated machine with

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an in-cab display collided with a redirected haul truck (Department of Mines and Petroluem, 2015c). This incident questions whether people are even observing intended truck routes. The redirected pathway, following a corresponding truck slide, highlights the operating boundaries of automation (Ockerman & Pritchett, 2002). Automated systems work well under designed conditions, yet they perform poorly when situations are beyond their design parameters (Billings, 2018). These situations can be compounded by machine logic that is able to identify a hazard, however, is unable to provide a safe way forward (Caterpillar, n.d.-c). Operational boundaries are attributed to a set of constrained instructions, which are insensitive to the continuous shift in priorities and objectives (Vul et al., 2014). While attempting to achieve an objective, brittleness upsets the process, with an inability to execute its part of the process (Ockerman & Pritchett, 2002). Therefore, the technology simply 'throws up its hands', effectively stopping the process or immediately handing back control (SlashGear, 2017).

The value of human supervisors is their ability to exercise unconstrained thinking (Lake et al., 2015). A human is capable of drawing information from external sources to improvise during novel situations. Leveraging from previous experiences allows humans to solve localised problems, which machines may be incapable of solving (Reason, 1990). Despite the benefits of a truck performing "exactly as the computer has programmed it do" (ADVI Hub, 2016), the downside is that they perform nothing else. Systems that are predictable, are not overly adaptable (Inagaki, 2003). Therefore, it is the system-based roles that cover the shortfall (Dekker, 2003). This trade-off raises an interesting conundrum of the value of replacing human work. With constant supervision and intervention, the value proposition diminishes (Noy et al., 2018). Despite the direct safety benefits of removing humans from a high-risk task (Palmer, 2019), the consequences are only just coming to fruition (Department of Mines and Petroluem, 2015c). After all, automation is 'stupid' (Domingos, 2015), exacerbating the reliance on humans to provide the context to make informed decisions. However, this can be difficult, with literalism restricting the reconfiguration of instructions (Billings, 2018). Difficulties arise when attempting to redirect an automated system. Not only enabling the machine to understand new instructions, yet to perform those instruction as expected (Woods & Hollnagel, 2006). Without them, the operating parameters simply retain the status quo, hiding the limitations of the logic while everything else adapts (Winfield & Jirotka, 2017).

Automated systems can appear adaptive when compared against the data set it was trained on (Prechelt, 2012). For example, parts of the programming data are held out for testing, so when machines are tested against humans, the performance appears comparable (Walker, 2016). However, the performance is not comparable, particularly when tested on non-training data (Buolamwini & Gebrum, 2018). This logic applies to driverless haul trucks and their ability to recognise objects (Caterpillar, n.d.-c). LiDAR and Radar technology are capable of identify objects, yet they are unable to distinguish between windrows and people (Teichman et al., 2011). Parameterisation problems become apparent when Global Positioning Systems (GPS) on driverless trucks are ineffective, which has reverse obstacle detections fail (McKinnon, 2019). Moreover, self-driving motor vehicles experiences a similar phenomenon, where the oncoming vehicle was unable to identify a pedestrian in time to stop (National Transportation Safety Board, 2018). Despite driverless technology coming along way, it is not there yet. There are more advancements to be made, with various industries that need to be made aware of machines functions and their technical capabilities (Payre et al., 2016).

Protectionism and Resilience

Engineering defence layers to protect a system from failure is widely accepted practice in risk management (Summers, 2003). Defence in-depth is philosophy grounded by intelligence hardware that assumes incidents unfold in a linear chain of events (Murphy, 2016). If this were the case, the more connected a human-machine system became, the more redundancy would be required to counter

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predictable domino-like reactions. The empirical basis for validating the success of controls are the absence of significant events; if the system has not had an incident then the arrangements are safe (ADVI Hub, 2016). Though this assertion can be misleading, Reason (1990) explains how automated systems are not known for their response to isolated hazards. As an example, a virtual intersection that is not demarcated in the physical mine laid dormant until a driverless vehicle needs to use it (Department of Mines and Petroluem, 2015c). Retrospectively, the installation of signs and devices could have assisted the human operated machine to identify potential interactions and avoid the collision. However, the physical demarcation of every intersection simply adds more layers of protection in already complex system, opening more disparities between the physical and virtual environment (Caterpillar, n.d.-b).

To safeguard against incidents, engineers often design extensive levels of protection to create new forms of failure (Caterpillar, 2013). Traditionally, the WA Mining Industry has prioritised layers of protection over resilience, implementing theoretical walls that are incapable of bouncing back (Willey, 2014). The rigorous test structures and fail-safe systems implemented as a means of insulating driverless technology from conventional incidents, seem to have created their own pathways that have mystified the industry (Department of Mines and Petroluem, 2014b). Technology introduced to replace human limitations (i.e. driver attention, concentration, fatigue) with layers of artificial intelligence (i.e. LiDAR, radar, pattern recognition) have now become the industries greatest weakness (Department of Mines and Petroluem, 2014a; 2014b; Teichman et al., 2011, 9-13 May). Perrow (1997) explains how the fallacies of "defence in-depth" can obscure the view on how systems behave when they are stretched and compressed. The result had left investigators puzzled how the driverless system became so opaque to those who use them. The regulator reported a "lack of system knowledge and understanding of how the autonomous equipment system works" (Department of Mines and Petroluem, 2014b, p. 1). What automation taught early adopters of automation, is that the more layers that are in place the more domain experts are removed (Billings, 2018). When users are reintroduced back into the control loop to solve system malfunctions, the processes can appear more peculiar than they did before, making the recovery method process much more difficult (Pritchett et al., 2013).

Assisting people to cope with complexity is at the heart of resilience engineering (Dekker et al., 2008). Technological innovation in the WA Mining Industry has resulted in dramatic improvements in decreasing injury rates since driverless technology was introduced (Caterpillar, n.d.-a). Nevertheless, it takes time for automation to magnify the inefficiencies in a process, even if the industries processes were benchmark in both safety and productivity (Bellamy & Pravica, 2011). The role of the human is radically re-engineered to remain the critical interface between sub-systems of complex whole, particularly if they are dealing with multiple 'expert' systems with various objectives and limitations (Fridman et al., 2018). How well a system withstands variations and disruptions outside of the design envelope is an indication of how resilient it has become (Chandler, 2014). Human flexibility and adaption are yet to be truly understood by cognitive scientists, with various skills sets to be engineered into a machine (Lake et al., 2014). Machine learning may be able to beat the world's best AlphaGo player; however, it still cannot drive to the match (McFarland, 2017). For a system to be agile and successful in this digital revolution, it must mature beyond machine literalism to be pivot and manoeuvre around danger (Srinivasan & Mukherjee, 2018). Ito and Howe (2016) believe that augmentation holds the key, fostering the relationship to create the foresight to anticipate risk and navigate the complexity of ever-changing landscapes.

Manual and Automated Modes

Whether a haul truck is in manual or automated mode depends whether it has been programmed into the machine. Moreover, if system engineers are yet to figure out how to automate the task, then trucks must be operated in manual mode. This can also be said for communication losses, where network must be maintained in order to control trucks automatically (McKinnon, 2019). A mode can be identified through the lighting system for ancillary equipment operators and via in-cab display for system-based roles (Caterpillar, 2013; Caterpillar Global Mining, 2019). While some mining operations mix manual and automated haul trucks, others choose to separate the differently operations entirely (Department of Mines and Petroluem, 2015a). This approach can alleviate the confusion behind determining whether the truck is manual or automated mode (Sarter & Woods, 1995). More importantly, the different functions and rules associated either mode (Glover, 2016). Endsley (2016) explains how the consequences emerge when people are surprised by equipment functions, which can ultimately lead to haul truck interactions. Alleviating the issue requires improving the dialogue on the overall objectives, operating envelope, next movements and resolution logic (Salas et al., 2010). Feedback loops are considered to be a starting point to merging the gap (Sklar & Sarter, 1999). Consequently, improving feedback could the minimise short phases of intervention, observed as the frequent cause of people who have lost track of machine assignments (Feldhütter et al., 2019).

Human factors research appears optimistic on the progress towards user comprehension of automated modes and configurations. Norman (2013) argues that the idea is to put knowledge into the world. While some academic papers promote the development of rich 'mental models' for automated systems, Sarter (2008) contests that the theory is empirical flawed. Regardless of what product vendors train their users on what to look for (Merritt et al., 2015), Sarter et al. (1997) claim that there will always be mismatches in the way humans supervise machines. Automation surprises are argued to be a normal by-product of a machine that undertakes work independently (de Visser et al., 2018). If a system required 'safety drivers' for motor vehicles, for example, the productivity value would soon diminish. However, when a driverless machine confronts a novel situation, it can become quite onerous when attempting to draw from external resources (Endsley, 2016b). Identifying the correct mode is a consequence of the system's design, not the fact that automation has gone too far (Norman, 2013). A mismatch in mode identification occurs when the machine's interface does not visibly display the mode, which requires users to remember a mode from hours earlier (Feldhütter et al., 2019). Casner et al. (2016) emphasised that designers should allow for possible intervening situations that can distract humans from remaining in touch with the machine's mode of operation.

The transition between manual and driverless control has been identified as an unconventional risk for the WA Mining Industry (Department of Mines and Petroluem, 2015a). Automation can generate unanticipated changes in a haul trucks' direction, leading to a loss of vehicle control. If the loss of control had indeed involved a mode change, then it is likely that this situation was recorded somewhere in the system. Björklund et al. (2006) explain how retrospectively, available data gives rise to engineering confidence that transitions are observed by human users, with the view that higher attention rates can avoid such occurrences. Nevertheless, researchers are left with a puzzling thought when people, who do not communicate with machines, understand what mode a machine is in. Dekker (2014b) suggests comparing the difference between the machine function and user's intentions, the disparity and similarities offers some indication of the persons' awareness.

3.2 Research Question 1

How are the theoretical viewpoints of human-machine systems influencing the approach to haul truck automation?

The theoretical viewpoints are underpinned by science and engineering. Both fields study systems by 'reducing' them to their most basic parts, analysing what is contained. Engineering attempts to replicate the components by reverse engineering human tasks. Machines are then programmed with the patterns that are recognised in basic human level performances. The technological advancements made

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available are then introduced into the system, reallocating activities to either human or machine. The system is theoretically 'reconstructed' by the designer, specifying tasks to be undertaken by driverless trucks (i.e. drive, load, tip) and residual work by humans (i.e. object clearance, surveys and assignments). When the system is theoretically reconstructed and put back together, existing relationships and connections are transformed to create new situations like the watercart incident (see Department of Mines and Petroleum, 2015c).

3.3 Processes in Human-Machine Systems

Opacity and Transparency

Augmenting the relationship between driverless trucks and their supervisors depends on the technology's transparency. Opacity is the by-product of a highly protected technology that reduces human capacity to comprehend its function (Billings, 2018). Therefore, the system provides minimal insight into how the algorithm decides an outcome (Dressel & Farid, 2018). For example, driverless trucks may perform U-turn at a loading source without notifying human supervisors on the reasons why. Demystifying the opacity requires the illumination of the decision-making process (Winfield & Jirotka, 2017). According to Wiener (1989, p. 244), pilots of automated aircraft frequently asked: "What is [the machine] doing? Why is doing that? What is it going to do next?" Automated systems can even be deliberately designed to limit their transparency. One of the reasons is to protect the designer's Intellectual Property (World Intellectual Property Organization, 2019), while another is to avoid the technology from being overridden. However, the consequences leave humans unable to track the machine's mode of operation (Sarter et al., 1997). Furthermore, the unanticipated actions of the machine can result in automation surprises (Woods & Sarter, 1998). Automation surprises are anticipation of one action (turn left), yet the machine performs something different (turns right). These surprises where previously alluded to by Norbert Wiener. His study of B-757 pilots found that 69% of participants were surprised by the automated actions, while 35% were unsure of the technology's modes and features (Wiener, 1989). This phenomenon was replicated in the WA Mining Industry, where an investigation found that people involved in a driverless truck incident had a "lack of system knowledge" (Department of Mines and Petroluem, 2015c, p. 1). Despite the protection of a truck's decision-making process, it appears the trade-off is stifling the creativity and understanding of driverless truck functionality.

The processes used to collaborate with machine can become increasingly vague to humans. Particularly as the technology evolves and progressively replaces more human work. The more people are promoted to a higher level of supervisory control, the more they are removed from the immediate process (Stanton et al., 2001). Moreover, the greater number of trucks that are automated, the smaller number of people available to understand suitable driving techniques. The intricate knowledge of a truck's gear range, turning circle, reverse capability and handling will be minimised. Therefore, the transparency of the system's capability will become increasingly important, explaining how the truck performs routine tasks. Contrastingly, in order to compensate, humans learn by observing how the truck behaves. Automation typically filters out direct information that explains the reasons for those actions (Zittrain et al., 2018). Consequently, the user implements more test structures to verify compliance to existing systems, simply adding more complexity and opacity to already multi-faceted piece of technology (Department of Mines and Petroluem, 2014b). Despite comprehensive training programs, Woods (1996b) explains how traditional training approaches may interfere with current monitoring routines and learned interpretations of automation functionality. Providing transparent feedback can be significant challenge, with interfaces required to provide vital pieces of information. The balance is presenting information people need, without overloading them with information they don't need, or know how to interpret (Salas et al., 2010). Warning signs can become hidden among

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complex web of information, the risk being no response at all (Dekker et al., 2008). The reverberations of opacity are a false sense of security that processes are working as intended (Rasmussen & Vincente, 1989). However, if the transparency is there, human supervisors may be able to provide the improvisations that they are designed to provide.

Tight and Loose Coupling

According to Perrow's Interaction/ Coupling Chart, conventional mining techniques are loosely coupled and highly complex in their interactions (Perrow, 1984). Prior to driverless technology, haulage operations contained conventional buffers with flexible tendencies that the industry came to understand (Department of Mines and Petroluem, 2015b). However, when driving responsibilities were transferred to an automated system, haul truck connections with others had changed (Department of Mines and Petroluem, 2015c). Where positive communication would be utilised to pass a haul truck, now requires the truck to be virtually locked before passing (Hansen, 2020). Moreover, if a driverless truck is assigned to tip at the crusher, the truck will remain stationary until it is cleared to tip, regardless of time (ADVI Hub, 2016). Since the algorithm propagates across the entire system, every truck performs the exact same activity. Such a highly connected system exacerbates the literalist thinking of a machine (Dekker et al., 2012). Therefore, supervisors must think quickly to change functions and instruct the automated system on what to do next (Miller & Parasuraman, 2007). Contrastingly, trucks drivers who notice the crushers' unavailability, simply ask the control room for another dump location (BHP, 2018). The flexible tendencies of a human to adapt and ask questions, enables the haulage system to become free flowing. Similarly, the situation occurs in losses of network communication (McKinnon, 2019). In a manual system, truck drivers could operate if communications were lost. However, for a driverless truck, the technology simply cannot operate unless communications are maintained (Hamada & Saito, 2018). While automated systems are constrained by a narrow set of objectives, the impacts of tighter coupling are experienced more rapidly (Jamasmie, 2019). Therefore, the inefficiencies and failures have a greater impact and are much more difficult to isolate.

Automated systems are historically known for introducing characteristics that produce 'normal accidents' (Perrow, 1984). An incident is considered normal when it involved normal people, completing routine work, under normal circumstances (Wears et al., 2015). The focus is often at the sharp end, arbitrarily reconstructing the sequence of events to evaluate human responses (Dekker, 2014a). The further the investigation moves back from the sharp end, the more coupled and connected interactions become (Weber & Dekker, 2017). Therefore, systematic explanations are often replaced with what was observed (Drury et al., 2012). This is where the notion of direct causes narrows our thinking, the tight connections in a complex system are oversimplified (Department of Mines and Petroluem, 2015c). As a consequence, the reductionist thinking leads to a broken component, while other latent and tightly coupled aspects are underrepresented (Dekker, 2010). For example, a driverless truck may slide out of lane, yet the loss of control could have been created by communications, traction controls, speed zones, wet weather or road material (Department of Mines and Petroluem, 2015a). Since the human response is to go after what did not work as intended, they immediately focus on failure (Hollnagel et al., 2015). However, coupling is about focusing on the interactions themselves, not the components themselves (Wears et al., 2015). In addition, all the components may have behaved successfully. Therefore, safety lies in the interaction in tightly coupled systems, not the perfectly engineered component (Hamada & Saito, 2018). Systems must be flexible, nimble and robust if they are to navigate the complexities of the interactions they face (Cilliers & Presier, 2010).

Explaining the non-linearity of interactions does not prevent vendors attempting to provide solution-driven products. Despite driverless capabilities being developed, the automated vehicle is unable to effectively communicate with the crusher (Hitachi, 2015). Transferring control to a machine can exemplify the inefficiencies that are contrary to the technology's original intent. For example, without information being shared between driverless trucks and the crusher, the reverberations of queue time at the crusher can be enormous (Brundrett, 2014). The impact on people is that they are now being required to intervene and reassigned the truck fleet. Although success is celebrated when technology is componentised into a supple chain (Rio Tinto, 2018), automation eventually reaches its peak of innovation (Panetta, 2019; Trudell et al., 2014). Eventually, technology becomes so standardised that supervisors forget that systems' defences can only protect against known causal pathways (Reason, 1990). Perrow (1984) points out that it only takes two or more components in a tightly couple system to interact unexpectedly. As an example, it was unexpected that a driverless truck was unresponsive towards a manual watercart, which was heading for its pre-defined pathway (Department of Mines and Petroluem, 2015c). The non-linear reaction towards the watercart was under-specified relative to its relationship, an oversight that caused a near fatal collision. And yet this problem would never have occurred to the designer who has designed further collision and avoidance systems. As a result, additional control systems can simply tighten the system's coupling, while opening up more possible interactions and pathways to failure.

Centralisation and Democratisation

Standardising residual human tasks is based on the predictive capacity of the designer. A capacity that assumes centralising the most basic steps can guide supervisors to the safest outcome (Dekker, 2014b). However, in a human-machine system, work instructions come with a caveat. A proviso that expects people to follow written instructions, yet improvise when operational practices demand it (Dekker, 2003). Reason (1990) explains how the 'Catch 22' of supervising a machine cannot be escaped: "Human supervisory control was not conceived with humans in mind. It was a by-product of the microchip revolution." (p. 2). As a consequence, the by-product is the result of designers unable to predict and plan for every contingency (Caterpillar Global Mining, 2019). Despite this, Domingos (2015) claims that his Master Algorithm will eventually equip machines with every contingency. Until then, human intuition must inject smooth layers of local adaption, pulling information outside of centralised sources to manage unanticipated situations (Pettersen & Schulman, 2016).

Spending countless hours training people in standardised methods is a common thread in safety. The assumption is that standardising methods will build a cognitive repertoire to combat irregular situations (Dekker et al., 2012). Moreover, designers will argue that their automated system has figured out it all out, and there is no need for human intervention (Dietvorst et al., 2016). However, when the machine malfunctions, supervisors must intervene in situations they may not truly understand (Tech Light, 2016). Reason (1990) made the point that automation denies machine supervisors the opportunity to practice their post-automation skills, which ultimately leads to degeneration of domain expertise. When human supervisors are eventually relied upon, they perform poorly (McKinnon, 2019). For example, driverless trucks may not need human assistance for hours, then suddenly required to clear a reverse object. In order to democratise their automated system, Toyota built their process from the bottom up. The purpose was to increase their effectiveness and quality of workmanship (Trudell et al., 2014). A company cannot "... simply depend on machines that only repeat the same task over and over again." argued Mitsuri Kawai, Toyota Executive Vice President (Mols & Vergunst, 2018, p. 122). Therefore, automated systems may be efficient; but they are not overly skilful. Reverse engineering human mastery in a machine will eventually become redundant (McCarthy et al., 2000). Thus, to compete with low cost companies, industrialised nations are realising that their prosperity resides in user-centred innovation (von Hippel, 2005). Improving a company's supply chain may mean cultivating their inner-Artisan, returning to the days of human craftmanship (Protzman et al., 2016).

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Historical experiences do not account for truly novel events. A procedure detailing every design aspect of the process does not always reflect the limitations of automated systems (Pritchett et al., 2013). For example, the actions of machine supervisors labelled as "not adhering to…" or "failure to respond…" may be an indication of the creativity required to get real work done under technological constraints (Department of Mines and Petroluem, 2015c). In contrast to compliance-based approaches, perhaps the use of procedures as recipes can democratise the system enough for the people to continuously innovate (von Hippel, 2005). As a result, processes can then leverage the problem-solving aspect of human intelligence, therein be more impactful than debating deviations from centralised procedures and contrasting individual experiences (Lake et al., 2016).

Virtual and Real-World Distinctions

Representing the physical world through virtual maps may suggest to human supervisors that the systems' interface is a true. Supervisors may also believe that physical controls are in place simply because the virtual representation displays it (Caterpillar, n.d.-b). Research surrounding the distinction between physical and virtual worlds however, points to something different: an ideal world that is free from localised constraints (Dahlstrom et al., 2009). For example, virtual displays can be a supreme worldview how the system should look and function from an engineering perspective. Salas et al. (2010, p. 10) argue that real-world problems are "far removed" and are replaced with simplistic representation. It is essential that virtual representations co-evolve, seeking human input as they attempt to solve frontline problems (de Visser et al., 2018). Local constraints consist of many different parts, which can produce surprising and unpredictable situations for the user (Sarter et al., 1997). Thus, when physical changes that are not retrospectively updated, the condition may not visible to the user to warn them of an upcoming intersection (Department of Mines and Petroluem, 2015c).

The regulator governing mobile autonomous mining systems in Western Australia (WA) appears fairly pessimistic about the representation of physical mines. The Department of Mines and Petroluem (2015a) highlight a number of hazards associated with integrating driverless machines into an existing environment, recommending a phased approach to the introduction of advanced technology. The segregation of manually and automated haul trucks is designed to manage the risk of virtually and physically controlled interfaces. Although the designer may have developed tools to redesign the virtual system to meet operational needs, technology cannot remove the problems that technology creates (Baxter et al., 2012). The challenge of pre-programming a machine is that operational problems just keep moving, pushing the innovation curve outside of the automated systems' pipeline (Trudell et al., 2014). Analysing what a process contains does not explain what it will do, which makes updating virtual displays a never-ending iteration (Woods, 2016). Moreover, representative samples of the physical world can differ from human perception, which are constantly re-framed for meaning and insight when displays are not in real-time (Rankin et al., 2016). Given the complexity of representing the physical world, the on-board computational requirements for automated systems are extensive. Therefore, there is a need for more computer power than what can physically fit on a machine, given the amount of data processing required to operate LiDAR, image recognition and radar technology (Goel, 2016).

Processing data gathered from vehicle sensors is critical to keeping visual representations real. Road network surveys allow a virtual road map to be created (Teichman et al., 2011). The location of each 'connected' vehicle can then be tracked against the virtual model to determine the vehicle's speed and direction (Hamada & Saito, 2018). Automated and manually operated vehicles can then identify the proximity of other vehicles, providing both agents with the means to reduce potential interactions (BHP, 2017). System supervisors are also given the capability of implementing virtual speed, traction zones and clearing obstacles (Caterpillar, 2013). Virtual zones allow users to make the connection

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between surveys and surfaces in line with the physical environment. Supervisors can also control the speed of the vehicle in the event that a machine is unaware of changing weather conditions (Department of Mines and Petroluem, 2015a). However, as previously discussed, the machine will do exactly what it has been programmed to do. Consequently, if a virtual zone has been surveyed beyond the physical boundary, a driverless machine will still attempt to drive to those parameters (Department of Mines and Petroluem, 2014b). Moreover, if a truck loses communication, the virtual mine model can only identify its last known location. In the event of an interaction, the truck is now considered an object and has the potential to cause a collision (McKinnon, 2019).

Active and Passive Workload

Transferring control to a machine may appear like a logical step to reduce human workload. Perform lots of analysis, work out the most effective method and then engineer those actions into a machine (Lake et al., 2016). Although the assumption here, however, is that the underlying conditions that make this method possible will remain unchanged. Eventually, an automated system will face situations beyond its training set (Buolamwini & Gebru, 2018). Ferris et al. (2010) explain how the workload of supervising machines are short intensive moments, backed up by long periods of inactivity. This workload phenomenon was uniquely observed by Perrow (1984) to cause workload 'bunching'. Bunching the demands for human input is an error inducing mode of operation according to Reason (1990). Moreover, humans can be faced with an influx of requests from a machine that may not even be executing a better job (Endsley, 2017). Attempts to evenly spread human workload is often confronted with more engineering (Dekker, 2004). Product vendors will claim that the user will always be in control (Rousseau, 2015). However, a quick transfer of responsibility can result in negative outcomes when humans are not equipped to take over control (National Transportation Safety Board, 2017).

Automating human techniques have been long argued as a performance optimiser than a workload minimiser (Prewett et al., 2010). Nonetheless, efforts are still being made to reduce human input often cloaked as 'augmentation' (Dressel & Farid, 2018). For example, a machine may be assigned to analyse data and offer solutions, however users are not privy to inputted data and how it arrived at a conclusion (Dressel & Farid, 2018). The inaccuracies of data prediction highlighted by Brantingham et al. (2018) and the clumsiness of automation noted by Lee and See (2004), undermines a supervisors' trust. Constantly verifying a machines' decision-making process is a highly cognitive task, meaning that humans will avert using algorithms altogether (Dietvorst et al., 2016). The workload of machine supervisors is argued to be a normal by-product of an automated system that proceeds without user input (Miller & Parasuraman, 2007). Contemporary research in cockpit automation found a misleading conclusion on workload, noting that automation is not 'autonomous' and cannot always be left to its own devices (Edwards, 1977). Despite fewer physical activities being performed, the cognitive demands of monitoring a computer system actually increases (Wickens, 2008). Moreover, it is less likely that the intervention methods needed to recover a machine are not memorised, nor would they unfold as the training proceeds them (Engle, 2016). The main driver for automation is not reducing workload per se, rather making a process safer and more productive (Yeomans, 2014). Therefore, the more reliable automated machines become, the higher the expectation to improve their performance will become.

Cognitive overload has contributed to many incidents in Aviation. Flight deck incidents have occurred in systems where human workload was thought to have been reduced (Wickens et al., 2016). For instance, an automated system failure led to pilots' performing a manual calculation for the aircraft's landing. At the same time, the pilots were unaware of the parallel problems of a single engine malfunction. Although the pilots eventually responded, the wrong engine (the only functioning engine) was subsequently shutdown (Salas et al., 2010). Prior to this event, the Aviation Industry would have

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celebrated the reallocation of workload to a machine. Allocating work to a machine is argued to relieve humans to focus on more important tasks (de Winter & Dodou, 2011). Yet, human users still find themselves monitoring a machine's activities for non-designed situations (Victor et al., 2018). The residual is a bi-directional bridge between physical and cognitive tasks, manoeuvring among monitoring and taking control over control in order to remain in touch with local constraints (Casner et al., 2016).

3.4 Research Question 2

What processes are designed to support automation to equip human supervisors to improvise during non-designed situations?

The processes of automation are residual tasks that the designer is yet to figure out how to automate. The processes work well when the system is performing as intended. However, when faced with novel situations, the processes are unable to be adapted beyond their design parameters. Since the designer is unable to imagine and prepare for every contingency, human supervisors must use their unconstrained thinking to draw from external information and previous experiences. Therefore, the processes work well in designed situations, yet lack the relevance and adaptability when situations do not unfold along pre-determined lines.

3.5 Human Factors

Mode Awareness

Mode awareness is recognising a machine's state and understanding its operational parameters (Funk et al., 2009). Driverless haul trucks operate in three different modes: autonomous (solid blue); autonomous-ready (flashing blue) or manual (green) (Caterpillar, 2013). Mobile equipment operators, maintainers and system technicians must understand the functions of each mode, particularly when mode changing a truck. Maintainers and system technicians are required to enter the truck's footprint to manually recover, refuel and inspect the machine (Department of Mines and Petroluem, 2015a). Therefore, the truck is required to be switched to manual mode for the duration of the task. A system interface located inside the light vehicle allows technicians to perform mode changes locally (Today Tonight, 2018). Alternatively, Mine Control is contacted via two-way radio to switch the truck's state to manual mode (Glover, 2016).

Driverless haul trucks can operate in the mine in manual or autonomous mode. Manually operated equipment must identify the mode of operation and satisfy the attentional demands. Sarter and Woods (1995) claim that when designers increase automated mode functions without the support of human cognitive requests, mistakes in mode identification is often the consequence. Errors in identifying operating modes have been a factor in human-machine systems for decades (Monk, 1986). The introduction of driverless haul trucks into a mining operation has the potential to replicate similar mode-related incidents (Sarter, 2008). Confusion around what mode a machine is in is at the heart of automation surprises, where a user instructs the system to do one thing, yet the mode allows it to perform something different (Sarter et al., 1997; Wickens et al., 2016). Studies into mode errors in Aviation have found that minimal system feedback, complex functions and mental models reduce mode awareness of pilots (Björklund et al., 2006; Sarter & Woods, 1995). In addition, the testing of partially automated vehicles is finding similar mode awareness problems in safety drivers, which identified a lack of mode awareness being driven by monitoring inattention (Feldhütter et al., 2019).

The importance of mode monitoring of driverless trucks is to anticipate the actions of the machine. Misconceptions can arise in a persons' mental model of automated systems, which underpins the

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expectation of what the system will do next (Salas et al., 2010). Mental models that are vague and incomplete, invite opportunities for automated systems to engage in functions not assigned by users (Rankin et al., 2016). Equipment operators are able to observe a haul truck's assignment; however, they cannot see the details of that assignment, performance restrictions or decision-makings. Instead, they must rely on their mental model of the driverless truck's function to manage the underlying process (Hansen, 2020; Today Tonight, 2018). For example, a technician will be unsuccessful in attempting to activate an emergency stop a truck manually controlled. Unlike automated motor vehicles, technicians are not expected to immediately regain control of a truck (Kyriakidis et al., 2017). As a result, driverless trucks that are unable to operate automatically come to a controlled stop and are driven manually to a safe location for observation.

Responding to Information and Warnings

Supervisors of driverless technology must be capable of responding to information and warnings. Information and warnings in driverless systems include obstacle detections, health events, proximity detections and truck performances (CAT, 2020; Glover, 2016). Therefore, observing and acting upon this information is critical to supervising automated systems. The modality of the information is presented in various forms, including visual and auditory cues (Caterpillar Global Mining, 2019). Investigations may find that supervisors of automated systems failed to respond to system warning. A critical point in time when someone should have intervened (Department of Mines and Petroluem, 2015c). However, the information that was available, is not necessarily the information that was observed (Dekker, 2014). For information to be observed, cognitive is work required to determine what the system is trying to tell them (Woods, 2018). Woods and Hollnagel (2006) explain that observability not only depends on visual displays, but on personal interests, workload, objects and attentional demands.

Humans are not passive receivers of information; they are actively acquiring, sensemaking and acting upon data. The basic ideology of information processing is surveying the surrounding environment and comparing it to stored memory (Dekker, 2019). For the processing of that memory, Engle (2016) considers Baddeley and Hitch's (1974) working memory system as a temporary storage of information that regulates attentional demands. When determining the relevance of that information, the process of sensemaking fills the gaps between in what was anticipated (remembered) and what was observed (stimulus) (Rankin et al., 2016). When a sudden mismatch occurs between the two, automation surprises start to emerge (De Boer & Dekker, 2017). Information processing has historically been modelled on computer functionality (Eysenck, 1993). Visual information was theorised to be a visual scratchpad that is situated in a working memory. For example, Parasuraman (2000) proposed that information was acquired, analysed, selected and responded to, through these four broad functions of human processing. The functions could then also be used as a basis for automation (de Winter & Dodou, 2011). This notion, however, has been argued as an arbitrary view on information sharing among human-machine systems (Dekker, 2019). Researchers also argue whether input-output devices should resemble human properties, as computer metaphors are artefacts that represent an over-simplification of human thought (Stensson & Jansson, 2014). Processing information is not the only problem, there are other collaborative issues such as transparency (Winfield & Jirotka, 2017), explainability (Gunning, 2016), feedback (Sklar & Sarter, 1999) and literalism (Billings, 2018).

Computers are rarely transparent in what they are doing and how they got there (Skeem & Lowenkamp, 2016). Technology often withholds the data sets that were used to decide an outcome. This is a normal by-product of automated systems. When working with a strong and silent character, the cognitive demands of interpreting its outputs are high (Christoffersen & Woods, 2002). The purpose of data, however, is not just providing information per se, its assisting the supervisor to

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understand what the machine is performing (Miller & Parasuraman, 2007). The critical test is when the device helps humans notice more than what they were specifically looking for or expecting (Sarter and Woods, 1997). The failure of this test is restricted to humans: not identifying information, observing information correctly, forgetting data and negatively reacting (Dekker, 2014a). However, it is a much more complex relationship between human and machine, not the sole processing capability of the human to observe, analyse and respond to information (Woods & Hollnagel, 2006). If humans are going to fulfil their role as machine supervisors, information needs to flow freely between human and machine. The impact of responding to information on supervisory roles are significant, given that the position direct trucks based on the system's information (Caterpillar Global Mining, 2019). Consequently, the available information has become an instrument to inform supervisors on what driverless trucks are likely to do next.

Craftsmanship and Skill Degeneration

While machines are replacing humans in repetitive tasks, a level of Artisan craftsmanship must still be retained (The Wheel Network, 2016). Domain expertise comes to fruition when a machine is unable to resolve a non-designed situation (Endsley, 2018). While automated systems are not known for improvising, the process they are repeating must eventually be improved upon (Trudell et al., 2014). As a machine becomes more reliable, supervisors are denied the opportunity to practice their marginalised existence (Berdicchia & Masino, 2018). The degeneration of skills forms a vicious cycle, where the domain expert begins realising their own incompetence and dependency on machines (Bravo Orellana, 2015). Even though manual skills are mastered through practical application, recalling those craft-like skills in an emergency are reduced (Li et al., 2014). Particular cases in automated driving point towards an over-reliance on automation (Körber et al., 2018). Salas et al. (2010) noted that pilots became heavily dependent on FMS-generated displays, which were reducing their ability to identify the proximity of travel way points. More immediate information is supposedly available in conventional methods such as flight charts. However, there is no real purpose of introducing advantageous technology if the value of the product is not being realised.

Taking advantage of automation means fully understanding the tool humans are using. The uptake is an indication of the trust people have in the machine's ability to operate independently (Hoff & Bashir, 2015). Although Lee and See (2004) observed a high level of trust, the consequence was a much higher dependency on automation. In contrast, a heavily manually operated system was a symbol of distrust, resulting in lower levels of utilisation (Payre et al., 2016). When users manually control a system to "help the robot through some situations…" (MIT Sloan CIO Symposium Videos, 2017), the local adaptions can be confusing when solving beyond the control loop (Dekker, 2003). What procedure to apply and when is the talent, especially when the recovery mission is novel, complex and the procedure is arbitrary (Goteman & Dekker, 2007). Users discovering their own competence in the application of a procedure can be misled, confronted by overlaps in the physical and virtual world that obscures the 'truth' (Reason, 1990). Furthermore, reflexivity is underpinned by the limitations of explaining failure and how their bias impacts on relevance (Holroyd, 2015). The cognitive skills that are vital to solving frontline problems are now on the peripheral, only 'flicking the switch' when needed.

The main reasons why humans are retained in automated processes is to help the machine through 'blind spots' (Noy et al., 2018). Aiding the machine meant that humans must also develop an adequate 'mental model' of how the system works (Strand et al., 2018). Product designers cannot imagine every scenario that is likely to be encountered, even if machine learning can help robots learn various scenarios from big data (Fridman et al., 2018). Therefore, users are often left to work out what the machine is capable of and what it is not (Lynas & Horberry, 2011). Suddenly re-introducing humans back into the control loop can leave them feeling disorientated (SlashGear, 2017). A quick transfer of

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control in aviation is considered by Endsley (2016) to be risky, as pilots are not necessarily aware of the situation that is arising. Recent evidence suggests that driverless processes are becoming so novel and complex, that humans are performing negatively (McKinnon, 2019). Reinforcing supervisors in residual recovery methods to combat non-designed situations may not even be relevant (Payre et al., 2016). Task simulation can mirror the process through virtual reality, however there is no guarantee that the situation will proceed in such a manner (Frimpong et al., 2003). Perhaps, it is not through big data that machines will learn how to perform human work, rather through the coaching and mentoring from the finest experts in the domain.

Intervention and Omission

People will always consider their 'tinkering' as a master stroke. Whether a supervisor is installing a speed zone, managing the fleet's saturation or pursing more tonnes for the day. Intervention is an extension of demonstrating that they know more about the situation than the machine. Conversely, designers view human intervention as an unnecessary step in the process (Caterpillar, n.d.-a). This is due to the fact that functions are already allocated on human and machine strengths (de Winter & Dodou, 2011). However, Dekker and Woods (2002a) rendered the MABA-MABA (Men-Are-Better-At/ Machines-Are-Better-At) approach irrelevant for human-machine systems. This rationale is that human-machine capabilities co-evolve over time. Not only do humans continuously learn how driverless trucks perform, the technology itself is subjected to software upgrades (Today Tonight, 2018). Since the both capabilities are continuously evolving, the evolution could explain the types of acts and omissions of observed on driverless mine sites (Department of Mines and Petroluem, 2014b). For example, a software upgrade may no longer require supervisors to upload a survey, however the automatic upload may not be suitable for use. Therefore, the human needs to intervene in order receive accurate information. This type of localised intervention, however, is often seen as non-routine and contradictory to standardised methods (Dekker et al., 2008).

Designers retain people in automated systems to monitor truck performances. A paradox emerges when deciding whether to intervene in the situation or not (Dekker, 2003). When pre-empting failure, driverless truck supervisors have the option to step-in and control the situation or allow the machine to manage itself. For example, emergency stop devices can bring the fleet to a controlled stop, yet an immediate stop can also generate its own set of risks (Department of Mines and Petroluem, 2015a). For instance, driverless trucks can slide out of lane as they attempt to suddenly stop. Moreover, the situation could be compounded if trucks were descending a ramp into an Active Mining Area (AMA). Conversely, if human intervention avoids failure, then the act is seen as a mark of expertise (Reason, 1990). Then again, if the action is not in accordance with a procedure, it can be considered a non-compliance towards the safety system (Dixon et al., 2007). When it comes to omissions, supervisors can simply be following the procedure, despite foreseeing the potential dangers. This is where human supervisors are held responsible for not intervening when they should have (National Transportation Safety Board, 2018). However, people can be heavily influenced by increases in false alarms and warnings (Wickens et al., 2009). This explains why safety drivers have turned off automated control systems in the past (Coppola, 2018). Nevertheless, closing the performance gap of automated systems is what intervention is striving to do, while omissions can be a sign that people are out-of-the-loop (Endsley & Kiris, 1995).

On the inside, informal work processes are powered people connecting the dots. As previously explained, procedures and RACI's (Responsibilities, Accountabilities, Consulted and Informed) are no more than the designer's imagination of the system (Glover, 2016). Real work is performed along the fringes through information systems and experimental invention (Protzman et al., 2016). Despite the designers' best intentions, there will always be instances where human supervision needs to help

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machines through sight, touch and sound (The Wheel Network, 2016). Therefore, formal processes can be scarcely inadequate to handle goal conflicts among the design and the application (Xu et al., 2007). While standardised work collides with conflicting goal conflicts, the tension between the person omitting just do their part, versus the intervention to ensure work quality, is heightened on the frontline.

Role Transformation

Driverless haul trucks have not only replaced truck drivers, automation creates residual roles and transforms tasks on the peripheral (Caterpillar, 2013). Haul truck drivers now fulfil system support roles, equipment maintainers or ancillary operators on transitioned mine sites (Palmer, 2019). Truck drivers who were once active participants, now passively monitor driverless haul trucks through a computer screen interface (Glover, 2016; Today Tonight, 2018). Monitoring automated systems is a higher level of supervisory control, which expects humans to intervene intermittently during non-designed situations (Banks & Stanton, 2016). People who may never have operated a computer before, are now virtually adjusting lanes, installing speed zones and clearing obstacles (BHP, 2017, July 6). Supervisory roles are not specially taught how to program a truck, they learn automated functions by observing truck movements (Caterpillar Global Mining, 2019, Dec 17). The irony of learning functions through observation is following the strict functional allocation, yet embody the improvised skills to recover from system malfunctions (Baxter et al., 2012).

Truck drivers also have the option to become ancillary operators. Although the activities remain manual, there are additional technological layers operators must learn (Caterpillar, 2013). Technology demands that operators build a mental model of the system (Sarter & Woods, 1994), particularly when operators are not involved in the programming. For example, grader operators may interact closely with the truck to witness how the system responds. Learning by doing helps operators build their knowledge base on automated systems. In addition, the introduction of mode lights requires ancillary operators to understand the meaning of each mode (Today Tonight, 2018). There is also a screen located inside the cab, which provides a predicted path for each driverless truck. Although the predictive capacity increases transparency, it is another capability of observation and information processing (Parasuraman et al., 2000). Traditionally, radio communication would be made in the event an ancillary machine wanted to communicate with a truck (BHP, 2018). However, the control room is now contacted, requiring trucks to be locked from moving before passing (Hansen, 2020).

The inclusion of system roles in automated systems is to aid robots through beyond design situations. Endsley (2017a) points out, however, that humans are not overly skilful in responding to system information. The reason is that supervisory roles are passive monitors of the system, suddenly handed back control of a situation (Reason, 1990). Even with the unique ability to recall domain expertise, supervisory roles are far removed from the immediate process (Miller & Parasuraman, 2007). In addition, the information they receive is filtered by a computer interface (Fridman et al., 2018). For example, intersections designed into the virtual mine model may not actually exist in the physical mine, which can leave mine controllers none-the wiser (Department of Mines and Petroluem, 2015c). There is a skill in locating information that is needed, when it is needed, while filtering through non-essential information to determine what is happening (Endsley, 2016b). When re-introduced back into the control loop, the recovery can become so complex and peculiar, that cognitive gaps in recovering the system safely can emerge (Endsley & Kiris, 1995).

One apparent means of solving the problem is repetitively training people in system recovery and diagnostics. Training humans to manage complex, opaque and tightly coupled systems can be difficult (Billings, 2018). If it were possible to simulate and gameplay an extensive suite of emergency situations, there is no guarantee that they would ever occur (Frimpong et al., 2003). Extensive use of automated systems can lead to deskilling and over-dependence, reducing the cognitive and

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psychomotor skills that required for manual control (Parasuraman & Riley, 1997). Moreover, as automated systems become more reliability, the less domain expertise is actually needed (Wickens et al., 2016). Toyota expressed concerns over automation creating too many laymen and not enough masters of the craft (Tech Light, 2016). By being so far removed, Bleicher (August 2017) explains how the human craft reduces overtime. Despite technology endeavouring to augment human work, it can also degenerate conventional skills and dependency on machines (Bravo Orellana, 2015). The replacement of drivers undoubtedly transforms mine site work, with unconventional situations confronting humans in their new formed roles (Department of Mines and Petroluem, 2014b)

Supervisory Control

Supervisory control was never conceived with humans in mind. Supervisors of automated systems involve a residual set of tasks that engineers are yet to figure out how to automate (Caterpillar Global Mining, 2019). More specifically, the role is in place to respond to non-designed situations to help driverless trucks navigate around them (Hansen, 2020). For example, a driverless truck is capable of identifying an object (Caterpillar, n.d.-c), however it is unable to clear or override the object (Caterpillar Global Mining, 2019). The unrestrained ability of humans to solve problems underpins their residual existence. Examining, monitoring and modifying processes that are otherwise executed by automated systems (Miller & Parasuraman, 2007). While carrying out online problems, supervisors are expected to monitor and tweak the system within the operating limits (Today Tonight, 2018). The difficult component of this, is whether to intervene or not in signs of weakness (Dekker, 2003). Supervisors can find themselves on a pathway to failure (Department of Mines and Petroluem, 2015c). The catch is whether the intervention will be successful in avoiding the situation. It is also can be their responsibility when they failed to intervene before an incident happened (National Transportation Safety Board, 2018). In contrast, if their intervention is unsuccessful, the supervisor is often the one who is accountable (McKinnon, 2019). Therefore, while ever automated systems are only responsible for a narrow set of parameters, the role of the supervisory controller is expected to cover the latter.

Supervisors are not taught how driverless trucks are programmed; they learn by observing them. In addition, supervisors are trained in how to work automation (i.e. press a button), not necessarily how it works (i.e. algorithms, logic) (MIT Sloan CIO Symposium Videos, 2017). Therefore, if a driverless truck performs something unintended, supervisors are not necessarily equipped with the knowledge of the underlying logic (Hebbar, 2017). Although the role is specified, from a design perspective, the re-introductions to control loops during novel situations are not (Endsley, 2016b). Non-designed situations require human improvisations to perform outside the box (Reason, 1990). Enabling people to work well under these circumstances, requires a collection of system knowledge, feedback loops (Sklar & Sarter, 1999) and greater transparency (Zittrain et al., 2018). However, automation is not always easy to work with, often described as an opponent rather than a team player (Christoffersen & Woods, 2002). Since the logic is fixated on achieving its goal, it will literally hold the ball until a human is needed. Multiply this by thirty to fifty times, and this gives some indication of the monitoring demands of a driverless fleet (Today Tonight, 2018). Automation is designed to operate independently, resulting in the human monitoring needs falling to the wayside (Sarter et al., 2007). Consequently, the focus becomes centred around the technology, other than user who is expected to assist the machine through difficult situations.

Assisting automated systems has been described as being bunched (Billings, 2018). Workload that is bunched is long periods of inactivity, followed by short intensive moments (Li et al., 2014). Human workload can appear in these situations as the bottleneck, with the inability of supervisors to respond and recover promptly (Prewett et al., 2010). Quite often, however, the machine has instantly reintroduced them back into a novel situation. Suddenly, the supervisor is confronted with multiple

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failures and is attempting to prioritise what should be done first (Miller & Parasuraman, 2007). Unlike self-driving cars, where the safety driver is expected to take the wheel in any situation and at any speed (Payre et al., 2016). Driverless trucks simply come to a stop wherever control is lost (International Organization for Standardization, 2019). The difficulty, however, for supervisors of driverless trucks is the recovery after a stoppage (Department of Mines and Petroluem, 2014b). For example, the task is likely to be conducted remotely by Mine Control. In addition, field technicians and ancillary operators become the eyes and ears to physically verify the situation. A combination of these roles enables the driverless fleet to execute their daily tasks (Caterpillar Global Mining, 2019). Although certain tasks are specified, situations emerge that require objects to be cleared (rock on road), surveys to be taken (updating mine model) and instructions to be given (send truck away) at various times (Caterpillar, 2013). Therefore, there is a unique relationship that forms among humans and machines, and it is not just those directly supervising the trucks either. The reverberations of supervisory control are as far reaching as drilling, blasting, ancillary equipment, equipment maintenance and the control room (Bellamy & Pravica, 2011).

3.6 Research Question 3

How does human adaptive behavior manage unanticipated machine performances and decide to intervene or not during beyond design performances?

Humans adapt to unanticipated situations by drawing from external information and previous experiences. Deciding whether to intervene or not is based on whether the supervisor believes that the automated system will recover from the situation. External information such as radio calls, weather forecasts and network systems provide external intelligence, while previous experiences of driverless trucks navigating downpours, pit interaction and potential network losses indicate whether intervention should occur. Interventions include speed restrictions, traction controls and setting changes. On the surface, the adaptability of the human can appear unnecessarily tinkering to upset the automated decision-making process. However, it is human who is held accountable if the outcome was negative and the system supervisor was deemed to have the opportunity to intervene and avoid the outcome.

4. DISCUSSION

The literature has highlighted the fascination with creating and designing new products. Especially when those products have the potential to advance the human race and provide a platform for improving the way humans live their lives. However, the immediate approach to designing a new product is to reduce the system into its most basic parts, separating the system into theoretical components to determine how things work (Dekker, 2010). The problem with a reductionist approach to understanding a system, is that a system is defined by what it does, not what it has. Designers are instantly on the back foot, engineering a vehicle to travel from A to B with little knowledge on how the mind made it possible (Victor et al., 2018). Moreover, the various paces of individual technologies have limited the full deployment capability of some AI products. For example, a vehicle may be capable of detecting an object, however it is yet to classify those objects for relevance (Held et al., 2012). Such limitations in the real world has already led to car manufactures turning off automated functionalities to accrue more travel time (Wakabayashi, 2018). Although researchers are attempting to design technology that correctly classify objects in a vehicle's travel path, the technology has a long lead time for being deployed into a real-world environment. Moreover, testing similar technology in the public sector has already highlighted the biases that exist in current engineering practices (Brantingham et al., 2018; Buolamwini & Gebrum, 2018). The impact on driving could see vehicles classifying objects incorrectly and applying the wrong functionality. For instance, the classification of a person for a tree would ignore the fact that the person may cross the road. Furthermore, attempts to navigate a road networks' signs and signals with implied road rules is a significant task for a machine, given that

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it may not have been confronted with those variables through previous interactions (i.e. green light and an emergency vehicle approaching) (Endsley, 2018).

The WA Mining Industry appears to be currently avoiding the complexities of object classification. Driverless haul trucks do not attempt to distinguish between objects, rather stopping when the object meets a size criterion (Caterpillar, 2013). This is a similar function to what Adaptiv claims to have been turned off by Uber (Coppola, 2018). Since the technology struggles to distinguish between objects, the vehicle would be constantly reacting to adversarial conditions on the side of the road (Eykholt et al., 2018). By turning off the object recognition function, the vehicle could then travel uninterruptedly and seek guidance from the supervisor only when required (National Transportation Safety Board, 2018). The circumstances are, however, marginally different, with haul trucks unlikely to be carrying passengers and therefore lowering the likelihood. Mining companies also have a team of well-trained professionals who are taught how the processes support the technology (ADVI Hub, 2016). Although, those processes are usually a set of residual tasks that were unable to be engineered into a machine. Standardised processes are only as effective as the designers' imagination, leaving the non-designed situations up to human intuition (Noy et al., 2018). Sharing the control between human and machine appears more realistic in the short term, becoming more transparent in the decision-making process to allow humans to navigate the vehicles through complex situations. Despite this, Intellectual Property and data protection concerns are stifling the pursuit of shared management (World Intellectual Property Organization, 2019), the algorithms are at the heart of any business product (Mitchell, 2018). On the other hand, for the technology to become truly 'self-managed', researchers and engineers must figure out how the technology can be more adaptive like a human. Until then, designers will have to do more to make shared technology more user-centered, allowing people to be more supportive in aiding driverless systems through complex situations (Fridman, 2018).

The literature has highlighted, however, that technology has not always been developed with humans in mind. The focus has always been to replicate and replace human labour, not partially succeed and allow humans to take control of the system. Through the deployment of automation in industry though, researchers have revealed that there is more to making a system work than allocating 25ecognize25ed functions to various roles (Strand et al., 2014). Disruptions may arise that requires the function owner to think outside the box. For example, if a weather system moves in, driverless machines and automated aircrafts are currently ill-equipped to 25ecognize the changing conditions (Jamasmie, 2019). The modes of communication between agents are not simple enough to explain that a weather system is approaching either, requiring the automated system to change speed or direction. Obviously, if the human supervisor was to argue 'that the task was not their job', the machine would likely put passengers at-risk by functioning as if the weather conditions were not present. The interface between human and machine is where this research investigation begins, not where it ends. Driverless technology has changed the connections that manual driving had originally formed. There have been numerous incidents on WA mine sites since the driverless technology was introduced, leaving researchers wondering why. The lack of knowledge in this field provides focus and reasoning, illustrating what research is yet to be fully understood and how objective findings can be drawn.

5. KNOWLEDGE GAPS

The reasons for incidents involving driverless haul trucks across the WA Mining Industry remains relatively unknown. Although individual investigations may point out errors from either human or machine, research is yet to explain the systemic influences of engineering a haulage system. For example, there is more to a truck–on–truck collision than an inability of humans to respond quick enough to a down pour of rain (Jamasmie, 2019). Certainly, having a process around the situation may have coordinated the response to reduce truck speed. However, this observation is after the fact, neatly

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joining the dots between the driverless machines' limitations and the expectation of human supervisors to manage the rest. It is often assumed that human supervisors will apply a smooth layer of local adaption to fill in the shortfalls of automation; becoming the 'eyes and ears of the operation'. Whether a human should adapt a localised practice is not always clear, facing various situations that rarely unfold in a predictable manner. Even though the assumption is that driverless machines are a like-for-like replacement for truck drivers, this view could not be further from the truth. Not only do mining companies transfer agency to the vendor when they automate the fleet, they appear to be left in the dark on the decision-making process of their haul trucks (Mitchell, 2018).

This is where the gap becomes apparent. What was once a haul truck system that was under local control is now transferred to a vendor's central algorithm. The interactions change and require other variables to adapt to the new relationships that are co-evolving on the mine. For instance, a truck no longer makes a call over the radio to pass a working ancillary machine. Instead, a screen interface is used to provide the intended route and alerts operators if they are too close. The different modes of communication between mining equipment on a haul road demonstrates one element of the adaption's humans are making. The full capability of a driverless machine is not necessarily explained to the user either, learning the strengths and weaknesses by observing its functionality over time. Therefore, a driverless machine's full capability is rarely understood upfront, leaning on local users to press the buttons along the fringes to 'feel out' the machine's parameters (i.e. what can this truck actually do?). Although there are processes designed to support the system's application, the processes are based on how to work the system (e.g. press the button), not how the system actually works (e.g. how does it function?). As the decision-making is not programmed by the user, the system has performed some surprising functions. Those functions are not necessarily aligned to the users' objectives either, driven by the designers' imagination and ability to reverse engineer best practices in mining. The impact of the outcomes arising from automating machinery sketches a landscape where unique incidents start to unfold, for which safety research must help the WA Mining Industry to understand.

With a backdrop of the arrangements that enable humans to be technically substituted for a machine, the emergence of uncontrolled situations gives rise to the potential negative consequences. There is no research exploring why truck slides out of lane and the potential those situations can cause. Perhaps the sensitivity around new technology and the competitive advantage of being first, hinders the WA Mining Industry's ability to share lessons that are being learnt. Moreover, if the new risk profile of driverless haul trucks is unknown, the risks can never be controlled. For instance, the LiDAR and Radar systems on trucks are not capable of predicting slippery road conditions, what other mitigating controls must be put in place? The explanation of the sequence of events and the contributing factors that led to the incident are paramount when improving the safety system. Research must go beyond the investigation findings that evaluates the trucks actions against its capability, which often reinforces the common statement that the machine 'did exactly what it was supposed to do'. If this approach to understanding incidents was to continue, the WA Mining Industry's knowledge will be forever constrained by the world imagined by the product designer. The limitations of the technology and local user adaptions that are taking place are forming new methods of work. The industry's assumption is that truck drivers are being replaced, and that technology removes the safety risks associated with haul trucks. However, the entire process is far from being substituted, leaving a set of residual processes that were technically difficult to automate. The interaction with driverless machines in operation still poses risks to those who remain. Moreover, the uncontrolled nature of reversing a driverless vehicle over a waste dump brings to mind other situations in which those circumstances could arise. Besides reporting the cause as the humans' inability to adapt, research must offer more constructive explanations to manage risk, enabling the industry to develop effective systems of work when deploying driverless haul trucks.

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6. CONCLUSIONS

Exploring the experiences of other benchmark industries in their application of computerised control systems is fruitful. The context in which negative events occur is important to examine, given the transferrable similarities in the way the systems are designed and how professionals are using them. Although there are many studies that consider the consequences of automation in various high-risk industries, research is yet to comprehensively analyse what impact artificial intelligent machines are having on WA mine sites. Furthermore, in light of recent events (McKinnon, 2019), understanding why incidents involving driverless haul trucks are occurring in particular instances (Department of Mines and Petroluem, 2014b). Thus, understanding the interactions between human and machine will explain how the relationship is evolving in WA. Coinciding with theoretical models of the human-machine relationship (Hancock et al., 2013), an examination of the contributing factors leading to incidents are needed. This research endeavors to extend this knowledge through real-world examples, demonstrating the causal pathways that have generated on a mine site.

The knowledge expressed throughout this study can inform the design of driverless technology, support the formation of work processes and accommodate the local adaptions of human users. Previous studies indicate that a human-centered design is central to positive performances in both safety and productivity (de Visser et al., 2018). Researching the context behind a range of incidents involving driverless vehicles has greater implications for the WA Mining Industry. The study highlights a range of systematic trends that are not present in any one investigation. Furthermore, the analysis provides an in-depth understanding of the phenomenon, which are often omitted and filtered when publishing the investigation findings publicly. The underlying hypothesis of this research is that incidents involving driverless vehicles are being shaped by WA Mining Industry's assumptions, which has inflated the expectation that the technology is a like-for-like replacement for haul truck drivers (Ernst and Young, 2019). However, as this study will explain, the technology is far from human-like. Despite its recent advancements, local domain expertise continues to sooth the novelties along the fringes, while the boundaries of its capability are continuously learn.

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Authors

Dr Todd Pascoe, MOccMedHlth&SaF, PhD is a Business Improvement Specialist in the Western Australian Mining Industry. Todd has worked in the Western Australian Mining Industry for over 10 years in specialised roles across Health and Safety, Mining Production and Business Improvement. Todd has extensive operational experience in the deployment and day-to-day running of an autonomous haulage system, including the development of risk assessments, health and safety systems and operational efficiencies.

Dr Shirley McGough, RN, MHN, Dip App Sc, BSc (Nursing), PG(Nurs), MNurs, PhD, Senior Fellow, Higher Education Academy. Shirley currently works at Curtin University and teaches mental health, behavioural and biosciences, conducts research and evidenced based practice. Shirley has extensive clinical and research experience in mental health and wellbeing, with substantial educational and leadership experience in the University sector.

Dr Janis Jansz, RN, RM., Dip. Tch, BSc. Grad. Dip. OHS, MPH, PhD, FSIA is an Associate Professor in Occupational Health, Safety and Environmental Health in the Western Australian School of Mines: Minerals, Energy and Chemical Engineering at Curtin University in Western Australia and is a Professor at the Xi'an University of Science and Technology, China. She also works for the Healthforce Group. Janis is the Director of the World Safety Organization National Office for Australia and Vice President of the Occupational Health Society of Australia. She has been awarded Life Membership of the Australian Institute of Health and Safety for many years of work improving, teaching and conducting research to advance occupational safety and health practices and for taking a leadership role the safety and health profession.

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