School of Public Health

An Evaluation of Driverless Haul Truck Incidents on a Mine Site: A Mixed Methodology

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Human Ethics. The research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research (2007) – updated March 2014. The proposed research study received human research ethics approval from the Curtin University Human Research Ethics Committee (EC00262), Approval Number HRE2017-0844.

Signature:

Date: August 2020

Abstract

Across Western Australia (WA), driverless haul trucks are being rapidly deployed on mine sites. Despite the direct benefits of removing the exposure to manual truck driving hazards, new incidents involving automated haul trucks are starting to emerge. Therefore, it is now evident that driverless technology introduces risks beyond those found in conventional mining operations.

The research aim was to evaluate driverless haul truck incidents on a mine site, as well as the contributing factors that led to a loss of control. A mine site in Western Australia (WA) recently transitioned to a fully automated truck operation. The first objective was to describe the hazards that emerged through the introduction of unconventional mining techniques at this work site. Secondly, explain the theoretical viewpoints that are influencing the approach to automation and describe the relationship developing among components that make up the performance of a complex system. Thirdly, outline the processes designed to support automation while determining whether those processes equip operators to improvise during non-designed situations. Fourth, identify the human adaptive behaviours for managing unanticipated machines performances, including the decisions to intervene or not when the system appears to be performing beyond design. Finally, to provide the Western Australian (WA) Mining Industry with an in-depth understanding of the changes to a site's risk profile while recommending strategies to control new risks that emerge.

A multi-industry analysis of the literature highlights the lessons of human factors. The review critically evaluated safety-related themes in human-machine systems across multiple industries. The aim was to explore the teachings of engineering human-machine systems, connecting to the residual consequences of introducing driverless truck on a mine site. The method identified keywords, phrases and contributing factors that were leading to driverless truck incidents. The literature was categorised into nine publication types, 11 separate industries associated with 182 pieces of information. Three broad categories were synthesised into (i) technology; (ii) processes; and (iii) human factors. Within those categories, there were 23 research themes found under the human-machine domain. The findings highlighted that the mining industry's knowledge gaps and can inform the design of driverless technology, the formation of work processes and accommodation of local human adaption.

The research methodology adopted a convergent parallel design to achieve the research aim and objectives. The first phase collected information on the predictors (i.e. safety incidents) from the mine site's safety incident database. Collecting incident data enabled the researcher to understand the number and types of incidents involving driverless trucks. The number of hours driven was also collected to normalise and compare the performance against the manual truck operation. A chi-square test determine a statistical significance between expected and observed frequencies. An exploratory-based technique yielded descriptive statistics, which summarised and enhanced the user's understanding of manual and automated operating systems. This method gave rise to the underlying causes of those events and associated hazards. In phase two the researcher facilitated 25 face-to-face interviews with a stratified (5.5%) cross-section of the workforce. The conversations were digitally recorded and uploaded into audio software for transcription. The collection from multiple cases was analysed through cross-case displays and always compared for themes when coding abductively. Field observations were recorded through handwritten notes on the different types of phenomenon observed firsthand. Moreover, the supporting documentation for the observed processes was collected, which outlined the work designed to coordinate human-machine interfaces.

The research results are comprised of five peer-reviewed journal articles that are under review for consideration of publication. The research findings inferred that unconventional incidents involving driverless trucks are emerging, with new and transformed hazards. The epistemology of automation was one of reduction, appearing more intelligent by excluding non-designed situations from operational parameters. Mineworkers' experiences indicated the introduction of new hazards and risks. A high level of trust developed, yet the system focused on performing its role and was unlikely to help others. There were also new skills developed by operators, including setting loading locations, calling in trucks and sending them away through in-cab displays. Local human adaptions occurred during a non-designed situation while personnel remaining in the loop via computer interfaces and radio communication.

An incident analysis found that 432 driverless truck incidents occurred between financial years 2014 to 2018; with an incident frequency of 864.4 events per million hours driven. The total number of manual incidents was 566, which resulted in 970.2 incidents per million hours worked. The majority of driverless incidents recorded were lane breaches (44.0%), proximity detections (31.3%) and truck damage (7.4%). The hazards associated with driverless events encompassed; road conditions (26.9%); clean-up machine interactions (15.3%); and road obstacles (10.9%). Whereas in manual, a large portion of manual truck incidents included;

driver injuries (24.0%); truck contact (23.7%); and procedural breaches (18.0%). Manual truck hazards were driver awareness (24.7%), loading unit interactions (18.9%) and truck ergonomics (15.5%). Data analysis illustrated how technology transformed the mine site's risk profile, rather than underpin the popular notion that automation eliminates safety risk.

Following the above analysis, the theoretical perspectives underpinning the approach to automation identified that artificial intelligence offered a promising route to a sustainable future for the WA Mining Industry, which automation will play a pivotal role. This study draws upon artificial intelligent systems research, comparing the practical constraints applied to smart systems in recognising dark human faces, classifying reptiles correctly, appropriate areas for policing and the likelihood of recidivism. Despite the predictive value proposition of artificial intelligence systems, the machines' predictive capacity generally puts non-designed situations outside of its operational parameters, making its narrow and very bias view of the world appear to be more intelligent. Therefore, driverless technology must embrace the intricacies of a mining operation, otherwise the industry may miss the mark and witness similar examples to when turtles were classified as rifles.

The research explores the experiences of mine employees working with driverless technology. The study examined the practical skills of frontline workers to understand risk, trust and teamwork associated with driverless truck operations. The transcripts of the interviews were analysed thematically to identify patterns and themes in the reported phenomena. Participants reported the emergence of new hazards and risks but built a high level of trust via automotive trucks predictable travel paths, adherence to instructions and diligence in stopping for objects on the road. Despite being deemed a team player in fulfilling their role, driverless trucks do not assist others. The results indicate that mineworkers develop a high level of trust with automated systems. The high confidence was despite research participants facing new risks and unanticipated situations.

Role transformations investigated mineworkers' new skills in driverless operations since the replacement of truck drivers with automation. The study explored the viewpoints of mineworkers on the role transformation, residual workload and local worker adaptions. A thematic analysis identified new skills developed rather than traditional skills diminish (96%). Participants described the workload of system-based roles as short intensive moments, with a majority (62%) of participants agreeing that residual activities were generated from machine limitations. A high number of participates (68%) reported facing situations outside of a procedure, with in-cab displays and radio calls keeping participants in the loop of the system.

The findings highlight that mineworkers develop new skills in driverless operations, yet residual extra workload emerges and requires workers to think outside the box and monitor situations strictly to remain in the loop.

The recommendations of this research emphasise the need to understand the new hazards and risks introduced through automation. Mining operators deploying driverless technology are recommended to update their risk profiles to reflect the results of this study. By updating the risk profile, the operation can redesign its safety systems, mining practices, and risk controls to embrace the human-machine interface. The results can also assist mining companies in determining whether driverless technology is suitable for their operation. The Department of Mines, Industry Regulation and Safety is recommended to update their Code of Practice: safe mobile autonomous mining in Western Australia, which needs to reflect the new hazards and risks identified through the research findings. It is equally essential for vendors of driverless technology to learn from practical experiences of this deployment, therefore improving the technology's response to hazards and mechanisms for interfacing with humans.

Recommendations of this research will assist the Mining Industry, mining operators, product vendors, regulatory authorities and frontline workers to safely deploy driverless haul truck technology. Moreover, this study paves the way for further research into the safety implications of driverless technology, as additional mine sites across Australia integrate this new technology in their operation.

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Finally, I would like to thank Tim Day and Rod Ballinger, who had planted the idea to investigate incidents involving driverless haul trucks on mine sites. If it was not for their motivation to improve safety across the WA mining industry, this phenomenon would not have been researched.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1. Background

In 1985, the haul truck was selected as the first machine to be automated for its apparent simplicity and scale. Automation has always inspired manufacturers to develop automated equipment, however the technology was originally considered a non-viable option for the mining industry (Glover, 2016). Technology advancements soon changed the capability of automated equipment, which showcased the opportunity automation can bring to safety and productivity.

With a genuine belief that haul truck automation could be achieved, manufacturers began experimenting with Global Positioning Systems (GPS). GPS coordinates and travel pathways were traced out with limited windows of opportunity to access global satellite communications. Navigating the mining environment meant exploring how truck drivers behaved and what functions the remote control system would perform (Caterpillar Global Mining, 2015). Prototypes eventually started to emerge in mining exhibitions, Defense Advanced Research Projects Agency (DARPA) challenges in the United States (Glover, 2016) and the initiation of trials in Western Australian (WA) mining industries (Schmidt, 2019; Validakis, 2014).

The introduction into the WA mining industry was a remarkable step in removing human exposure to driving hazards. Removing human exposure can reduce recordable injuries and significant events involving haul trucks on mine sites (Palmer, 2019). There are many safety factors that contribute to driver harm when operating haul trucks; including sitting for long periods, driving over rough road conditions and being loaded heavily by excavators. Therefore, the removal of drivers can have an immediate positive impact on safety.

Despite the direct benefits of removing human exposure, there have been a number of significant incidents involving driverless trucks. Since 2013, there have been 21 notifiable automated truck incidents reported in the Safety Regulation System (SRS) (Department of Mines Industry Regulation and Safety, n.d.). The incidents highlight the unconventional nature in which driverless haul truck incidents can occur. As a consequence, the Department of Mines and Petroleum (2014) published a Mines Safety Bulletin seeking the safe use of autonomous equipment on mine sites. The bulletin summarised four incidents involving driverless haul trucks: (1) A driverless haul truck reversed over a waste dump; (2) a manual water truck and a driverless truck collided on a haul road intersection; (3) a driverless truck collided with a manual grader when it pulled out in front of the truck; and (4) a driverless truck backed over a tip head that had been undercut.

The following year the Department of Mines and Petroleum (2015) released the Code of Practice: Safe mobile autonomous mining in Western Australia to provide the WA mining industry with practical guidance in achieving occupational health and safety standards. The code states that, "The operation of autonomous equipment can introduce hazardous situations not normally encountered on a conventional manned mine site" (Department of Mines and Petroleum, 2015, p. 4). In addition, the automated technology can change the conventional safety systems of a mining operation. The change has already been observed in the Aviation Industry: "Automation, or any new technology, changes the tasks that it is designed to support or replace" (Dekker, 2014, p. 207). The changes have resulted in more recent events, where a driverless truck reversed into another driverless truck that lost network communications (McKinnon, 2019). While another automated truck had slid out of lane and collided with second driverless truck after a downpour of rain (Jamasmie, 2019). The evolving situation highlights the need for more research to assist the Western Australian mining industry to fully understand why automated incidents occur.

It is plausible that the automated system controlling driverless trucks are contributing to workplace incidents, given that the driverless systems operate independently for a large part of the cycle. Unravelling the contributing factors that are leading to a loss of control can assist in the development of interventions to improve human-machine collaboration. Moreover, studying the context of mobile automated systems within mine sites explores the practical constraints and consequences of replacing trucks drivers. Traditional risk evaluation methods such as job hazard analysis, failure mode and effect analysis are only as good as the understanding of the system and how its components interact. A purpose of this research was to highlight new hazard pathways that have been created. The industry cannot expect to identify hazards or evaluate failure modes that they do not understand or know exist. If the industry knew what those failures were then traditional methods may have identified them based on data and facts. However, since the research site was the very first mine to automate, this data did not exist.

There are many countries now deploying driverless haul trucks to realise the economic and safety benefits of automation. However, with unconventional incidents starting to emerge (Department of Mines and Petroleum, 2014), there is a need to understand these driverless truck incidents and their contributing factors. Therefore, the following research aim and objectives have been designed to generate this new knowledge.

1.2. Research Aim and Objectives

The aim of this research was to evaluate driverless haul truck incidents on a mine site by describing the contributing factors that led to a loss of control.

The objectives of this research were to:

1. Describe the hazards that have emerged through the introduction of unconventional mining techniques and the extent risk profile changes have contributed to workplace incidents.
2. Explain the theoretical viewpoints of a system that is influencing the company's approach to haul truck automation and relationship emerging between components that make up the performance of a complex system.
3. Outline how system processes are designed to support haul truck automation and determine if operators are equipped to improvise in non-designed situations.
4. Determine if there are human adaptive behaviours managing unanticipated machine performances and how operators decide to intervene or not when the system appears to be performing out-of-design parameters.
5. Provide the Western Australian Mining Industry with an in-depth understanding of the changes to a mine site's risk profile through the introduction of haul truck automation and recommend strategies to control new risks that have emerged.

1.3. Current Industry Knowledge

Incidents involving haul trucks on a mine site has been well researched when under manual control (Drury, Porter, & Dempsey, 2012). However, since truck drivers have been replaced, there is little knowledge of the full scale of driverless incidents that have occurred. Despite a small number of notifiable incidents reported in the safety regulation system, these reports do not include the profile of incidents involving driverless trucks. In addition, the notifiable summaries do not provide an in-depth investigation or evaluation of the situations that can emerge. Department of Mines and Petroleum (2015) provide examples of incidents and hazard controls, however the examples are general in nature and are not based on a risk profile. Therefore, new knowledge is needed to understand the situations that being encountered and what hazards are contributing to them.

1.4. New Knowledge

The findings of this research document a shift in how safety systems manage haul truck operations on mine sites, complements the lessons of human factors across high-risk industries and makes the unique connection to haul truck automation in the Western Australia mining industry.

Through the findings of this research new knowledge has been generated surrounding the introduction of new hazards and risks of harm. These unconventional risks transform a mine site's risk profile, which requires the review of safety systems to manage human-machine interactions. This research identified unconventional incidents involving driverless haul trucks. The most frequent incidents include lane breaches, proximity detections and process breaches. These most frequent and associated hazards involved road conditions, clean-up machine interactions and road obstacles. Legitimising the current progress of artificial intelligence and highlighting the residual human work, the need to enhance the users' knowledge of computer programming and machine learning techniques has been identified. In contrast to external perceptions that automation has eliminated human tasks, driverless technology created new roles and transformed existing activities. The new tasks included building the virtual mine model, clearing objects detected by the trucks and calling trucks into the loading area. The results confirmed that haul truck automation transforms mining roles, with residual tasks that require local adaptions to overcome non-designed situations.

The research findings identified that artificial intelligence has offered a promising route to a sustainable future for the WA mining industry. The success, however, hinges on the ability of artificial intelligence to embody the complexity around it. The theoretical views surrounding automation is one of reduction. However, reductionism has already faced practical constraints and generally places non-designed situations outside of its parameters. The technology then appears to be more intelligent by what it excludes. Therefore, if the technology cannot embrace the intricacies of a mining environment, it may face similar instances where technology is expected to operate beyond its context.

Exploring the experiences of mineworkers found that personnel do believe that driverless technology has introduced new hazards and risks of harm. Those hazards included virtual and real-world distinctions, human complacency and communication losses. In addition, the mineworkers developed a high level of trust towards driverless technology. The trust was underpinned by predicted pathways, strict adherence to instructions and trucks stopping for small objects. Moreover, mining employees trust levels never wavered after being involved in a driverless truck incident or unintended situation. Despite mineworkers considering driverless technology to play its role effectively, the system does not necessarily engage in team play.

The research findings are original and make significant contributions to the Western Australian mining industry and internationally where automated haul trucks are used in mining. It is argued that the research findings will be utilised more broadly across the Australian mining industry. The study reveals the incidents involving driverless haul trucks and the factors that lead to a loss of control.

1.5. Research Significance

There is currently no research published on driverless truck incidents and the factors leading to losses of control. Although the assumption is often that automation has eliminated safety risk by removing human exposure, this research reveals that risk exposures remain for system-based roles, manual equipment operators and supervisors. In addition, an evaluation of the types of driverless incidents are yet to be published. Therefore, this research fills that gap and provides in-depth knowledge into driverless haul truck incidents.

This study also identified that there are new hazards and risks that were introduced by haul truck automation on the mine site. This new risk profile provides an opportunity for the Western Australian mining industry to update its Code of Practice for the safe use of autonomous mobile equipment. Moreover, this research provides empirical evidence of the safety risks associated with driverless technology, which allows mining companies looking to deploy driverless trucks the opportunity to develop effective risk management strategies.

The theoretical viewpoints that underpin driverless technology was revealed. The reduction of a haulage system highlights the practical constraints that are applied when attempting to reverse engineer processes to human work. By uncovering the practical constraints of a driverless trucks' predictive capacity, mining operators are now equipped with the types of non-designed situations that emerge. Those non-designed situations are what often causes human intervention and breakdowns between mineworkers and driverless trucks. The research can be used to improve the WA mining industry's knowledge in driverless technology and equip them to work with product vendors in embracing the intricacies of their mining operation.

The practical experiences of mineworkers interacting with driverless haul trucks was insightful. The hazards and risks shared by participants highlighted the transformation of risk. The experiences of mineworkers were consistent with the insights of the incident analysis. What was telling, however, is how high the participants trust levels were for automation. Despite participants being involved in an incidents or unintended situation, their trust levels did not waiver. What this explains is how the transparency of actions and performance that are in line with design, result in personnel maintaining trust levels regardless of the outcome. The caution, however, is that mineworkers may become complacent and rely too heavily on the technology. Although the driverless trucks were considered by the participants to play their role, they were not necessarily considered team players as the technology just operated as programmed. Therefore, the experiences of mineworkers provide an opportunity for the WA mining industry to appreciate the new risks, understand the balance of worker trust and work with product vendors in developing automated systems to engage in teamwork.

The research found that the introduction of driverless haul trucks transformed the roles and tasks of mineworkers. Despite the significant reduction in haul truck driving, new system-based roles were developed, while conventional roles were redefined. The study highlighted the residual activities such as building virtual mine models, clearing detected objects and calling trust into loading areas. The experiences had a profound impact on mineworkers, with new technology and computer-based skills being developed. The insights from this research highlight the future pathways for mineworkers and the human capabilities that are required in a driverless truck system.

1.6. Limitations of Research

The driverless truck incidents evaluated in this research were only analysed from a single Western Australian mine site. There are also an increasing number of driverless truck products, which have different functions and capabilities. It is therefore assumed that the incidents involving those automated systems could be different.

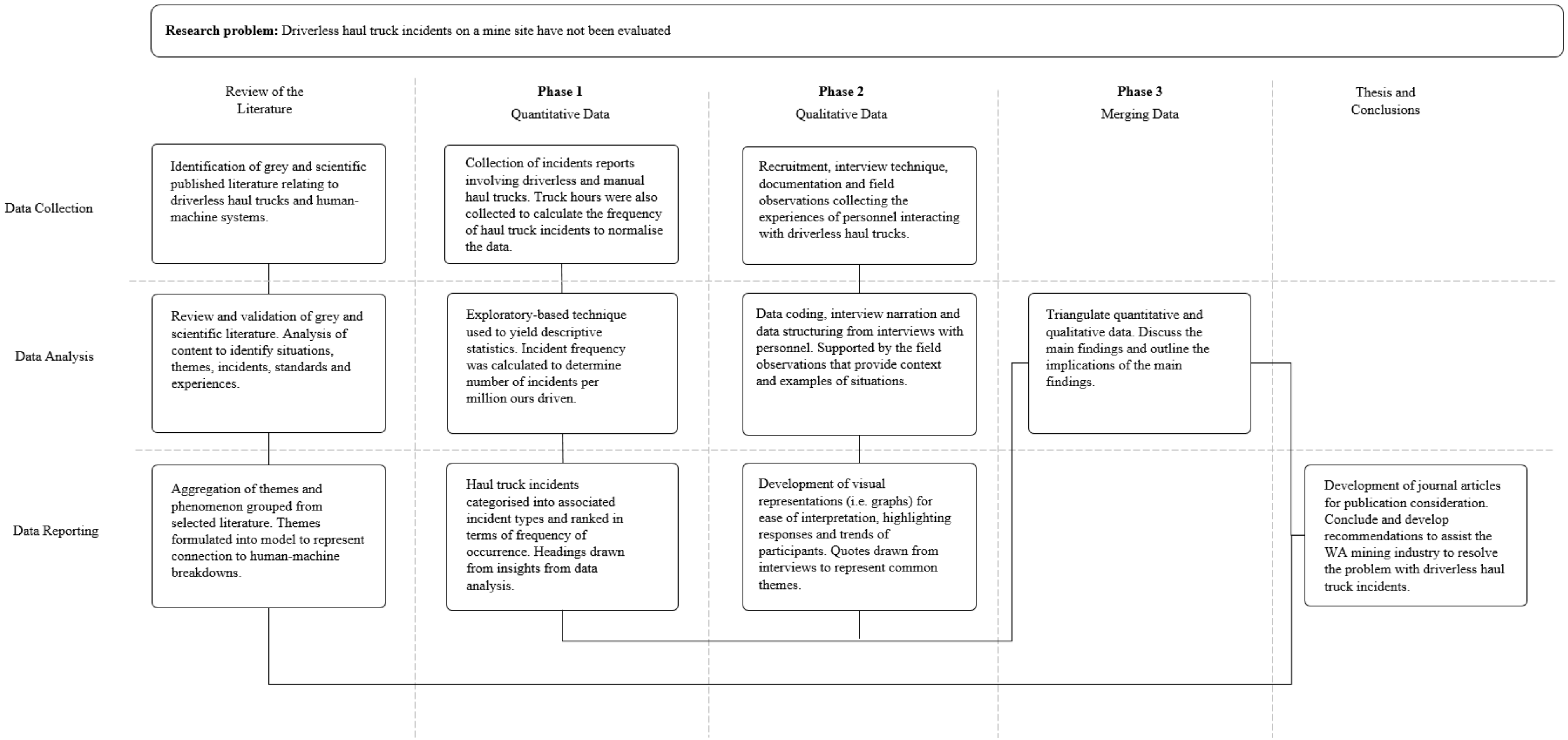
Despite the high level of reporting on the mine site, not every incident may have been reported. As a result, there may be incidents or hazards that existed in the operation, however, they were not reported in the incident database. Moreover, the incidents were coded by the researcher, therefore the incident and hazards descriptions may differ depending on other researchers' background experience.

1.7. Thesis Structure

This thesis is comprised of eight chapters. The research begins with an introductory chapter describing the background to driverless trucks incidents. Chapter 2 embarks on a literature review, exploring human-machine systems across multiple industries and their connection to truck automation. The research methodology is detailed in Chapter 3, outlining how this mixed methodology utilised a convergent parallel design to maximise the results. Chapter 4 analyses driverless truck incidents to manual truck incidents, revealing the changes to the site's risk profile. In Chapter 5, the theoretical perspectives that underpin automation are uncovered, highlighting the practical constraints of artificial intelligence. Chapter 6 explores the practical experiences of mineworkers and how driverless technology has influenced their perspectives on risk, trust and teamwork. These experiences are extended in Chapter 7, where the research seeks the perspectives on the changes to roles and skills through automation. Results are discussed in Chapter 8, with the conclusions and recommendations closing out the research in Chapter 9.

Figure 1.

Research roadmap



Chapter 1

Introduction

The introductory chapter has described the background information leading to the evaluation of driverless haul truck incidents on a mine site. The background information was then followed by the study's aim and objectives. Current industry knowledge outlined what was currently known about driverless haul truck incidents, highlighting the where new knowledge has now been created. The significance of the research was described and illustrated how the industry can progress with more foresight. The limitations were also described, followed by collectively outlining the research report.

Chapter 2

Literature Review

The literature review in Chapter 2 explores the lessons of engineering human machine systems and the residual consequence of automation. Three broad categories are sythnesised to include: (i) technology; (ii) processes; (iii) human factors. Within those three categories, 23 research themes were found under the human-machine system domain, highlighting the knowledge gaps in informing the design and operation of driverless technology.

Chapter 3

Methodology

The methods chapter outlines the three phases of the research. The first phase analyses the quantitative data by adopting an exploratory-based technique to yield descriptive statistics. The second phase analyses qualitative data collected from multiple cases and analysed through cross-case displays. The third phase merged both forms of analysis, constructing meta-inferences by comparing quantitative and qualitative data via triangulation.

Chapter 4

From Truck Driver Awareness to Object Recognition: A Tiger Never Changes its Stripes

This chapter analyses incidents involving driverless haul trucks and compares them to manual truck incidents. Incidents are compared based on their characteristics and investigation findings. Data analysis demonstrates how technology transformed the mine site's risk profile, rather than underpin the popular notion that automation eliminates safety risk.

Chapter 5

Haul Truck Automation: Beyond Reductionism to Avoid Seeing Turtles as Rifles

Chapter 5 presents the theoretical perspectives that underpin the approach to haul truck automation. Reductionism has already applied practical constraints on artificial intelligence, therefore its success hinges on the ability to embody the complexity. Its predictive capacity generally puts non-designed situations outside of its parameters, making its bias and narrow view appear more intelligent. This chapter highlights that technology must embrace the intricacies of a mining, otherwise the industry may miss the mark and witness similar examples of turtles being classified as rifles.

Chapter 6

The Experiences of Mineworkers Interacting With Driverless Trucks: Risk, Trust and Teamwork

This chapter investigates the practical experiences of mineworkers interacting with driverless technology. The results from mineworker interviews indicate new hazards and risks have been introduced through automation. Despite this, high levels of trust were developed for driverless technology. Although the technology is perceived to play its role, it does not assist mineworkers and engage in team play.

Chapter 7

From Truck Driver to Systems Engineer: Transforming the Miners' Contribution

Chapter 7 explores mineworker perspectives on role transformations, residual workload and local adaptions when transitioning to a driverless operation. The findings highlight the introduction of new roles and transformation of existing employee roles. Participants explain new tasks such as building a virtual mine model, clearing of objects and calling trucks into loading areas. Despite truck driving tasks drastically reducing, new technology skills and computer-based skills were developed in assisting automation vehicles through non-designed situations.

Chapter 8

Discussion

In Chapter 8 the discussion reflects on the findings of the research to contextualise against existing literature. The discussion describes how the findings integrate with existing knowledge and what the research contributes to the body of knowledge. In addition, the implications of research findings are discussed, highlight where further research is needed and where attention is required as driverless technology evolves.

Chapter 9

Conclusions and Recommendations

Chapter 9 provides concluding remarks and makes a number of recommendations in addressing the findings of the research. The conclusion provides finishing remarks that summarize important research findings. It provides a way forward for the Western Australian mining industries and recommends risk management strategies to navigate the application of driverless technology.

1.8. Introduction Summary

This research was the first study to evaluate driverless haul trucks incidents on a Western Australian mine site by describing the factors that led to a loss of control. The following chapter is a literature review that explores the lessons of engineering human-machine systems and the residual consequences of introducing driverless haul trucks. Note that a human-machine system is the integration human operators with machine, with an emphasis on interacting as a single entity.

Chapter 2

Literature Review

This chapter has been submitted for the publication:

Pascoe, T., McGough, S. & Jansz, J. (2020). A multi-industry analysis of human-machine systems: the connection to truck automation. *Cognition, Technology and Work.*

2.1. Abstract

This research literature review is a critical review of safety-related themes in human-machine systems across multiple industries. The aim of this literature review was 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 used involved identifying key words, phrases and contributing factors, which have led to driverless truck incident events to-date. An eligibility criterion aided the selection of relevant human factors research associated with artificial intelligence, automated systems and augmentation. The literature is arranged into 9 publication types, with 11 separate industries associated within 182 pieces of research material. Three broad categories were synthesised to include: (i) technology; (ii) processes; and (iii) human factors: with three research questions framing how this study applies to truck automation. Within these categories, 23 research themes were found under the human-machine system domain. The findings highlight the Mining Industry's knowledge gaps to improve the design of driverless technology, formation of work processes and the accommodation of local human adaption.

2.2. Introduction

More than a decade ago, Rio Tinto trialed the first driverless haul truck in Western Australia. Driverless haul trucks do not need a safety driver and can operate independently via machine algorithms (Hamada & Saito, 2018). Machine algorithms are responsible for controlling the actions of a haul truck and enable every truck to perform within the same operating parameters. The only difference is that the trucks are assigned individual tasks by system-based roles in order to deliver the daily plan. In addition, the system-based roles and ancillary equipment operators complete leftover tasks that are designed to help driverless trucks through non-designed situations (Caterpillar, 2013). With residual tasks still being undertaken, driverless trucks are considered semi-automated and frequently interact with humans to achieve operational tasks.

Driverless haul trucks have introduced a new set of hazards and risks, which appear to be transforming the risk profile of mine sites who are deploying this automated technology (Department of Mines and Petroleum, 2014a). The inherent nature of automated system design and architecture introduce properties like complexity, reductionism, literalism, and brittleness into the system (Billings, 2018; Dekker, 2014b; Ito & Howe, 2016). An engineered human-machine system can be considered a 'joint' system, where both agents are required to collaborate as a team. It is evident that the Aviation Industry has learnt the most on how to cooperate human and machine in one system (Christofferson & Woods, 2002). 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 the haulage process (Department of Mines and Petroleum, 2015a).

In Western Australia (WA) alone six significant driverless truck incidents have been reported since 2014, which illustrates the importance of human factors research (Department of Mines and Petroleum, 2014b; Jamasmie, 2019; McKinnon, 2019). The emergence of new risks 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 are argued to be "people in systems, rather than people versus systems" (Dekker, 2019, p. xix). This view will allow the Western Australian Mining Industry to become more human-centred when designing and deploying driverless technology (Giacomin 2015). Therefore, as a joint human and machine system, despite being two completely different agents, should complement one another. Thus, within the context of human-machine systems, human factors study the design of technology must be developed to suit 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 centred (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 conducted by 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 underpins the reason for undertaking this research. More 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.

The review is structured to initially provide an overview of the research methodology. Secondly, the results of the analysis provide insights into human factors and safety-related themes associated with automation. Thirdly, the discussion outlines how the industry themes apply to automated haul trucks. Lastly, the concluding remarks provide a way forward for the industry and pass on lessons learnt from published literature to avoid automation pitfalls.

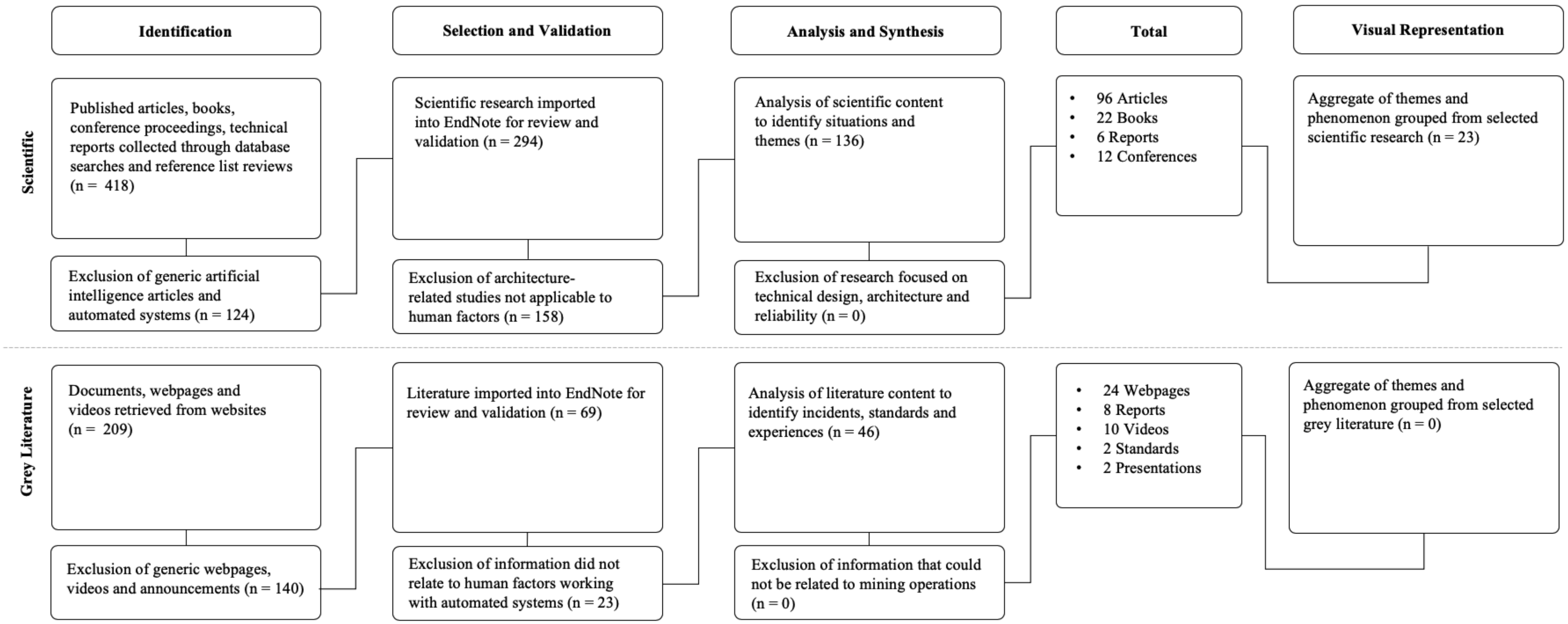
2.3. Methodology

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

1. Identifying studies and key words, search databases and websites.
2. Collecting at least 50 research studies, prioritise them and validate the abstracts, chapters and conclusions.
3. Designing a literature map to visually represent the groupings.
4. Summarising and organising the literature into themes and concepts to identify knowledge opportunities.

Figure 2.

Process flowchart for reviewing the literature



2.3.1. Study and Literature Identification

The literature review originally began by evaluating two driverless incidents reports from the Western Australian mining industry (Department of Mines and Petroleum, 2014b; 2015c). Both reports were analysed to identify key words, phrases and contributing factors that led to the incident. 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, the Department of Mines and Petroleum (2015c, pp. 1-2) summarised an incident between a manually controlled watercart and a driverless haul truck. The report noted, "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.

2.3.2. 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 avoid unintended situations needed to be included. 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 papers were arranged into their reasons for exclusion. Secondly, the content of the literature was evaluated for substance and relevance, excluding those papers that could not be impactful in a mining context. Thirdly, the papers that were more focused on human adaption, cognition and response were included, while the technical architecture of the automated systems was removed. Despite this, the majority of the 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

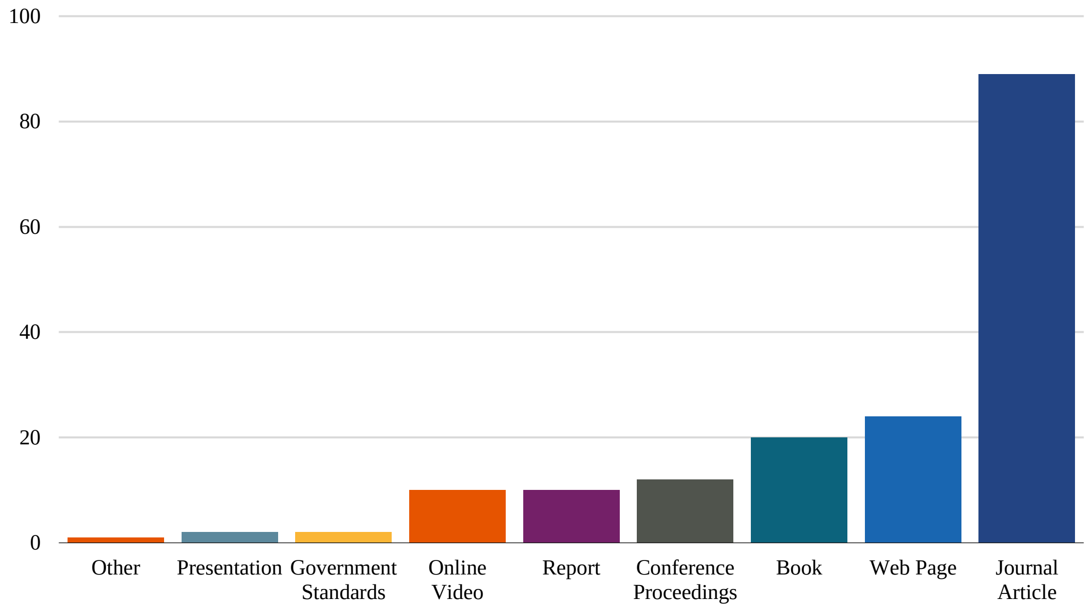
Selection	Component	Scientific Literature	Grey Literature
		Conference proceedings, peer-reviewed articles, books and chapters, interviews.	Government reports and standards, publicly released incidents, YouTube videos, announcements, Company tutorials and public engagements.
Inclusion	Title	Key words: 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.

2.3.3. Analysis and Synthesis

The selected literature was categorised into their associated publication type. The purpose of analysing associated publication types helps frame where the research was published. This was necessarily given that the technology is relatively new to the WA Mining Industry and academic research is yet to explore this area of interest. Moreover, it also highlights the magnitude of research that can be drawn from other industries who have already deployed automated systems. As Figure 2 illustrates, the majority of literature included in the research was scientific papers. This can be explained by the volume of research that has been undertaken in the Aviation Industry shown in Figure 2 (see below). 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 3.

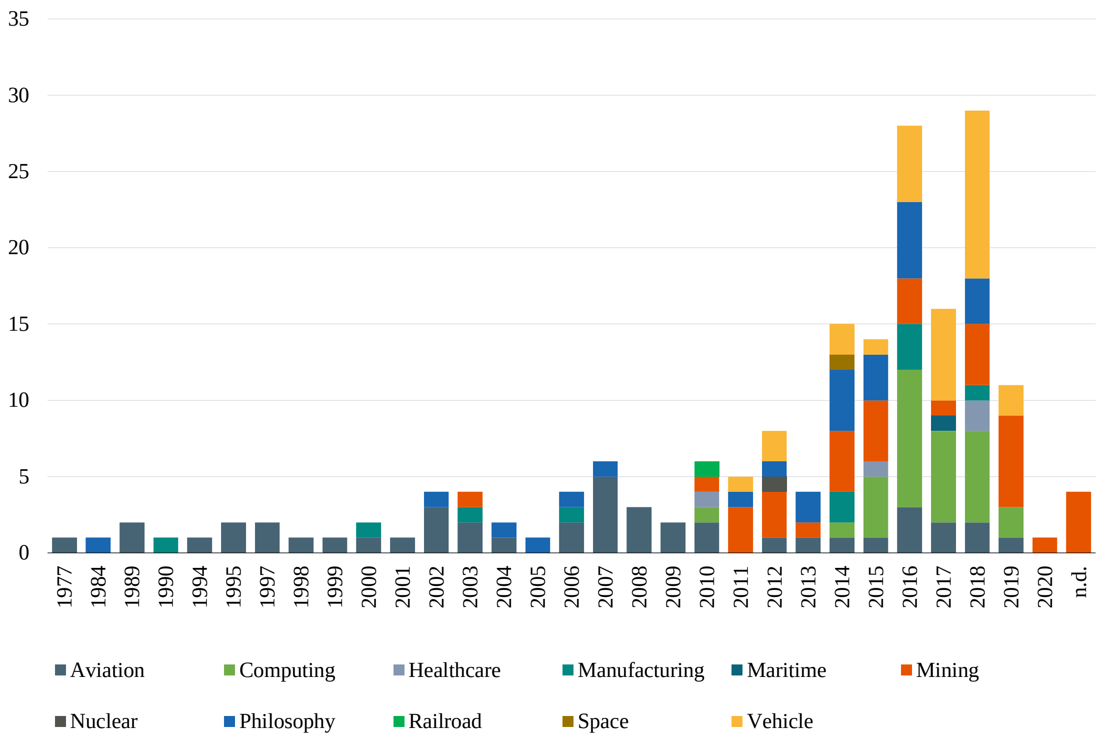
Analysis of literature by type



The timeframe, industry and focus of the research are presented in Figure 3. There were 11 industries identified within the 182 pieces of literature included in the research literature review. By including the industry where the research was undertaken, readers are given an indication of where automated systems have been deployed. More specifically, where research has been able to take place and explore the consequences of replacing human work. Figure 3 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 the aviation industry insights on human factors. The key purpose of this literature review was to do exactly that for the WA Mining Industry, avoiding the pitfalls of automation to leverage the lessons learnt from existing research and optimise their current designs and systems of work for findings to be used.

Figure 4.

Analysis of industry publication by timeframe



Three broad categories 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, the sub-theme machine modes formed a part of technology, which reinforced how the technology was presented in the workplace. In addition, the sub-theme mode awareness described 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. 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 5.

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

2.4. Findings

2.4.1. Engineering Human-Machine Systems

2.4.1.1. 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). Once the haul cycle has been completed, the process is then repeated. A system is simplified in this way to allow technology to substitute human tasks where it can technically perform (Lake et al., 2016). Often, the replacement is dependent on what technological advancements make it viable (Panetta, 2019). This means that driverless trucks must achieve or exceed human level performances. However, human level performances are being evaluated in isolation, focusing on one constituent part in a complex whole. That constituent part is reverse engineered into a machine and designed to follow a narrow set of instructions (Fridman et al., 2018). On the surface, the restructured system can appear to operate as intended and perform what is it programmed to do. Yet, it is the reverberations along the fringes where the consequences of the replacements are taking place (Department of Mines and Petroleum, 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 and the complex interactions between components. Consequently, the properties of haulage system arise after drivers have been replaced, which can be difficult to predict (Department of Mines and Petroleum, 2014b). Complex systems create their own individual structures, which can be defiant towards engineering design. Therefore, in response, the environment begins to modify itself and restructure the entire system (Dekker, 2014b).

Complex systems are difficult to understand through the analysis of independent tasks. That is because complexity evolves through the interactions of the components, not the components in isolation (Cilliers, 2002a). Automation creates interdependencies that generate non-linear relationships that are not linear input devices as they are often metaphorically described (McCarthy et al., 2000). Humans do not simply undertake individual tasks, while the automated system performs another (Mitchell, 2018). A system is a complex web of relationships, transformations, trade-offs to influence how the system responds (Dekker, 2019). Despite automation allowing trucks drivers to perform ‘more important’ tasks, the reality is that driverless trucks are becoming silent, awkward and difficult to instruct (Christoffersen & Woods, 2002). What used to be a mine site filled with radio calls, now has the autonomous truck executing the task quietly and independently. The difficult and clumsy part of this, is how the apparent simplicities turn into physical complexities (Woods, 2018). The automation of sub-driving tasks, asks engineers to focus on the components and 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 to improve productivity (Hamada & Saito, 2018). However, the simplification is achieved from what the system excludes. Complex systems are ignorant of local control and external influences that leave the system vulnerable to situations beyond engineering predictions (Chandler, 2014). For example, a design engineer who is located internationally, can simply change truck system settings to influence an entire fleet of driverless trucks. This is the reason why driverless haul truck systems are becoming so complex. The systems connections are becoming wider, closely connected to a socio-technical system far more reaching than the mine site itself (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 Petroleum, 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 an 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 Petroleum, 2014b).

2.4.1.2. 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 an 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 has arrived at its conclusion (Hurley & Adebayo, 2016). Automated systems are marginally transparent, given that their algorithms are considered the Intellectual Property of the designer (World Intellectual Property Organization, 2019). Therefore, automated systems operate independently from their users, limiting the user's own decision-making abilities and processes to solve 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-centred improvement cycle (Giacomin, 2015). Transferring driving tasks to a machine, redistributes all the tactical information previously communicated by truck drivers (Caterpillar, 2013). Where originally a simple discussion could be held with a truck driver, tactical information 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 research theories that try to explain the outputs of automation. The WA Mining Industry transferred haul truck agency to a machine via automation, which was previously understood and actively controlled by truck drivers (Department of Mines and Petroleum, 2015b). As haul trucks systems were engineered, the interaction and dependencies on other changes yielded more complex by-products (Department of Mines and Petroleum, 2015a) as vehicle interactions evolved from complex situations (Department of Mines and Petroleum, 2015c), requiring equipment operators to use data to navigate and foresee these situations. Interpretation of data is unique to that person and cannot be reconstructed by any other person (Sieck et al., 2007). As more truck driving tasks are automated, the further people are removed from the immediate process (Wessel et al., 2019), therefore, the data outputs can become more mysterious than they were before in a manual (Rankin et al., 2016). Although the developer designs the haulage system, it is the user who is responsible for determining what that data actually means (Endsley, 2016). The interconnections of automated systems can quickly distribute that data across the entire 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 enables 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, it is argued that a solution-driven approach will 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 operational aspects (Sarter & Woods, 1995). Whether data informs people on what to execute, or simply supervise a machine to perform a task, people must be able to 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 was minutes before, making it difficult to return the system to a safe state (Stensson & Jansson, 2014). Although display functions may list rules that decided on a specific 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 processes are more useful than solutions (Zittrain et al., 2018). Furthermore, if the aim of using data is to augment human work, then the human must be creative with that data. While the ontology of the data is biased (Bolukbasi et al., 2016), opaque (Buolamwini & Gebrum, 2018), solutionist (Ross & Swetlitz, 2018) and specialised (Skeem & Lowenkamp, 2016), it will continue to reinforce old habits and underpin the optimisation problems that led to automation.

2.4.1.3. 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 increases the certainty around what the machine will do next. However, despite this level of transparency, a manually operated machine with an in-cab display collided with a redirected haul truck (Department of Mines and Petroleum, 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). Brittleness is an attribute of a system that is not functioning properly when the system is operating close to its design parameters (Billings, 2018). Therefore, the technology can 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 to 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 Petroleum, 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 but also to perform those instructions 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 identifying objects, yet they are unable to distinguish between windrows and people (Teichman et al., 2011). Parameterisation problems become apparent when Global Positioning Systems (GPS) which have reverse obstacle detections failure rates on driverless trucks, are ineffective (McKinnon, 2019). Moreover, self-driving motor vehicles experience a similar phenomenon, where the oncoming vehicle is 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 needing to be made aware of machine functions and their technical capabilities (Payre et al., 2016).

2.4.1.4. 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 would become and the more redundancy would be required to counter predict domino-like reactions. The empirical basis for validating the success of controls are made in 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 was not demarcated in the physical mine laid dormant until a driverless vehicle needed to use it. The use of the turnaround loop was not anticipated by a watercart operator and resulted in a driverless haul truck crossing in front of the machine without warning (Department of Mines and Petroleum, 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

Petroleum, 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 Petroleum, 2014a; 2014b; Teichman et al., 2011). Perrow (1997) explains how the fallacies of “defence in-depth” can obscure the view on how systems behave when they are stretched and compressed. Incidents involving mobile autonomous vehicles on WA mine sites has left investigators puzzled how the equipment 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 Petroleum, 2014b, p. 1). What automation has taught early adopters of the technology is that the more layers 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 benchmarked 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 the 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 able to flexible around danger (Srinivasan & Mukherjee, 2018). Ito and Howe (2016) believe that augmentation holds the key, fostering component relationships to create the foresight to anticipate risk and navigate the complexity of ever-changing mine sites.

2.4.1.5. Manual and Automated Modes

Whether a haul truck is in manual or automated mode depends on 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 networks 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 companies combine the operations of both manual and automated haul trucks, others choose to entirely separate manual and automated haul trucks (Department of Mines and Petroleum, 2015a). This approach can alleviate the confusion behind determining whether the truck is manual or automated mode (Sarter & Woods, 1995). More importantly, there are different functions and rules associated either mode (Glover, 2016). Endsley (2016) explains how consequences emerge when people are surprised by equipment functions, which can ultimately lead to unanticipated interactions and incidents occurring. 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 between anticipated and actual machine function (Sklar & Sarter, 1999). Consequently, improving feedback could minimise any short phases of intervention, which are observed to be driven by people who have lost track of machine assignments (Feldhütter et al., 2019).

Human factors research appears optimistic about 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 Petroleum, 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 or understand what mode a machine is in. Dekker (2014b) suggests comparing the difference between the machine's function and the user's intentions, the disparity and similarities offers some indication of the persons' awareness. This observation can reveal how the theoretical viewpoints of the human-machine system are working in practice.

2.4.1.6. Question 1

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

The theoretical viewpoints of human-machine systems are underpinned by both science and engineering. Science studies a system by 'reducing' the network to its most basic parts and analyses what is contained. Engineering attempts to replicate those 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 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, and 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).

2.4.2. Processes in Human-Machine Systems

2.4.2.1. 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 a 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 an anticipation of one action (turn left), yet the machine performs something different (turns right). These surprises were previously alluded to by Norbert Wiener, whose 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 (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 Petroleum, 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 a 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 an already multi-faceted piece of technology (Department of Mines and Petroleum, 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 a significant challenge, with interfaces required to provide vital pieces of information. The balance is in presenting information people need, without overloading them with surplus details, or with information that they do not know how to interpret (Salas et al., 2010). Warning signs can become hidden amongst a complex web of information, with the risk of there being no response at all to the warning signs (Dekker et al., 2008). The reverberations of opacity create 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 supporting roles are designed to provide.

2.4.2.2. Tight and Loose Coupling

According to Perrow's Interaction/ Coupling Chart, conventional mining techniques are loosely coupled and highly complex in their interactions (1984). Prior to driverless technology, haulage operations contained conventional buffers with flexible tendencies that the industry came to understand (Department of Mines and Petroleum, 2015b). However, when driving responsibilities were transferred to an automated system, haul truck connections with others changed (Department of Mines and Petroleum, 2015c). Where once positive communication would be utilised to pass a haul truck the requirement now is that a truck has to be virtually locked before passing another truck (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, truck 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 involves 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 and the tight connections in a complex system are oversimplified (Department of Mines and Petroleum, 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 its 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 Petroleum, 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 (Wears et al., 2015). In addition, all the components may have behaved successfully. Therefore, safety lies in the interaction in tightly coupled systems and not in a 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 coupled 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 (see Department of Mines and Petroleum, 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 (Mining Dot Com, 2014). As a result, additional control systems can simply tighten the system's coupling, while opening up more possible interactions and pathways to failure.

2.4.2.3. 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).

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 Petroleum, 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).

2.4.2.4. 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 Petroleum, 2015c).

The regulator governing mobile autonomous mining systems in Western Australia appears fairly pessimistic about the representation of physical mines. The Department of Mines and Petroleum (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 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 Petroleum, 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 Petroleum, 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).

2.4.2.5. 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, 2016).

Automating human techniques have been long argued as a performance optimiser more 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 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).

2.4.2.6. 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.

2.4.3. Human Factors

2.4.3.1. 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 Petroleum, 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 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 if a truck is 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.

2.4.3.2. 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 a system warning. A critical point in time when someone should have intervened (Department of Mines and Petroleum, 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, sense making 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 sense making fills the gaps between 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 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.

2.4.3.3. 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 is 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 requires talent; especially when the recovery mission is novel, complex and the procedure is arbitrary (Goteman & Dekker, 2006). 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 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.

2.4.3.4. 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 Petroleum, 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 Petroleum, 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 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 people omitting to just do their part versus the intervention to ensure work quality, is heightened on the frontline.

2.4.3.5. 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's 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, who suddenly are 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 Petroleum, 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 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 Petroleum, 2014b)

2.4.3.6. 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 Petroleum, 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 on 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 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 Petroleum, 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 trucks away) at various times (Caterpillar, 2013). Therefore, there is a unique relationship that forms among humans and machines, and it’s 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).

2.4.3.7. Question 3

How does human adaptive behavior manage unanticipated machine performances and decision 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.

2.5. 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 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 of deaths occurring. 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-centred, 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 to 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 standardised 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 recognise 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.

2.6. 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 prompt 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 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, so 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.

2.7. Conclusion

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 Petroleum, 2014b). Thus, understanding the interactions between human and machine will explain how the relationship is evolving in Western Australia. 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 been 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-centred 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 Western Australian 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 is often omitted and filtered when publishing the investigation findings publicly. The underlying hypothesis of this research was that incidents involving driverless vehicles are being shaped by Western Australian 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 has explained, 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 learnt.

Chapter 3

Methodology

3.1. Introduction

This chapter outlines the methodology for the study. This research was conducted in three phases. The first phase of the study analysed the quantitative data, including safety incident reports and operating hours of the mining operation. An exploratory-based technique yielded descriptive statistics to summarise and enhance understanding of the events. The second phase analysed qualitative data, including interviews, field operations and documentation. Interpretive data collected multiple cases was analysed through-cross-case displays and compared for patterns and themes. The third phase merges both forms of data for analysis, constructing meta-inferences by comparing quantitative and qualitative through triangulation. A mixed analysis transforms the data to make statistical and analytical generalisations.

3.2. Research Design

The mixed methodology combined the use of qualitative and quantitative data. The research process utilised both approaches to minimise the limitations of one method while leveraging the strengths of another. Therefore, the value of the mixed methodology is the combination to strengthen the research results, developing a more comprehensive understanding of the phenomenon under study (Creswell & Clark, 2011). In addition, the convergent parallel design analyses the data sets separately, then merges the two forms of data. Merging the data enabled qualitative variables to be measured and quantitative variables to be contextualised (Creswell, 2014a). As a result, the mixed methods approach not only collects and analyses data separately, the various predictors and perspectives of risk were integrated (Miller & Crabtree, 2005).

A convergent parallel methodology was selected to develop a comprehensive understanding of the predictors and perspectives of risk. The predictors of risk included the safety incidents involving driverless haul trucks, highlighting the factors that led to a loss of control.

Contrastingly, the perspectives provide key insights into the experiences of mineworkers interacting with driverless technology. The multi-faceted approach analyses incidents and operators' experience separately before merging to draw inferences (Tashakkori & Teddlie, 2010). The design cross-references driverless truck incidents and compares them to the variables present in mineworker experiences. The integration of the two methods occurred in the connection between the collection of quantitative data and the analysis of qualitative data (Creswell, Klassen, Plano Clark, & Smith, 2011). This design assisted with the identification of variables that formed the construction of the interview instrument. Generally, the exploratory-based technique was useful for exploring the phenomenon on why driverless incidents were emerging, expanding on those findings to clarify the types of contributing factors through subsequent phases (Creswell & Creswell, 2018).

The purpose of the study underpinned the rationale for a mixed-method design. The aim was to compare qualitative and quantitative data through triangulation. The justification was to capitalise on the combined analysis to transform the data and make generalisations about the research phenomenon. The approach informed one another to validate the constructs and enhance research results (Creswell et al., 2011). Single data streams can impact the validity of a convergent parallel design. Therefore, although the qualitative themes and quantitative variables have been developed concurrently, they were kept separate until interpretation was required (Tashakkori & Teddlie, 2010). Validity threats can emerge when asking different questions of the data streams when concluding. Therefore, the data streams asked similar questions and equally favoured by mixing the data when drawing inferences.

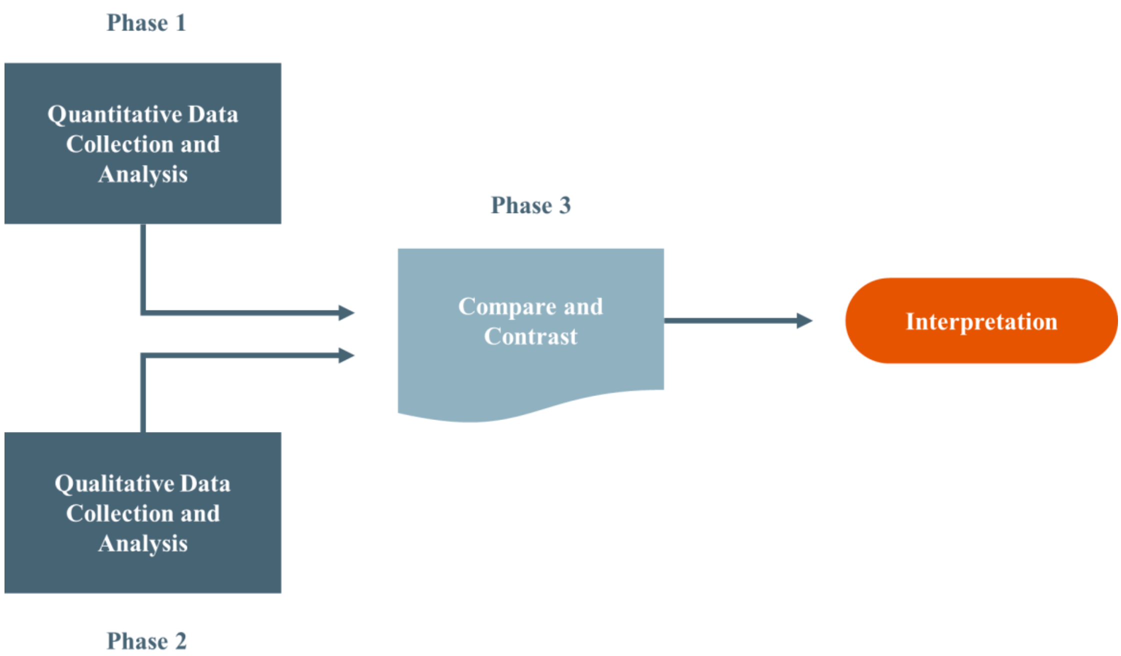
No published research was identified that explored the incidents involving driverless haul trucks and the contributing factors that lead to a loss of control. While research has been conducted in manual truck environments, technology has significantly transformed the risk profile. Therefore, to address the research need, a convergent parallel mixed methodology was designed and undertaken. The results of the literature review and quantitative data assisted in developing themes relating to human factors in technological systems, which were used to construct the interview instrument. The investigation enabled the quantitative variables to be contextualised (Creswell, 2014b).

3.3. Research Structure

There were three main components to the convergent parallel approach (see Figure 1). The first component involved analysing quantitative data to yield descriptive statistics. The experiences of mineworkers provided interpretive data from multiple cases, which were analysed through joint displays. In addition, the processes and methods were observed during field-time to identify the phenomenon first-hand. The final component constructed meta-inferences by cross-referencing and comparing data through triangulation.

Figure 6.

Research structure



3.4. Defining the Population

The occupational population under study were employees and contractors who supervise, operate and work with automated haul trucks. The size of the population was approximately 450 people, who each perform specific roles and functions with characteristics pertinent to the research. A single-stage sampling procedure was undertaken as the researcher had direct access to the participants and understood the population under study (Teddlie & Yu, 2007). Fowler (2014) explains how the population must be known before stratification of the sample can occur to obtain an accurate representation of the population's characteristics. Therefore, stratification was undertaken and identified the following roles and features:

- Control room operators who monitor the performance of the trucks and make decisions via a computer interface and communicate through radio;
- Pit Technicians and System Builders who operate light vehicles within autonomous operating zones and build virtual truck lanes based on the physical haul roads identified in the real world;
- Ancillary and haul class operators who control mobile equipment and interact with the autonomous trucks during their day-to-day work; and
- System and software vendors who are involved in the design and pre-programming of the automated system to perform particular functions.

The stratified sample was utilised in a single-stage technique (Teddlie & Yu, 2007). The single-stage method relied on the researcher understanding the full names and positions of the people in the population. Creswell (2014a) explains how a random selection may not represent the population in its entirety. Therefore, the specific roles were targeting for their specified characteristics. The sample size was not pre-determined, which allowed the results to dictate when data saturation had been achieved (Corbin & Strauss, 2015). During the study, there were 25 participants recruited for the research to ensure the validity of the results, which represented 5.5% of the population.

3.5. Research Site

The three phases described in the methodology required separate data collection methods, which intended to seek multiple avenues of data in parallel. In addition, to achieve the research objectives, the study needed to identify a research site to conduct the investigation. The mine site chosen for the study was located in Western Australia's Pilbara region. The reason for selecting the mine site was for the operation's technological innovation. More specifically, the mine site was one of the first mining operations to introduce driverless technology. At the beginning of the study, the mine site had been operating automated haul trucks for five years. Thus, there was sufficient experience and data available to substantiate the research taking place.

Secondly, there were safety incidents involving driverless trucks reported on the mine site. The incident reports revealed the unconventional nature in how those situations occurred. Therefore, the mine site provided a unique opportunity to investigate the contributing factors and start to understand why automated truck incidents eventuate. In addition, the events highlight the scale of the risk types and how they compare to a manual truck operation. The frequency of the incidents helped determine the prevalence of risk types and how those risks influenced the site's risk profile transformation. More importantly, the timing of the evaluation through the transition period, from manual to automated control, increases the validity of the risk profile changes.

The research site employed 450 people to supervise, control and operate manual equipment. The experiences of those workers interacting with haul trucks provided an opportunity to explore the perspectives of the risk. The views offer insights into the contrasts between the relationships that form in manual and driverless control. Transformations in the relationships uncover the factors that are contributing to an increase or decrease in incidents involving haul trucks. In particular, the influences of the technology, which may change the behaviours of mineworkers interacting with haul trucks.

The mine site work system included eight active open-cut mining pits and three primary crushers (see Figure 9). The open-cut pits were originally mined by manual haul trucks, however they were converted to the driverless operation over the four-year study period. The driverless system began in the most southern section of the mine, expanding the operation pit by pit. The trail began with one excavator and six trucks, increasing to 57 trucks and 11 excavators at full expansion. In addition, there were a number of ancillary machines and haul class equipment, including manually-operated watercarts, track and wheel dozers, graders and light vehicles.

The haulage system works by using wireless communications to travel between loading sources (i.e. excavators) and dumping destinations (i.e. dumps, crushers and stockpiles). Wireless communications enables the driverless truck fleet to be controlled remotely by a central control room (see Figure 8). Each control room operator works a 12 hour shift and is responsible for monitoring 25 driverless trucks. Control room operators give individual assignments to instruct driverless trucks on where to travel. For example, Dump Truck 1 is to be loaded at Excavator 1 and dumped at Primary Crusher 1. A permission-based control system divides haul roads into segments to coordinate and permit trucks to travel within any one section (see Figure 7). Road segments provide the travel route to adequately separate the trucks from one another and avoid collision.

Figure 7.

Permission-based control system

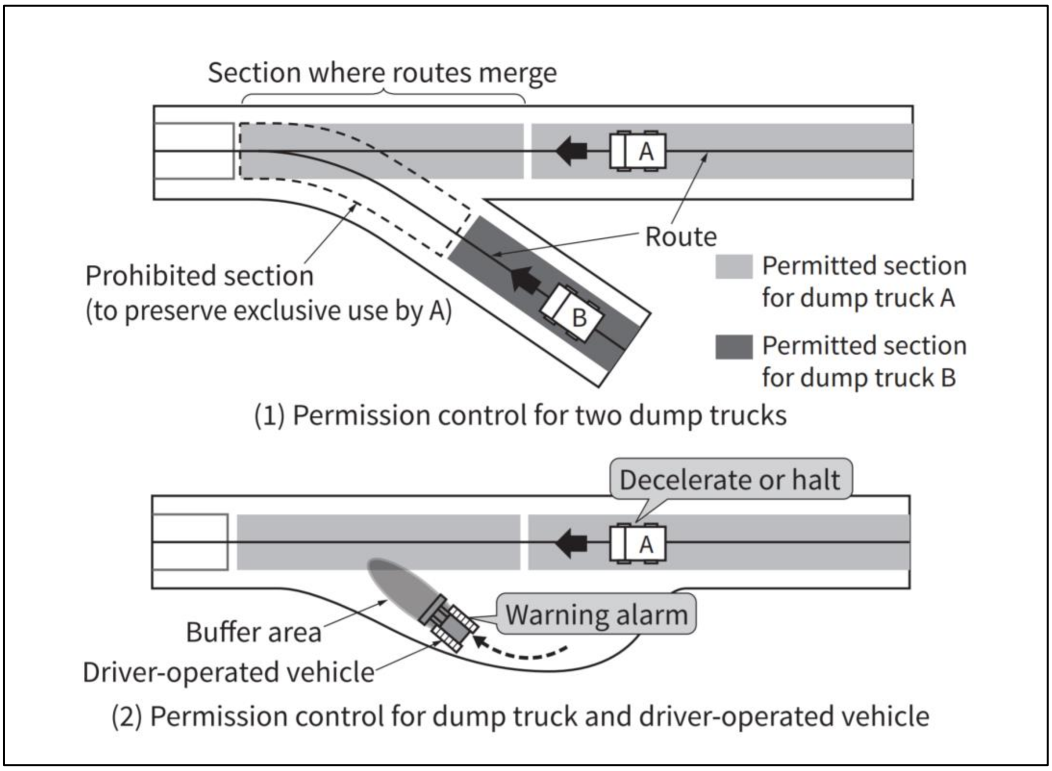
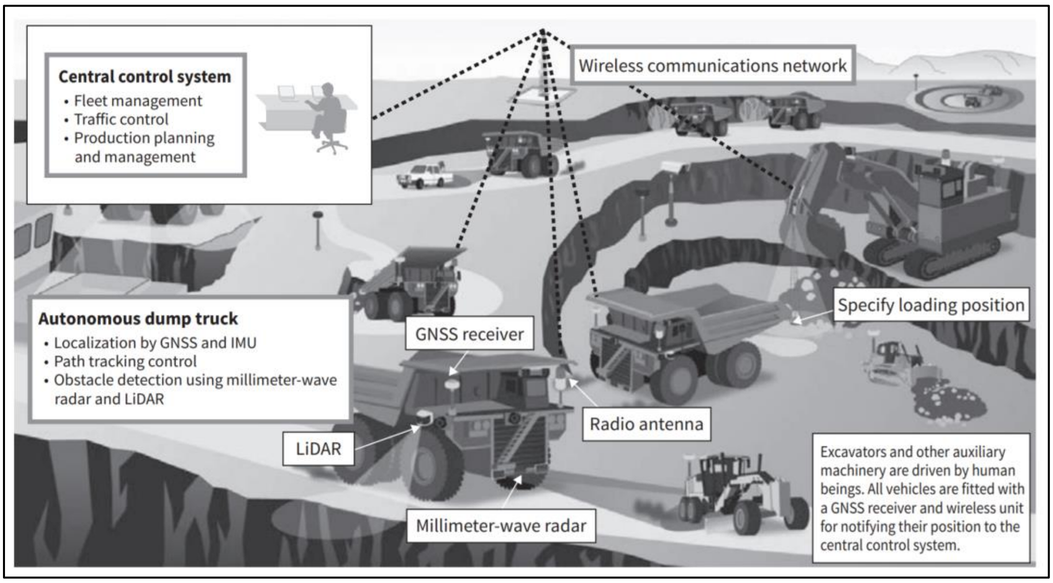


Figure 8.

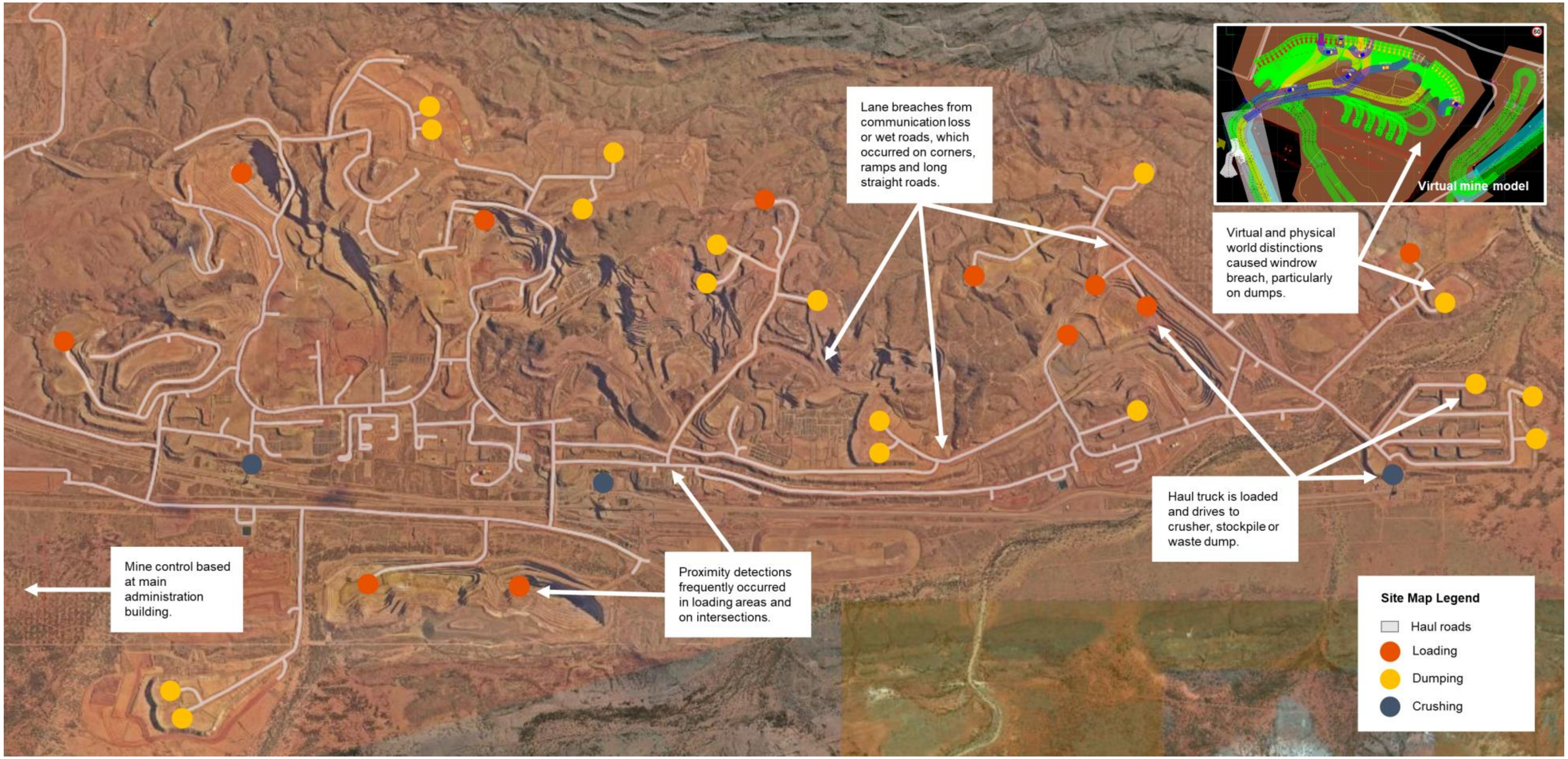
Overview of driverless haulage system



Note Figure 7 and 8. Adapted from “Autonomous Haulage System for Mining Rationalisation,” T. Hamada and S. Saito, 2018, Hitachi Review, 67(1), 87-92.

Figure 9.

Mine site work system



3.6. Phase 1: Quantitative Data

3.6.1. Introduction

The first phase focused on collecting and analysing quantitative data. The quantitative data included safety incident reports from both the manual and driverless truck operation. Additionally, the number of hours driven by both fleets were collected to normalise the incidents against the number of operating hours. The purpose of compiling incident reports was to determine the whole number of uncontrolled situations involving manual and automated haul trucks.

3.6.2. Data Collection

3.6.2.1. Incident Reports

The methodology involved collecting health and safety incidents involving manual and automated trucks. Incident data was extracted from a safety database, setting a date range from Financial Year 2014 (FY14) to 2018 (FY18). This four-year timeframe reflects the WA mine sites' transition period from manual to full haul truck automation. The transition period enabled the research to follow the entire deployment of driverless technology and the implications on safety.

Collecting raw incident data required setting specific parameters in the database. Firstly, each department's data was selected to obtain the entire range of haul truck-related incidents. Department incident data was filtered for health, safety, environment and financial impacts. This method was adopted to ensure every incident reported could be found. Moreover, events that may have been incorrectly assigned impact types could be identified (i.e. environment over safety). There were also noteworthy observations made during data collection. The researcher was made aware of specific haul truck-related incidents; yet, they were unable to be located in the system. Search functions had only been set for health and safety. It was soon found that a significant portion of driverless incidents was allocated 'financial' impacts over 'safety'. Once financial consequences were added, a number of additional haul truck incidents emerged. This observation was an interesting finding leading into the research. The discovery left the researcher asking, 'how were driverless haul trucks incidents being assessed?

The exported information was tabled into an excel spreadsheet. Incident data was automatically presented into various columns for every event. Columns included the incidents' unique identifier, date, department, title, investigation, severity and who had reported. Incident findings were obtained from the long description of the report. Investigation findings were included in the original notification; specific causes were outlined in a separate report. As investigation' root cause' types were not overly insightful, the researcher analysed and coded individual reports to identify whether a truck was involved. This interpretative process provided the platform for data analysis.

3.6.2.2. Truck Driving Hours

Truck driving hours were collected to calculate the frequency of incidents involving haul trucks. Driving hours were the total number of hours operated by manual and driverless haul trucks. The hours were obtained from the mine site's production database, where individually operating hours could be collected. The selected dates ranged from July 2014 to June 2018, which totalled 1,083,640 over the four years. On an individual basis, the manual truck operation drove a total of 584, 557, and the driverless truck operation completed 499, 094.

3.6.3. Data Analysis

3.6.3.1. Descriptive Analysis

An exploratory-based technique will yield descriptive statistics to summarise and enhance understanding of the incidents (Onwuegbuzie & Combs, 2010). The raw data was required for each event to be coded individually. Since there were no incident types, limited root cause category and hazards assigned, more context needed to be drawn. Therefore, data coding was undertaken to ask more investigative questions of the data set:

- Did the incident involve a truck?
- Was the truck in manual or automatic control?
- What was the incident type?
- What was the associated hazard?
- Was the hazard new, conventional, or has it transformed?

These questions not only provided more context, but it also enhanced the quantitative aspects of the data. For example, the analysis could determine the frequency of incident types and hazards. Calculating a rate substantiated the impact of each occurrence and its condition. In addition, the methodology of coding gave rise to more structure in the data. Formation increased the researchers' understanding of the phenomenon by highlighting key themes. These themes provided a clear link between incidents and their associated hazards. Drawing the connection between new, removed and transformed hazards to highlight the technology's impact.

3.6.3.2. Incident Frequency

Calculating an incident frequency substantiated the impact of each occurrence and its condition. Manual and driverless truck hours were collected in an attempt to normalise the incident data. The total number of incidents were not comparable when considering the fluctuation of each operation. Moreover, self-driving car companies are using similar metrics to measure driverless safety performance. Waymo, for example, is utilising the number of miles travelled to measure reliability (Waymo Team, 2018). Frequency of occurrence comparisons are useful; however, caution is expressed when using it as an absolute figure to measure driverless 'safety' reliability. Driverless vehicles and their equipment failure modes are a minimal component in an open, dynamic and complex environment. Therefore, the frequency of incidents was used as an indicator, not a baseline for failure modes. Nonetheless, in this study, the results provide an interesting perspective on the consequences of introducing driverless technology on a mine site. Haul truck incident frequencies were calculated as follows:

$$\text{Incident frequency} = \frac{\text{Number of haul truck incidents}}{\text{Number of truck hours driven}} \quad x \quad 1{,}000{,}000{,}000$$

3.6.3.3. Analytical Statistic Methodology

A chi-square test was performed to determine whether the difference between manual and driverless haul truck incidents were statistically significant. The observed data included incidents involving driverless haul truck, while the expected data encompassed conventional incidents in manual operations. The chi-square statistic assisted the research to quantify how well the driverless incidents fit the distribution of manual truck incidents. A goodness of fit test verified the sample proportion against the sample and whether it reflected the manual frequency of incidents.

$$X^2 = \sum \frac{(O - E)^2}{E}$$

3.7. Phase 2: Qualitative Data

3.7.1. Introduction

The second phase analysed qualitative data, including field observations, interviews, and documentation. Interpretive data collected from multiple cases will be analysed through cross-case displays and constantly compared for patterns or themes when coding abductively (Tashakkori & Teddlie, 2010).

3.7.2. Data Collection

Interviews were conducted with mineworkers to gather perspectives of the risk. The views are linked to the experiences of participants working with driverless trucks. The lessons provide meaningful relations between humans and machines. Furthermore, Creswell (2014b) explains that the 'core feature' of qualitative analysis is gathering evidence to connect the theme with a broader perspective. Guided by inclusivity, pragmatism, and social science theory, the collection aims to remain open to emerging ideas and multiple perspectives to highlight potentially divergent viewpoints.

3.7.2.1. Recruitment

A Western Australian mining company provided the research site for the study. The participants were 25 mining employees who worked within the mine site's automated truck operation. A stratified sample guided the invitations and posters developed to invite employees to partake in the study. The signs included information about the research the contact details of the researcher.

Mine site employees were able to contact the researcher in person, by phone or email. A cross-section of the workforce was included in the study, which encompassed a variety of roles and characteristics to provide different perspectives. A consent form and information sheet were developed for the study. The information sheet provided background information about the research (see Appendix 4); outlining the purpose and ethical considerations. The consent form was provided to participants after they had read the information sheet. All participants read and signed the consent form.

3.7.2.2. Interview Technique

The primary source of data utilised for the qualitative phase was the interviews with mineworkers. Interview questions were designed explicitly for this study. The scope of the meetings was guided by the incident reports (see Chapter 4) and the literature review (see Chapter 2). Accordingly, the interview questions were indicators of the risks, trust, teamwork, role descriptions, residual workload and local adaptions. A mixture of closed and open-ended questions were utilised to explore mineworker perspectives. The interviews contributed thematically to knowledge and promoted positive interactions. Closed-ended questions offered the opportunity to quantify participant responses, while open-ended sought in-depth descriptions of the experience (Creswell, 2014a). Semi-structure interviews were organised by the researcher in a logical manner, which assisted in the flow between questions. The technique of using a semi-structured interview is to enable the questions to reflect experience, the participants' knowledge and associated demographics (Doody & Noonan, 2013).

The benefit of semi-structured questions is also to provide flexibility and seek further clarification of the experience. Additional perspectives and problems are discovered when offering freedom to explain. The researcher was able to adjust questions and allow the conversation to flow freely. The research gathered from the literature review generated ideas about the human-machine interface, coupled with practical knowledge and theoretical perspectives (Doody & Noonan, 2013). Face-to-face interviews took place on the research site, with the location organised by the researcher which was the central hub administration. Interviews were conducted during lunch breaks. Participants were known to the researcher; therefore, trust and rapport had previously been developed. The atmosphere was relaxed and provided an opportunity for mineworkers to speak freely. Background information about the research was explained before one-on-one interviews commencing. Participants were assured that the experiences shared during the meetings would remain confidential. Any phrases or names mentioned during the discussion were to be de-identified. In addition, the researcher explained how there were no wrong or right answers. Interviews were audio-recorded and transcribed through an online database. There were no adverse impacts on the participants' feelings or emotions after the conversations occurred.

3.7.2.3. Documentation

The documentation provided the processes that were designed for mineworkers to safely interacting with driverless trucks. Each process outlined the task steps to be undertaken, providing supporting images, best practices and essential information. Task steps highlighted the methods that were being used by workers, which offered an opportunity to compare with practices in the field. Comparing practices against designed standards enable comparisons to be made against the design aspects, revealing the methods that may have been contributing to workplace incidents. Processes were collected from the fleet management system database and utilised during field observations to observe workplace practices.

3.7.2.4. Field Observations

Data was collected from workplace observations and field notes to provide further context to the phenomenon. The researcher had undertaken pit observations with the operators, builders and supervisors as a vehicle passenger, asking open-ended questions that sought an in-depth descriptions of their experiences working with the system (Creswell, 2014a). During workplace observations, field notes were taken to transcribe the responses to the questions and any other situations observed that may arise during the execution of daily tasks. For example, how the operators monitor the system for technical issues and recover an automated haul truck from objects that are detected within the virtual network. Observations were undertaken in the control room, which was located in the central administration hub on site. The researcher sat with the controllers to seek their perspective on working the system and ergonomic factors, asking operators to elaborate on the methods and thought processes controlling driverless trucks.

3.7.3. Data Analysis

Data analysis involved transcribing the viewpoints of the participants through the analysis of the qualitative text. The qualitative analysis was linked to the participants' experience interacting with automated haul trucks: "[describing the experience] … meaningfully while keeping the relations between the parts intact is the stuff of analysis" (Miles & Huberman, 1994, p. 56). Creswell et al. (2011) suggest that the analysis is "coding the data, dividing into small units (phrases, sentences, or paragraphs), assigning a label to each unit, and then grouping the codes into themes" (p. 208). The mixed-methods approach was well suited to constant comparative analysis. Tashakkori and Teddlie (2010) claim that the process is "systematically reducing data to codes, then developing themes from the codes" (p. 605). The analysis utilised field notes, interviews and observations in an effort to "… [start] thinking consciously about possible meanings of the data" (Corbin & Strauss, 2015, p. 117).

3.7.3.1. Data Coding

The following process steps were followed upon the completion of the interview:

- The interviews were transcribed in an online database
- Transcribed interviews were checked to validate each question had a corresponding response
- Interviews recordings were verified against the transcribed documents
- Identified themes were coded in line with quotations and statements from the audio
- Research themes were compared and contrasted against cases

3.7.3.2. Interview Narration

A narrative analysis was conducted from the experiences shared in the interviews. Actively listening to the participants' story helped develop a clear understanding of the persons' perspective (Holloway & Jefferson, 2012). Participants shared their experiences working with automated haul trucks, which were compared to enhance the understanding of the phenomenon.

3.7.3.3. Data Structuring

Qualitative interview data was analysed through case-case displays. The displays highlighted rich text and data for coding. The interpretive data from multiple cases were analysed and compared for patterns and themes. The presentation provided a visualisation that enabled the research to identified trends across the stratified sample.

The cross-case display and its associated elements are as follows:

- Participants' role: The role of each participant is highlighted to determine trends across individual functions for comparisons.

- Demographics: Participant demographics provided an opportunity to identify the links between mining experience and working background.
- Question set: Each question asked of the participants to compare responses across the sample group.
- Coding: the collected interview data was coded to identify relevant themes and the development of nodes.
- Cluster analysis: Exploratory-based technique to identify patterns in the content. This approach identified the comparisons amongst the sample group and similarities in responses.
- Mind maps: A process to branch out themes associated with the central topic and idea
- Graphs: Provide a visual representation of each participants' response and enabled the qualitative data to be measured. Quantifying the data underpinned the prevalence of the theme.

Coding and pattern matching was undertaken to identify the themes in participant responses. The responses represented the perspectives of the stratified sample in relation to interacting with driverless haul trucks. The transcripts were downloaded from an online storage database and exported into a cross-case display and then the data was coded into categories and analysed for concepts (Creswell, 2014b). The analysis process synthesised the primary description into groupings. Therefore, the researcher could start thinking consciously about the meaning and how it connects to a broader perspective (Corbin & Strauss, 2015).

3.8. Phase 3: Merging Data

3.8.1. Introduction

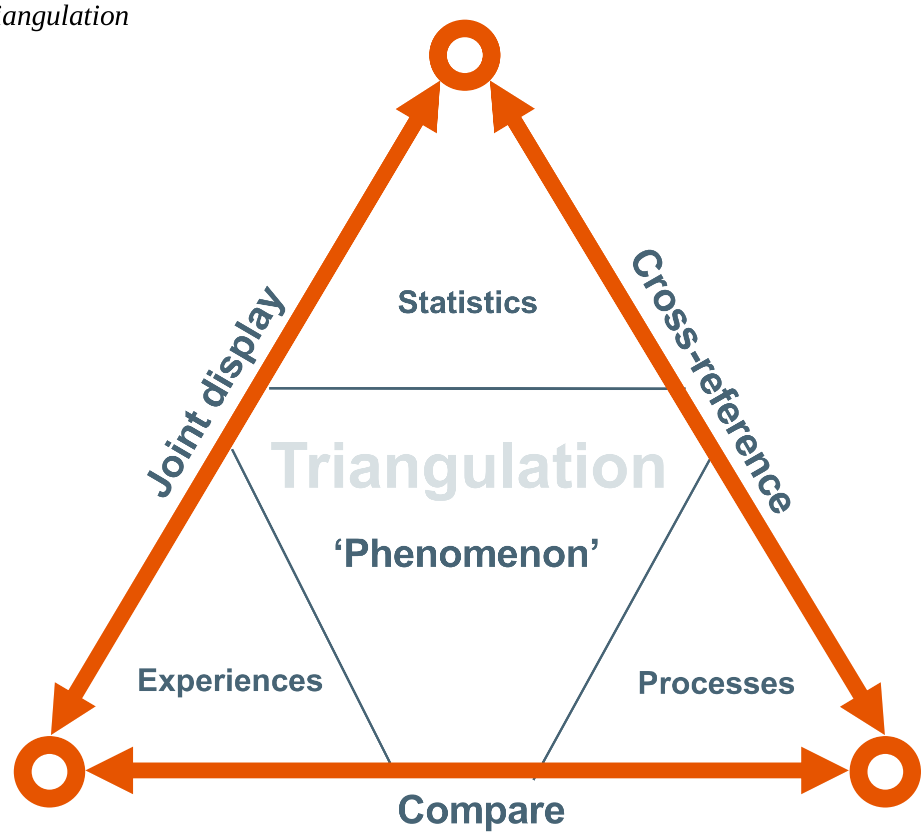
The third phase merged the quantitative and qualitative data for analysis. The purpose was to create meta-inferences by comparing data sources through triangulation (Teddlie & Tashakkori, 2009). A mixed-method study transforms the data to make statistical and analytical generalisations about the phenomenon (Creswell et al., 2011).

3.8.2. Triangulation

The mixing of data consisted of analytical techniques to merge both forms concurrently. The process involved analysing the findings of both phases and addressing the questions of the mixed method (Creswell et al., 2011). Meta-inferences could then be drawn to interpret quantitative and qualitative data strands. Accordingly, and remaining consistent with mixed methodologies, the data was first compared side-by-side to present the findings. The presentation acts as a vehicle for confirming and disconfirming the results (Mizrahi & Rosenthal, 2001). A joint display compared both data steams directly through figures and axis (Li, Marquart, & Zercher, 2000). The texts phrases were quantified for each theme and subtheme within the text, which enhance and strengthen the qualitative findings (Creswell, 2014b). Therefore, the results were compared and transformed by cross-referencing during further analysis (Onwuegbuzie & Combs, 2010).

Figure 10.

Triangulation



3.9. Research Validity

Creswell (2014b) explains how single data streams can impact the validity of a convergent parallel design. Therefore, although qualitative themes and quantitative variables were developed concurrently, and they were kept separate until interpretation, as this was required to avoid discrepancies (Tashakkori & Teddlie, 1998). Tashakkori and Teddlie (2010) noted that validity threats could emerge when asking different questions of the data streams when concluding. In an effort to avoid this issue, both streams of data were asked the same questions when drawing inferences about the phenomenon. The differences in sample sizes can also cause validity concerns since the size of the safety incident data was much larger than the number of mineworkers who participated in interviews. The qualitative sample includes a range of personnel who participated in discussions to increase the richness of data and provide an enhanced perspective on trends in safety incident data (Tashakkori & Teddlie, 2010).

3.10. Generalisability

The study was conducted in one mining operation in Western Australia. The operation had deployed one of an expanding number of haulage systems in the world. Conclusions were drawn from this one operation, which may limit the generalisability of the results. However, the research has explained the variables under which those incidents occurred, which allows the reader to determine the transfer of knowledge (Maxwell & Chimel, 2014). Nonetheless, a majority of events explain the complexities and dependencies that emerged between humans and machines, regardless of the system's level of automation. The impact of introducing an automated system is described, with unique situations that seldom can occur in a conventional mining operation, therefore, preserving the nature of the change by refraining from drawing general conclusions about the phenomenon under investigation. The research remained grounded by the natural clusters in the data when 'generalising', increasing the validity of the study and avoiding the risk of 'selective anecdotalism' (Gibbs, 2008).

3.11. Reflexivity

Teddlie and Tashakkori (2009) outline the importance of reflecting during the study. Reflexivity allowed the researcher to explain why a mixed-methods approach was used, theoretical viewpoints and assumptions that may influence the research process (Corbin & Strauss, 2008). Since the mining company employed the researcher, a reflective journal was be maintained throughout the study to outline the observations, interpretation and potential biases that may be present (Creswell & Clark, 2011).

3.12. Ethical Considerations

Ethical approval was obtained from the Curtin University Committee before commencing the collection of data (See Appendix 4). The ethical approval number for the study was HRE 2017-0844. The researcher avoided asking specific questions that could emotionally or mentally harm the participants. The participants were given the opportunity to stop the interview at any time.

3.13. Commercial in Confidence

The process for research publication will include a review of the thesis by the company's External Affairs function. The purpose of this review is to ensure that the information and associated material does not identify the mining company in any way. The thesis does not identify the mine site or the participants involved; therefore, the researcher was given the academic freedom to publish. However, if commercial concerns are raised around crucial pieces of information relating to the research outcomes, the company is satisfied to discuss the matter further to ensure commercial confidence and academic excellence.

3.14. Chapter Summary

The convergent parallel design was chosen to develop a comprehensive understanding of the various predictors (i.e. safety incidents) and perspectives (i.e. one-on-one interviews) of the risk (Creswell & Clark, 2011). The multi-faceted method analysed safety incidents, operators' experiences and documentation separately, merging them to draw inferences (Tashakkori & Teddlie, 2010). Cross-referencing incident compared the variables of a situation against the operators' experiences and standard systems of work. Complex reasoning accommodated theory for emerging root causes, and deductively for validity and testing; working back and forth until saturation and significance were achieved (Creswell & Poth, 2017).

Chapter 4

From Truck Driver Awareness to Obstacle Recognition: A Tiger Never Changes its Stripes

This chapter has been submitted for the publication:

Pascoe, T., McGough, S. & Jansz, J. (2020). From truck driver awareness to obstacle recognition: A tiger never changes its stripes. *Policy and Practice in Health and Safety*.

4.1. Abstract

Driverless truck incidents on a Western Australian (WA) mine site were analysed to understand the implications on safety. The incidents were compared to manual truck incidents based on their characteristics and investigation findings. From Financial Year 2014 to 2018, manual operations averaged 970.2 incidents per 1,000,000 hours driven with driverless operations averaged at 864.4. Driver awareness was the most frequent hazard associated with manual trucks, whereas road conditions (objects identified or not) were the highest for driverless trucks. Data analysis demonstrates how technology transformed the mine site's risk profile, rather than underpin the popular notion that automation eliminates safety risk. Therefore, risk management should focus on enhancing users' knowledge of computer programming and machine learning techniques that is driving the industry's progress to-date. Such a focus would legitimise the current progress of artificial intelligence and highlight the residual human work that is transforming and adapting to the introduction of driverless technology.

4.2. Introduction

Haul trucks are a vital component of a mining supply chain. They also hold the potential to cause fatal incidents when situations malfunction. According to the Western Australian (WA) Department of Mines and Petroleum (2014a) there were five fatal haul truck incidents between 2000 and 2012. Although the elimination of haul truck incidents is yet to be achieved, driverless technology is being introduced to remove human exposure to truck driving hazards. Automated systems have also been proven to be effective in reducing significant incidents (Udd, 2019). This is largely due to the permission-based control system coordinating truck movements by permitting exclusive sections for truck travel (Hamada & Saito, 2018). Manual equipment is provided with a system-based interface to manage haul truck interactions, whereas digital interfaces highlight the location of surrounding vehicles and sections of road occupied by driverless trucks. However, despite the direct benefits of automation, new hazards and risks have emerged. These hazards and risks are unique to a driverless operation and have played a key role in unconventional incidents involving driverless trucks (Department of Mines and Petroleum, 2014b).

The WA mining industry's risk transformation is being driven by the rapid introduction of artificial intelligence (Gray, 2019). According to recent reports, there are now more than 350 automated haul trucks operating in the Pilbara region (BHP, 2019; Fortescue Metals Group Limited, 2019; Jacques, 2019). BHP also plans to expand its driverless truck strategy across its entire iron ore and coal open cut operations (Palmer, 2019). Introducing automated systems, however, has highlighted a number of important lessons (Department of Mines and Petroleum, 2014b), which have already been learnt elsewhere in aviation, maritime and manufacturing (Dekker & Woods, 2002; Lee & Morgan, 1994; Woods, 2016). Over the last six years, driverless haul trucks have been involved in a number of significant incidents (Department of Mines and Petroleum, 2015b; Jamasmie, 2019; McKinnon, 2019). The same signs and symbols of human–machine breakdown appear to be repeating themselves—just simply in another industry context. These new types of incidents have sparked interest in the safety aspects of driverless vehicles. More importantly, how automated systems are transforming and adapting to complex situations that evolve on mine sites.

For driverless technology to succeed, there is an urgent need to assist the WA Mining Industry with empirical research on the risk profile changes. The WA Department of Mines and Petroleum published a Code of Practice on the safe use of autonomous mobile equipment

(2015a). However, like any new technology, there are limited empirical studies on the safety implications of its practical application. This can also be said for research publications, where driverless technology is yet to be critically evaluated in a complex mining environment. As such, there is a real need for this research, not only to support the mining industry on their journey but also to assist academia in keeping abreast with the industry's technological innovation.

Driverless technology has so far been viewed as the solution to safety. A computerised system that can do no wrong (ADVI Hub, 2016). The assumption is that the substitution of human cognition can eliminate the risks of truck driving. Without a human, there can be no possible lapses in concentration or fatigue-related events from monotonous driving. A truck is expected to navigate corners and bends, while also reversing towards excavators, dump faces and drop cuts. Removing the driver effectively eliminates human exposure to such high-risk tasks. Secondly, by substituting the operator, people are no longer exposed to 'hazardous' human driving behaviours. The assumption is that once control is transferred to a computer the people who remain are no longer exposed to a 400-tonne haul truck. Trucks are now given assignments, execute those instructions and perform nothing else. On that basis, the value proposition stacks up, given that these assumptions reign true. However, if automation was to eliminate the risk entirely, then there would not have been any significant incidents.

Although there are no longer people driving trucks, the uncontrolled nature of a driverless truck incident highlights the possible consequences. There are also light vehicles, dozers, loaders and excavators still operating manually on the mine site. Even if driverless trucks were the only vehicles involved in an incident, investigators would be hard pressed to argue how people could not be exposed. The evaluation of risk in this digital era is a real balance between foreseeable and tolerable risk. A bandwidth between treating every incident as significant, versus the perception that there is no risk at all. The point here is that if systems and processes breakdown when humans are not involved, who is to say it would not happen when they were. This study is not a criticism of driverless technology but rather it makes the case that if it is not deeply understood, there is a real possibility that the industry could discard driverless technology entirely. Technology can be discarded through the hype cycle when failing to deliver in a trough of disillusionment (Panetta, 2019). There is reason why this paper is titled: "From driver awareness to obstacle detection: a tiger never changes its stripes". The introduction of driverless technology has not eliminated safety risk, rather it has removed human exposure to driving trucks and transformed what manual tasks remained. The trucks are still big, yellow and mobile: they are just now being controlled by a computer.

4.3. Methodology

4.3.1. Data Collection

The methodology involved collecting safety incident data relevant to manual and automated trucks in operation on the mine site. Incident data was extracted from a safety database, with a date range set from Financial Year 2014 to 2018. This four-year timeframe reflects the WA mine site's transition period from manual to full haul truck automation. The transition period enabled the research to follow the entire deployment of driverless technology and the implications on safety.

Collecting raw incident data required setting specific parameters in the database. Firstly, each department's data was selected to obtain the entire range of haul truck-related incidents. Department incident data was filtered for health, safety, environment and financial impacts. This method was adopted to ensure every incident reported could be easily found and incidents that may have been incorrectly assigned impact types identified (i.e. environment over safety). There were also noteworthy observations made during data collection. The researcher was made aware of certain haul truck-related incidents, which were unable to be located in the system. This was because search functions had only been set for health and safety aspects. It was soon found that a significant portion of driverless incidents was allocated 'financial' impacts over 'safety'. Once financial impacts were added, a number of additional haul truck incidents emerged. This observation was an interesting finding leading into the research. The discovery of this left the researcher asking, 'how were driverless haul trucks incidents being assessed?'

The exported information was tabled into an excel spreadsheet. The incident data was automatically tabled into various columns for every event. Columns included the incidents' unique identifier, date, department, title, investigation, severity and who it was reported by. Incident findings were obtained from each report's detailed description. For example, "At approximately 10:30am DT xxxx [Dump Truck] was travelling loaded towards Pxx Rom waste dump from Ex xxxx [Excavator]. DT xxxx has encountered muddy conditions causing it to briefly lose traction and breach lane". Investigation findings were included in the original notification with certain causes outlined in a separate report. As investigation ‘root cause’ types were not overly insightful, the researcher analysed and coded individual reports to identify whether a truck was involved. This interpretative process provided the platform for the data analysis.

4.3.2. Data Analysis

The raw safety data required each incident to be coded. Since there were no incident types, limited root cause categories and hazards assigned to each event, more context needed to be extracted by analysing every incident. Therefore, data coding was undertaken to ask more investigative questions of the uncontrolled situations:

- Did the incident involve a truck?
- Was the truck in manual or automatic control?
- What was the incident type?
- What was the associated hazard?
- Was the hazard new, conventional or has it transformed?

These questions not only provided more context, it enhanced the quantitative aspects of the data. For example, the analysis could determine the frequency of incident types and hazards. Calculating a frequency substantiated the impact of each occurrence and its condition. In addition, the methodology of coding gave rise to more structure in the data. The structure of the data increased the researcher’s understanding of the phenomenon by highlighting key themes. These themes provided a clear link between incidents and their associated hazards. For example, road conditions and network communication losses were the major contributors to truck lane breaches, thus drawing the link between new, removed and transformed hazards to highlight the technology’s impact.

Manual and driverless truck hours were collected in an attempt to normalise the incident data. For instance, even though the manual fleet had a higher number of incidents, the number of driving hours were much higher. The total number of incidents were not comparable when considering the fluctuation of each operation. Moreover, self-driving car companies are using a similar metrics to measure their safety performance. Waymo, for example, are utilising the number of miles travelled to measure reliability (Waymo Team, 2018). Frequency of occurrence comparisons are useful; however, caution is expressed when using it as an absolute figure to measure driverless 'safety' reliability. Driverless vehicles and their equipment failure modes are a very small component in an open, dynamic and complex environment. Therefore, the frequency of incidents should be used as an indicator not a baseline for failure modes. Nonetheless, in this study the results provide an interesting perspective on the consequences of introducing driverless technology on a mine site.

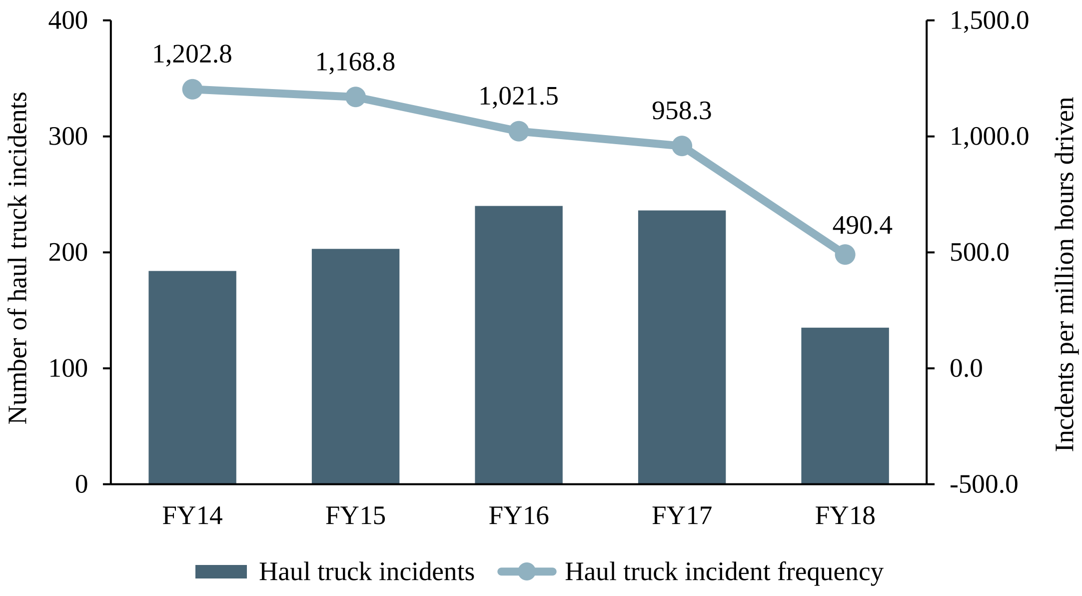
4.4. Results

4.4.1. Site Haul Truck Incident Frequency Reduced

The mine site's truck incident frequency significantly reduced over the four years as illustrated in Figure 1. Figure 1 highlights a 59% reduction in site haul truck incidents from Financial Year 2014 to 2018. A total of 998 trucks incidents were identified in the database. The data represents the incidents that occurred during the transition from manual to driverless control. Reducing the site's incident frequency was driven by an uplift in truck hours and a reduction in the number of incidents.

Figure 11.

Site haul truck incident frequency [a]



[a] Frequency was calculated based on the number of incidents in both the manual and driverless operation, divided by the number of hours driven, times a million.

The mine site's incident frequency averaged 921.4 incidents per million hours driven. Over a million truck hours were driven by manual and driverless operations. The highest incident frequency was recorded in the manual operations. Manual trucks recorded 970.2 incidents per million hours operated. Despite manual driving hours exceeding the driverless operation, the hours did not offset the high number of incidents. In comparison the driverless operation registered 864.4 incidents per million hours driven. Although there was a year-on-year increase in 'unconventional' incidents involving driverless trucks, the uplift was not substantial enough to impact the frequency. Moreover, as the driverless operation expanded the number of truck hours increased. Therefore, as manual operations transferred more control, the positive impact of the driverless fleet reduced the site's truck incident frequency. A significant portion of incidents were reduced by removing human exposure to truck driving hazards. For example, trucks heavily loaded by excavators, drivers being seated for extended periods of time and driving over rough roads. This resulted in neck, back and shoulder injuries that were the largest contributor to manual truck incidents. The second most frequent incident was tray damage. The repetitive nature of loading trucks left excavator operators vulnerable to misjudging the tray's position. In addition, the dust generated from digging material reduced the excavator operators' visibility of the tray.

Procedural breaches in manual operations were predominately traffic management breakdowns. Communication breaches occurred when drivers did not gain permission before passing another machine. Moreover, there were instances where the correct radio protocols were not utilised prior to trucks overtaking other vehicles. There were also priority rules in place to give more important equipment right of way. For example, watercarts needed to give way to loaded haul trucks. The most common breaches were between haul trucks themselves. Drivers were either unsure who took priority, had not observed oncoming traffic or forgot to give way. Secondly, graders were given the highest priority when considered to be 'working'. Therefore, truck drivers needed to determine whether the grader's blade was grounded. Trucks had not given way when the blade was observed to be lifted or working graders appeared to be heading in the opposite direction. Another example were truck U-turns on haul roads. U-turns were performed unassisted when drivers were lost or assigned to a new load unit. Drivers were also unsure of the process to block the road to prevent smaller equipment from travelling into the truck's turning circle.

Mobile equipment was expected to maintain a distance of 50 meters from one another. However, close interactions occurred frequently in the loading area and on haul road intersections. While heavily focused on the task, clean-up machines lost track of their proximity to other machines. For example, while watching the blade, a grader operator in one incident reversed out in front of a haul truck. In addition, trucks drove into Active Mining Areas (AMAs) when they were not permitted. Light vehicles (LV) closed the AMA when conducting workplace inspections, operator change-outs or equipment breakdowns. Drivers entered the AMA if they did not hear the radio call or identify an LV in the area. Manual trucks frequently made contact with haul road windrows, where drivers either misjudged the corner or did not identify the centre divider. Centre dividers are intended to prevent haul class equipment from cutting corners and contacting smaller equipment ("HWE Mining to face retrial over death of Adam Sargeant at Yandi mine," 2014).

When loaded haul trucks tip at the crusher, a lighting system is in place to indicate whether the bin is above its threshold with a red light. A number of incidents occurred when truck drivers tipped on a red light. Red light tipping occurred when drivers were distracted by two-way communication, assumed the light was green or forgot about the light altogether. While trucks were tipping at the crusher, there were truck drivers who also made contact with the structure. Truck drivers had either misjudged the bay width, or were distracted by radio communications or visually obstructed by dust. On a waste dump, there were instances of manual trucks pushing through tip edge windrows. Windrow breaches occurred when the windrow was either inadequate in height or constructed with incompetent material.

Operators were required to isolate trucks before entering the footprint. Truck drivers entered the footprint to refuel or visually inspect the machine. Drivers entered the footprint while the machine was energised during refueling or shift change. Isolation breaches occurred when drivers attended to oil leaks, material hang up or mechanical issues. Furthermore, during driver interchange, trucks also made contact with the boarding ramps. When attempting to park beside the ramp, drivers misjudged the distance from the truck to the edge of the boarding ramp.

Table 2.

Manual haul truck incidents

Incident Type	Description	Total (#)	(%)
Driver injury	Harm was sustained in association with a truck (i.e. hurt while on/in a truck)	136	24.0
Truck contact	Truck was impacted by another machine (i.e. excavator)	134	23.7
Procedural breach	Tuck did not follow the procedure (i.e. entering controlled mining area)	102	18.0
Priority rules breach	Truck did not give way to another truck who had way of right	74	13.1
Delineation contact	Truck made contact with a road divider	54	9.5
Crusher contact	Truck came in contact with a crusher while attempting to tip	24	4.2
Truck slide	Truck slid on the haul road (i.e. wet road or low-grade road base)	20	3.5
Windrow breach	Truck pierced through the separation windrow on the dump	5	0.9
Boarding ramp damage	Truck contacted the ramp while swapping out the operator out of cab	5	0.9
Truck alarm	An alarm was sounded due to a maintenance issue	4	0.7
Fuel hose damage	The hose used to fuel the truck was damaged	3	0.5
Boom gate damage	The gate to prevent entry into mining area was damaged by a truck	1	0.2
Exposed edge	A truck was exposed to an open tip head in the pit	1	0.2
Fume inhalation	Truck driver inhaled diesel fumes from the machine	1	0.2
Rock spillage	Rocks were spilled on the road from a loaded haul truck	1	0.2
Uncontrolled movement	Truck had rolled or moved unintentionally without control	1	0.2
Total		566	100.0

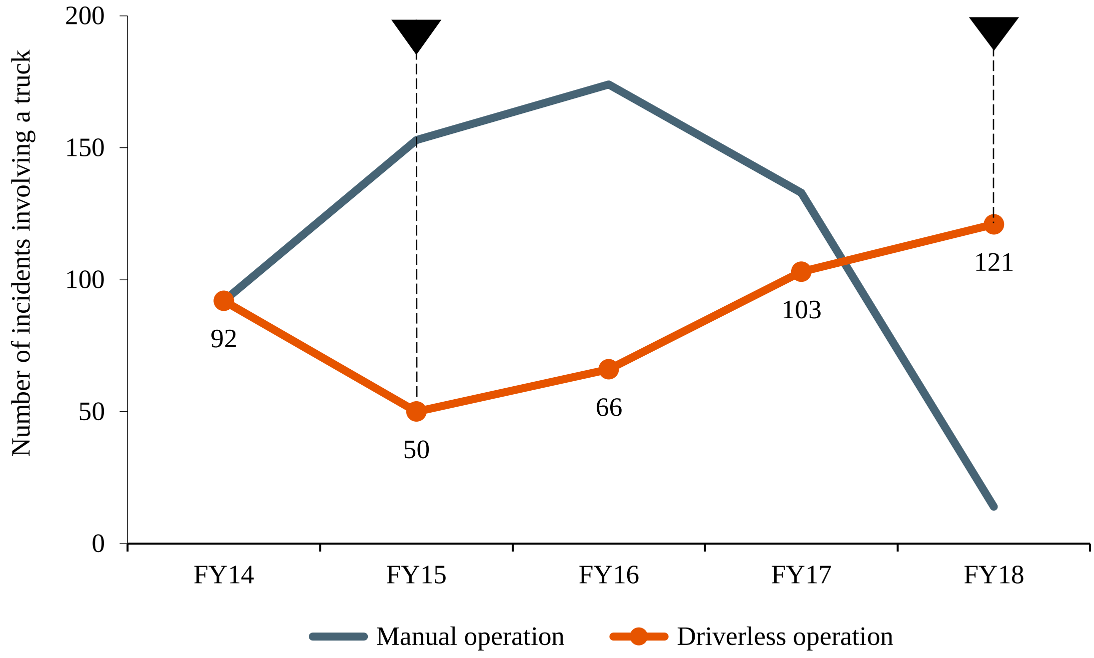
4.4.2. Despite Direct Safety Benefits, Unconventional Incident Types Emerged

Naturally, as a mining operation expands, the number of workplace incidents are likely to increase. However, a year-on-year increase in the number of unconventional incidents is vastly different, given that they were never before encountered on the mine site. Truck slides occurred in manual operations; however, the incident pathway in driverless haul trucks were novel and more frequent. Lane breaches were caused by communication losses, speed zones or wet road conditions. Loss of network immediately stopped trucks and frequently caused lane breaches. Similarly, in the early stages of use on the mine site, when a 20 km/h zone was reached, a truck would immediately reduce its speed from 60 km/h. Additionally, when roads were wet, the situation was compounded. Driverless trucks could not 'see' wet roads, instead they relied upon traction and speed zones to be put in place. Road objects that were suddenly detected caused a number of trucks to slide out of lane. Since LiDAR systems are yet to distinguish between objects (Teichman, Levinson & Thrun, 2011), trucks could not determine the difference between tumble weed, centre dividers and non-site aware vehicles.

Process breaches were quite similar to procedural breaches. Yet, the processes were residual human tasks based on technical limitations. Automation did not eliminate trucks from tipping on red lights. Mine Control were still required to remotely tip failed truck assignments. Therefore, controllers needed to observe the lighting system before overriding the truck. Remotely tipping reinforced the difference between available and observable information (Lützhöft & Dekker, 2002). Although automation successfully prevented trucks from entering closed AMA's, the system relied heavily on LV's to virtually lock the AMA. Driverless trucks drove into AMA's when LV's forgot to lock or engage the button effectively. Vehicles and equipment also overtook stationary trucks before taking control of them. Driverless trucks can move at any time and have limited detection capability from the side. Despite this, proximity detection enabled driverless trucks to determine the location of other vehicles. In addition, predicted travel capability detects vehicles headed for truck routes much earlier than before. Therefore, driverless trucks could be more adaptive, reducing their speed prior to the interaction. This capability had only been introduced into the WA Mining Industry post the collision between a watercart and a driverless haul truck (Department of Mines and Petroleum, 2015b).

Figure 12.

Driverless haul truck incidents increased as manual incidents declined



Permission-based control simplified priority rules and was far more passive. As a result, priority rules breaches between haul trucks were reduced to zero. However, despite engineering controls, interactions remained administrative for manual equipment. Clean-up machines such as graders and dozers in dynamic areas recorded the highest number of incidents. Dynamic lanes are able to shift from one side of the excavator to another. Dozer operators not watching in-cab displays were surprised by lanes generated in their work area, which allowed trucks to 'sneak up on them'. Equipment icons also flipped to cause reactions to driverless trucks, which was evident in the movement of clean-up machines.

Truck damage continued to occur through the transition to driverless technology. As previously stated, removing the truck driver reduced the consequences of injury, however it did not prevent truck trays from being struck. Conventional tyre separation and equipment breakdowns continued to occur. The automated technology had simply transformed the way the trucks responded to the situation. Similar to loading and dumping areas when the material was not surveyed into the mine model, the risk was that trucks could collide with ore stockpiles. In addition, full dump locations meant that trucks would attempt to reverse over the material already tipped, resulting in truck damage. Vehicles under escort were also unable to be identified by the trucks. A broken escort left non-site aware vehicles with fewer layers of protection, even though the trucks could identify them as obstacles to avoid colliding with.

Personal injuries had been sustained during truck refueling, testing and fault finding. Since drivers were tasked to refuel their own truck, injuries during manual refueling were captured. A shoulder injury in a driverless truck was sustained when lifting a hose into place. During truck testing, a production technician was injured in the passenger seat when the retarder had engaged. In another incident, a technician experiencing difficulties mode changing a truck had put their hand into a rotating LiDAR when it appeared to be stationary.

Truck recoveries referred to the retrieval of bogged trucks after travelling through wet roads. If the lane had been surveyed, then the area was permissible despite the conditions. Trucks had also reversed over windrows that were not surveyed into the virtual mine model. The trucks would detect the windrow initially, however once overridden by system technicians the trucks would attempt to achieve the dump location. To a technician, it can appear that there are no objects at all. This was identified in the survey mismatches, where trucks were using dump surveys that did not reflect the physical layout of the mine. Accurate survey data did, however prevent trucks from contacting crushers with pre-defined lanes. Crushing facilities were not dynamic areas like waste dumps and loading areas, although the fixed lanes did not prevent trucks from tipping large rocks that could damage the crusher.

Table 3.

Driverless haul truck incidents

Incident Type	Description	(#)	(%)
Lane breach	Truck had drifted outside of the assigned pathway	190	44.0
Proximity detection	Detection of potential pathway collision with machine	135	31.3
Truck damage	Truck has contacted or been contact by another machine	32	7.4
Process breach	System-based task did not comply with the procedure	31	7.2
Object detection	Identified object and stopped suddenly	14	3.2
Reversed into material	Truck reversed into a dump pile	7	1.6
Broken escort	Non-site aware vehicle became separated from escorts	4	0.9
Technician injury	Person was injured while attending to a truck	3	0.7
Production loss	Truck fleet down for extended period of time	3	0.7
Bogged truck	Caught in wet ground material	2	0.5
Uncontrolled movement	Rolling backwards or forwards uncontrollably	2	0.5
Windrow breach	Truck protruded through windrow on dump	2	0.5
Tipped on wrong pile	Incorrect material type was tipped on a stockpile	2	0.5
Truck collision	Truck was had contact another truck	1	0.2
Rock breach bund	Rock tipped over a waste dump and breached bund	1	0.2
Procedural breach	A procedure was not followed in the execution of a task	1	0.2
Failed truck assignment	Truck unable to execute given assignment	1	0.2
Crusher contact	Rock fell from tray and damaged the crusher	1	0.2
Total		432	100.0

4.4.3. Unconventional Incidents Driven By New and Transformed Hazards

The emergence of unconventional incident types created a new risk profile. A profile that comprised of risks that not only transformed hazards but also formed new ones. Transformed hazards were those that existed in manual operations but simply changed shape. Key differences were in the pathway to failure and how the trucks approached the situation. For example, wet roads existed in manual and driverless operations. However, both systems managed them in vastly different ways. A driver could easily spot increases in rainfall, adjusting their speed and drive to conditions. Truck drivers also spoke amongst themselves to be mindful of certain road conditions on the circuit. Driverless trucks, on the other hand, relied upon traction controls and system users to install speed zones on impacted areas. The operation's 'eyes and ears' were effectively replaced with satellites and sensors.

Driver awareness was entirely removed and replaced with road conditions. Attention has shifted from the person to the environment. Road conditions were always there; however, it appears that if truck actions were engineered, they were accepted. Load unit interaction remained, simply changed the consequence from driver injury to truck damage. Without drivers, the ergonomics of sitting behind the wheel was no longer the focus. Attention soon turned to road objects and clean-up machines. Since the trucks were not technically capable of distinguishing between objects, the focal point shifted to removing the objects. Haul road interactions remained, however there were no longer radio calls from a truck. Trucks passively remained in idle or sounded a subtle beep sound on the in-cab display to warn operators of their presents. In terms of the crusher, the fixed lanes remove the risk of striking the structure. The repetitive nature of reversing a truck was removed; however, it was replaced with remote operations occasionally overriding the system manually.

Table 4.

Hazards associated with manual haul truck incidents

Hazard Type	Description	Associated with incident (#)	(%)	Transformation [b]
Manual truck hazards associated with incidents (removed or transformed hazards)				
Driver awareness	Driver unaware of situation	140	24.7%	R
Load unit interaction	Heavily loaded or struck by excavator	107	18.9%	T
Truck ergonomics	Seating and steering arrangement	88	15.5%	R
Haul interaction	Truck interaction with haulage class	78	13.8%	T
Road conditions	Rough, wet or slippery conditions	32	5.7%	T
Plant interaction	Structure contact can cause truck damage	25	4.4%	T
Boarding ramp interaction	Ramp used to swap out truck drivers	20	3.5%	R
Heavy loading	Large rocks dropped from height	18	3.2%	T
Light vehicle interaction	Truck interacting with small vehicles	15	2.7%	T
Diesel fumes	Fumes airborne in truck cab	9	1.6%	R
Mechanical breakdown	Base truck mechanical problem	6	1.1%	T
Road maintenance interaction	Interaction with equipment working on road	5	0.9%	T
Changing crush lights	Crusher lights changing from red or green	4	0.7%	T
Refuelling hose	Contacting or leaving hose attached	3	0.5%	T
Clean-up machine interaction	Clean-up machine moving around in loading area	3	0.5%	T
Oversize material	Large rocks block crusher or damage truck	3	0.5%	T
Material logging	Material is identified incorrectly (ore vs waste)	2	0.4%	T
Open edge	Exposed height with windrow protection	2	0.4%	R
Access and egress	Climbing up and down truck access ladders	1	0.4%	T
Airborne dust	Dust inside truck cabin	1	0.2%	R

Procedure knowledge	Driver unsure of traffic procedure	1	0.2%	R
Falling material	Large rocks fall out of the tray onto the road	1	0.2%	T
Tyre failure	Ruptured tyres from use or heat	1	0.2%	T
Machine simulation	Simulation working environment	1	0.2%	R

[b] Manual Truck Hazards: R = Removed (262, 46.3%), T = Transformed (304, 53.7%)

Boarding ramp interactions had been removed since there were no truck drivers, however trucks still needed to be refueled and inspected. Therefore, a person was required to interact with the trucks. Despite this, the exposure to diesel fumes in the cab were removed. Predefined lanes also allowed driverless trucks to be more accurate in parking beside the fuel bay. Although personal injuries continued to be sustained during driverless truck refueling. Mechanical breakdowns continued to occur; however, technology-based functions such as communication losses were introduced. Without a network, driverless trucks will immediately stop, which drove the increase in lane breaches in the driverless operation. Where trucks would previously breach AMA’s, light vehicles became the centre point. The risk simply shifted to another proponent, hence the increase in zone locking hazards. Material that was dumped into a loading or dumping area never used to be a hazard. However, since the technology had limited vision of dumped material, the stockpile needed to be surveyed into the virtual model to determine the boundary. Similarly, non-site aware vehicles could not be identified in the virtual system, therefore driverless trucks had to rely upon LiDAR and RADAR technology to identify them.

Matching the virtual world to the physical world has never been more important. Manual mining equipment could operate if the virtual mine model was inaccurate. However, with a driverless truck system, the risk is that a truck can reverse over physical objects if the survey boundaries is not accurate. Therefore, open edge risks to truck drivers were replaced with virtual dump locations that are behind windrows. This has the potential for driverless trucks to reverse over windrows and down into areas below. It could be argued, however, that there is no risk given that there is no human inside the cab. Yet, the point here, is that it’s not the consequence in isolation, it’s the systematic breakdown in the coordination between humans and machines that is the concern. If the breakdown was connected to another situation, it is only imaginable what could occur.

Table 5.

Hazards associated with driverless haul truck incidents

Hazard Type	Description	Associated with incident (#)	(%)	Transformation [c]
Driverless truck hazards associated with incidents (new or transformed hazards)				
Road condition	Wet and slippery road conditions	116	26.9%	T
Clean-up machine interaction	Clean-up machine moving around in loading area	66	15.3%	T
Road obstacle	Truck detects windrow or rock	47	10.9%	N
Communication loss	Truck loses communications	38	8.8%	N
Haul road interaction	Truck interacting with haulage class equipment on road	30	6.9%	T
Load unit interaction	Truck being loaded heavily or struck by excavator	27	6.3%	T
Road maintenance interaction	Truck interacts with equipment working on road	22	5.1%	T
Operator awareness	Manual equipment unaware of truck presents	20	4.6%	T
Non-surveyed material	Material not surveyed into mine model	7	1.6%	N
Zone locking	Virtual zones not in place or applied properly	6	1.4%	N
Speed zones	Zones triggering significant truck speed decrease	6	1.4%	N
Non-site aware equipment	Equipment loses escort and does not have a predicted path	6	1.4%	N
Light vehicle interaction	Truck interacting with small vehicles	5	1.2%	N
Technology breakdown	Technology hardware breakdowns	5	1.2%	N
Full dump spot	Dump location already has material	4	0.9%	N
Stationary truck	Truck stationary on haul road	3	0.7%	T
Icon spin	Icon in virtual system flips to cause truck reaction	3	0.7%	N
Truck assignments	Truck loses assignment or lifts tray in loading bay	3	0.7%	N
Tyre separation	Tyre has separated from rim	2	0.5%	T
Single lane access	Virtual system moves trucks into oncoming lane	2	0.5%	T

Machine bubble	Virtual safety mechanism causing trucks to brake instantly	2	0.5%	N
Material logging	Material type in truck does not match the system	2	0.5%	T
Mechanical breakdown	Base truck mechanical problem	2	0.5%	T
Refuel hose	Lifting refuel hose resulting in injury	1	0.2%	T
Survey mismatch	Virtual mine planned on wrong survey	1	0.2%	N
Changing crusher lights	Lights changing between red and green	1	0.2%	T
Full dump	Truck tips on full dump and material reels over windrow	1	0.2%	T
Fixed plant interaction	Truck recovered and manually tipped contacting crusher	1	0.2%	T
Spot point behind material	Tipping location placed over edges	1	0.2%	N
Oversize material	Large rocks block crusher or damage truck	1	0.2%	T
Rotating technology	Rotating LiDAR system potentially contacting technician	1	0.2%	N

[c] Driverless Truck Hazards: N = New (301, 69.7%), T = Transformed (131, 30.3%)

4.5. Discussion

The analysis of driverless truck incidents offers some remarkable insights. Over the four-year transition period from manual to driverless control, the technology revolutionised the mine's risk profile. Although the value proposition for automation highlights a direct contribution to safety, new hazards and risks have emerged. It appears that the WA Mining Industry is yet to fully understand the safety implications that driverless technology can introduce. Since the occurrence of a number of unconventional incidents (Department of Mines and Petroleum, 2014b), there are signs that the industry is starting to rethink how it approaches the expansion of driverless technology (Department of Mines and Petroleum, 2015a). This empirical research study will enable the industry to improve their safety systems and leverage the lessons learnt from this mine site.

The original assumption was that the replacement of drivers would eliminate the safety risks of truck driving. Removing the driver from behind the wheel gave the impression that technology took care of concentration lapses and fatigue-related events. This may have been the case, as driver awareness was found to be the most predominant hazard in manual operations. At the same time, however, as the site removed one conventional hazard, technology was simply introducing another. Shifting the most common hazard from driver awareness to road conditions. Therefore, the allocation of driving functions to a machine did not underpin the popular notion on safety. Without truck drivers the mine site did however, achieve a reduction in haul truck incidents. Those incidents were also less frequent given the hours driven by both operations. Personal injuries in operations were almost non-existent, however the three injuries discussed earlier show how humans are still interacting with haul trucks in an operational environment.

The transition saw a haul truck incident frequency reduction through an uplift in operating hours and a reduction in incidents. The uplift was due to a natural expansion of the operation, while the reduction in incidents were realised through removing exposure and engineering elements of the haulage process. For example, automation removed exposure to vibration, sudden seat jolts and tray impacts. The permission-based control system coordinated truck interactions, increased travel lane accuracy and removed the need for associated infrastructure. Coordinating truck movement removed priority rule breaches and traffic management non-compliances. Specific travel paths avoided lane divider contact, refuel hose damage and crusher damage when reversing. All of which, made significant contributions to improving the mine site's safety, productivity and financial performance. However, as conventional incidents were being removed, technology was exploiting residual risks and cultivating new hazards of its own.

The introduction of unconventional incidents should be addressed with caution. Particularly in how they evolved and what appeared to be 'normal operations'. It was not a simple broken part; it was a complex human-machine interaction trying to achieve a goal: moving dirt. Technical limitations of driverless technology saw support roles locally adapt to keep the wheels turning. This was evident in the application of speed zones, road obstacle clearances and truck reassignments. Design parameters neatly threaded humans along the fringes, creating a system that leveraged human redundancy to overcome non-design situations. Engineering capability coupled with residual tasks created a new system of work. A system that only expected what had been engineered. Human tasks were therefore filling in the gaps and learning through practice. Learning that driverless trucks needed speed zones in wet weather, clearance to proceed passed obstacles and new assignments when instructions were irrelevant. As a consequence, the risk profile extended beyond functional models and failure modes. It was a complex arrangement between driverless capability, residual work processes and the frontline joining the dots.

4.6. Conclusion

Despite the original assumption that safety risks could be eliminated through haul truck automation, this research highlights that the technology is not there yet. This is evident through the emergence of a new risk profile that was explored in this study. The risk profile is considered new when comparing the hazards and risks of a manual truck operation. Hazards were reflected in the incidents involving driverless trucks, which were unique to their operation, due to novel pathways and situations that emerged through its introduction. This pinpoints the significance of identifying the safety risks when introducing driverless technology into a mining operation.

Significant progress has been made on removing human exposure to high-risk tasks. Automation was successful in reducing injuries to frontline personnel and coordinating the interactions between haul trucks. This highlights the value proposition of haul truck automation to the mining industry. It must be noted, however, that the industry cannot become complacent. The results of this study clearly show that mining companies must truly understand the capabilities of the system they are using. Improving their knowledge in not just how to work automation, but truly understanding how driverless truck systems work. This will allow the industry to work more closely with the system and improve the transparency between humans and machines.

Based on the results of this analysis, it is recommended that the Western Australian Mining Industry, in particular, review their relevant Guidance Notes and Codes of Practices to reflect the hazards and risks that were identified in this study. Modern innovation in safety practices need to be implemented to assist mining companies to thrive in this digital revolution. The automation of haul trucks is just one example however the principles on human-machine collaboration can be applied more broadly. An example would be explaining the importance of matching the physical mine to the virtual model. There are necessary steps in physical verifying digital models before automated equipment is clear to proceed. Developing new work practices can enable mining companies to redesign their safe systems for this next iteration.

This study was based on haul truck incidents that occurred on a mine site in Western Australia. The fact that it was only conducted on a single mine site, with one product, is a limiting factor. There are an increasing number of automated systems working across the mining industry. Despite the incidents being an indication of possible breakdowns in the system, the data may not reflect all the situations that resulted in an incident. In addition, the incident descriptions were interpreted to the best of the researcher's knowledge. As a consequence, incidents could have been grouped or labelled differently to reflect the data. Moreover, not every haul truck incident may have been reported. Nonetheless, there is a sufficiently large enough sample size to allow the research to draw conclusions, with each incident and hazard type that were used to inform the study's findings.

Chapter 5

Haul Truck Automation: Beyond Reductionism to Avoid Seeing Turtles as Rifles

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5.1. Abstract

Artificial intelligence offers a promising route to a sustainable future for the Western Australian (WA) Mining Industry, in which haul truck automation will play a pivotal role. This paper contends that the success of driverless technology hinges on the ability of artificial intelligence to embody the complexity of the world around it. The epistemology of automation is one of reduction. Reductionism has already applied practical constraints on the ability of intelligent machines to recognise dark faces, classify reptiles correctly, determine appropriate areas for policing and the likelihood of a criminal recidivism. The value position of artificial intelligence is one of prediction, and the machines' predictive capacity generally puts non-designed situations outside of its parameters, making its narrow and very bias view of the world appear to be more intelligent. Thus this paper argues, that technology that is applied in a mining environment must embrace its intricacies, otherwise the WA Mining Industry may miss the mark and witness similar examples of turtles being classified as rifles.

5.2. Introduction

In a recent study of neural networks, researchers found the existence of adversarial imagery in real-world systems. The study manipulated patterns on a turtle to fool image classifiers into identifying the reptile as a rifle (Athalye et al., 2018). Neural network classifiers are vulnerable to conflicts in the physical world and remain open to varying perspectives. What this highlights, is how artificial intelligent systems are operating in a pre-programmed view of the world re-arranged by the designer. Designers engineer artefacts by reducing them to their most basic parts. For example, the body, pattern, head and tail of a turtle are all stereotyped and fixed. Secondly, if it is process that we are trying to engineer, then the techniques are often analysed through time and motion studies. A great deal of 'science' is performed, determining what efficiency techniques should be standardised. Standardised methods provide the platform for automation, which attempt to lock-in the relentless repetition of that one best method.

Haul truck operations can be considered complex, where the constituent parts do not represent the function of the whole. In order to understand a haulage system, the process cycle is divided into component tasks: travelling empty; queuing and loading at source; travelling loaded and tipping at destination (Hamada & Saito, 2018). With technology becoming increasingly popular researchers are raising doubts about the future of work in open-cut mining, as technology is now capable of completing a large portion of truck driving tasks. For example, a driverless truck can drive from source to destination with what appears to be limited interruption. What is not always known, however, is the localised adaptions that make driverless haulage possible. There are multiple supervisory roles working in the background to join the dots (Caterpillar, 2013). Connections are being made between what has been designed and what occurs in practice. This is because driverless systems are only as good as the designer's imagination of how each mining system functions. If we only allow engineers to develop this technology on a reductionist view of the world, driverless trucks will be less adaptive and restricted to innovative ways of working.

When technology systems are designed as expert systems, they run the risk of operating way out-of-context. While they were originally designed specifically for a workload or optimisation problem, their success has led to them being applied more generally. This has resulted in a product facing situations that are beyond its design parameters (McKinnon, 2019). Strict parameters may even lock in the biases and inefficiencies that steered the Western Australian (WA) Mining Industry to automation in the first place (Bellamy & Pravica, 2011). Industries are often drawn to automation to release latent capacity and to fix supply chain inefficiencies. However, more often than not, the algorithms simply compound existing methods and inefficiencies. Technology transforms the aspects that it was designed to substitute or replace. What was imagined to be a simple substitution of a driver for a machine has turned out to be rather complex. Users find that there are residual activities that cannot be completed by automated systems. Therefore, human supervisors are given a number of residual tasks to help the truck fleet navigate around a mine site (Caterpillar Global Mining, 2019). Moreover, despite the designed activities, there are also unspecified tasks with highly cognitive problem-solving aspects that automated systems are unable to resolve. As a consequence, what was once imagined as a like-for-like replacement, while reducing cycle delays and removing human exposure, ensued the creation of new strengths and weaknesses (Department of Mines and Petroleum, 2015a).

Haul truck automation has been adopted to respond to increasing operating costs and to reduce human exposure to danger. However, this paper argues that engineering a haulage cycle needs to go further to resist reduction and embody the complexity of physical mining. The design in application needs to revisit the many ways of transparency and explainability. If such focus is not given, then both safety and productivity will be compromised. There are numerous safety proposals that highlight the removal of people from danger. While others explain how the inattention, fatigue and attitude-related aspects can be eliminated (Brundrett, 2014). However, before engineering a haulage system, the consequences and trade-offs need to be considered. In this research, the approach to reductionism, functional allocation and reconstruction of haulage systems will be explained, while offering empirical evidence on the impacts of truck automation within the WA Mining Industry-to date.

5.3. The Reduction of a Haulage System

5.3.1. Simplifying the Haulage Cycle

A simplified haulage system represents a number of components that work seamlessly together to load, haul and dump. Reductionism distinguishes between what the system has and what it does, achieving simplicity through what it excludes. The practice also distinguishes between what humans and machines undertake (Dekker, 2014). The simplification of haulage systems rests on the belief that components operate independently, without non-linear interactions disrupting the flow of the cycle. This is achieved by breaking down the system into its most basic parts, re-allocating tasks to either human or machine (Pritchett et al., 2013). The system is then put back together again, with isolated components that operate independently. This enables engineering to contain incidents and serious breakdowns in the design of the haulage cycle.

The reductionist approach aims to understand each of the components of a cycle individually within the system (Hamada & Saito, 2018). A simplified system improves upon knowing the behaviours of the constituent parts and being able to lock-in the productive methodologies for automation. It removes the variability and increases the predictability in what the system will perform. Haul trucks in a simplified system will therefore appear to be foreseeable and controlled in the way they execute the tasks. Therefore, trucks working within the design parameters will ultimately improve workplace safety and haul truck productivity. This constitutes the set of appearances that sit behind a much simpler haulage system.

5.3.2. Understanding Truck Driver Contributions

Now that the system has been simplified to its most basic steps, haul truck activities within the system are analysed to determine the contributions of a truck driver. For example, a driver may enter the intersection, indicate left, turn left and then accelerate away. This is where the components in isolation unfold as expected without interruption. What is not always clear, however, is the types of interactions that are likely to occur on that intersection. There are various situations that could emerge, such as trucks entering the intersection, graders maintaining road conditions, or broken-down machines being recovered. A truck driver has various means of adapting to any of these situations. Firstly, the truck driver can follow priority rules and either proceed or allow other trucks to enter the intersection. Secondly, a driver is capable of communicating with grader operators via a two-way radio and requesting to make a pass around the machine. Thirdly, the driver can request permission via two-way radio to Mine Control to pass broken-down machines. Consequently, the ability of a human to analyse and adapt to a single example, such as this, makes reverse engineering truck driver contributions very difficult.

Despite the high levels of confidence in manufacturing how the brain and mind work, people learn and think by acquiring knowledge from one instance not tens of thousands of examples (Lake et al., 2016). The ability of humans to adapt, particularly in novel situations, is unprecedented. If a crusher is unavailable, a truck driver will call Mine Control to ask what is happening. Furthermore, a driver will ask to dump their load at a stockpile in order to keep the trucks cycling. Oncoming trucks observing the queue at the crusher, radio ahead and request to drive to another crushing location. On route, truck drivers may observe rock spillages and windrows that impede their travel path. The ability to classify objects and avoid them can often be taken for granted. Even in wet conditions, truck drivers have the capacity to observe wet roads and adjust to impeding conditions (Jamasmie, 2019). There are also experiences and lessons that have been learned and retained. For example, knowing that a ramp is made out of clay material and is widely understood to be slippery in wet weather. An automated truck cannot remember this information. Despite having driven over that particular part of the road numerous times before, driverless trucks will not retain the data for future reference. Trucks may even slide out of their lane on the same road multiple times. Therefore, without humans injecting smooth layers of adaptive performance, such as traction controls and avoidance zones (Caterpillar, n.d.), driverless trucks would continue to operate on haul roads as they would previously. By truly understanding the truck drivers' contributions, it can be observed how far technological advancement has come, and where it still needs to evolve.

5.4. Engineering a Haulage System

5.4.1. Technological Advancement

Engineering a haulage system attempts to reverse engineer what activities manual haul trucks perform. It combines the understanding of the haulage cycle in loading, haul and dumping, with what we know about the human mind and brain. Without that intricate knowledge, the technology will just be making trucks available without optimising the circuit. Nonetheless, whenever automated systems are deployed, there is always a specific safety or optimisation problem that the user is trying to solve. For example, reducing driver delays, increasing truck availability or removing human exposure. Therefore, automated systems, at this stage, are all 'expert' systems. Expert systems require specific training data in order to program the execution of activities to be undertaken. Quite often, the training data comes from the users themselves, with the technology simply replicating the knowledge that is contained within those facts and statistics. Earley (2016) explains how there cannot be artificial intelligent systems without high-quality sources of data. For this reason, driverless trucks are limited to the data sources that are collected, coupled with the intricate knowledge of the activities undertaken by truck drivers.

Data sources are now considered a key enabler for becoming an incumbent disruptor in industry (Araujo, 2018). However, data is not always free from biases and discrimination and may simply reinforce the problems of the past. A study on predicting crime, for example, found that the prediction on future crime was based on how many arrests occurred in a particular area. Therefore, the technology simply redirected police to ‘crime’ where they were already policing (Lum & Isaac, 2016). Technology is concerned with recognising the patterns in a data set and compounding the information that is contained. With enough data, designers are able to recognise recurring themes and the common types of ideologies. Whether it is language processing (Hermjakob et al., 2018), computer vision (Brandt, 2017), robotics (Frohm et al., 2006) or self-driving vehicles (Goel, 2016), they all contain basic visual scene understanding, pattern recognition and the ability to recognise objects. This aside, there are other aspects, like the ability to communicate over the radio to pass another machine. Equally important is the ability to recognise the physical artefacts that surround the truck. LiDAR and Radar are capable of representing physical objects by bouncing light and radio signals, though it does not truly ‘understand’ those objects. Understanding dates back to the thought experiment of the Chinese Room. The experiment highlighted that if someone was given a set of questions in Chinese and followed those instructions to look up the required responses, it could appear to outsiders that they understood Chinese (Hermjakob et al., 2018). While this may be the case, this situation is very different to navigating real-world aspects that have never been confronted before.

Narrow-minded expert systems can be exposed when faced with non-designed situations. When automated systems are developed and tested against the data they were trained upon, automated systems can appear to achieve human level performance (Firmin, 2019). However, when faced with a novel situation or adversarial images, machines can operate beyond their context (Athalye et al., 2018). This may result in unintended interactions, misclassifying the object or not identifying the objects at all (Department of Mines and Petroleum, 2015b). Although technological advancements have made object detection possible, it is not there yet (Teichman et al., 2011). There are attempts to reverse engineer more human-like reasoning systems in machines, allowing them to become more adaptive outside their design parameters (Lake et al., 2016). Bridging the gap between science and engineering intends to increase our understanding of human intelligence, while figuring out the techniques to build human capabilities in a machine. The important part of this, is teaching the WA Mining Industry how driverless technology works, not just how to work it. Therefore, mineworkers can be empowered to understand the computer systems they work with, equipping them with the knowledge to observe non-designed situations and failures to predict future interactions reliably.

5.4.2. Supporting Roles, Functions and Tasks

The supporting roles of a driverless system are never conceived with humans in mind. Roles, functions and their tasks are leftovers from what engineers are yet to automate. The residual is based on technical limitations and the premise that human-machine capabilities are fixed (de Winter & Dodou, 2011). However, the strengths and weaknesses are never static; their abilities will co-evolve as people learn and technological systems are upgraded (Woods & Hollnagel, 2006). At the beginning, supporting roles are residual tasks that are allocated to human supervisors. The arrangements of the system are studied for what is contained (i.e. a truck driving from A to B), which excludes how the driver is deeply connected to how the system functions. For example, calling another machine to clarify whether a load unit is down for maintenance. Therefore, although supporting roles are given specified functions by design, the inability of a truck to think outside the box requires more human intervention than was once thought necessary.

Functions are areas of responsibility that are found along the fringes of the role. Although a truck driver is expected to travel from load source to destination, they are also expected to communicate via two-way radio, identify hazardous road conditions and respond to emergency situations. The literalism of a machine agent, however, does not provide the same levels of insight to supervisors (Billings, 2018). The explainability for what a driverless truck performs can be quite low, which forces supporting roles to learn truck functions through observation. This can be observed in driverless trucks that perform a U-turn while waiting in queue to be loaded. While Mine Control may analyse the assignment engine to work out the reason for its actions, ancillary equipment operators can be left confused as to why the truck did not wait in line to be loaded. Where radio communications were used to advise others of truck movements, are now hidden among computerised interfaces and systems. System-based roles have different functions and levels of system access. Therefore, it can also be difficult to determine the right level of information for each role and avoid inundating people with information they do not need or know how to interpret.

There are a residual set of tasks that have been developed by design. Uploading surveys, calling trucks to be loaded and verifying dump locations are examples of tasks created for support roles (Caterpillar, 2013). Human support roles play a critical role in ensuring the safety of driverless operations. The tasks support the verification of the virtual world to the physical world, a task that has failed to be verified correctly in the past (Department of Mines and

Petroleum, 2014). This is where the processes between humans and machines become so important. Even though the process does not unfold in a predictable manner, support roles must have the foresight to prevent trucks from falling into sticky situations. A driverless truck, for example, may be attempting to achieve a reverse point that is located behind a windrow. Despite the dump being verified correctly, Mine Control may have simply corrected the boundary in order to become a straight line. Local adaptions are continuously evolving, adjusting and maneuvering around danger that continuously emerges. The supporting roles, in effect, are now the eyes and ears of the operation.

5.4.3. Processes for Supervisors and Team Members

Processes are instructions that enable people to work with driverless haul trucks. These instructions are the tasks that provide the driverless operating environment or supply chain interfaces. Moreover, instructions are underpinned by the designers' imagination of operational practices. For instance, to mode change a truck, there is a sequence of steps to follow when executing the task (Glover, 2016). However, it is dependent on whether the task proceeds along predicable lines. The engineered component of a task theorises the truck responding to a person's requests. Its simplicity comes with the exclusion of the complexities that arise in real world applications. Designers are unable to plan for every contingency, and therefore, call upon humans to solve problems. Consequently, when a conflict between the design and the real world emerges, it is human adaption thinking outside the box that is required to close the gaps.

Conflicts emerge when a person identifies a truck function that is beyond the prescribed parameters. Despite the design allocating tasks to be undertaken by either human or machine, there will undoubtedly be unique situations. The paradox, however, is intervening to prevent a truck failure or cause one. This is the distinct situation that occurs in supervising automated systems. If a driverless truck is unable to achieve the reverse location at the crusher, supervisors would be expected to resolve the situation. Although the truck has been assigned a particular process by design, the unspecific creativity necessary to recover the situation will be novel and complex. Operational practices are a collection of individual experiences and external information. Nonetheless, automated systems offer little opportunities for people to practice their marginalised skills. Therefore, when those skills are called upon, people can perform poorly. Rather than debating deviations from design processes, leveraging the problem-solving aspect of human intelligence can enable supervisors to assist automated system navigate operational complexities.

5.4.4. Protecting the System From Negative Outcomes

Layers of protection are controls that are designed to prevent the system from failure (Willey, 2014). On the surface, the linear causal chain gives the appearance that the system is well protected (Glover, 2016). The assumption, however, is that the trajectories of workplace incidents are linear. The indirect sequence may not even commence at the top of the theoretical walls of protection. When the interactions are non-linear, interactions can arise from various angles, and those linear protections can become ineffective. Despite the layers of defense being engineered, automated systems are not known for their response to isolated failures. Rigorous fail-safe systems and test structures designed to insulate driverless technology have manufactured their own causal pathways that have mystified the WA Mining Industry (Department of Mines and Petroleum, 2014). No one would have imagined that a driverless truck would be unresponsive towards an impending truck collision (Department of Mines and Petroleum, 2015b). The consequences of engineering a complex system is that the outcomes are generated from complex interactions, not the failure of the individual components themselves.

Engineering more layers of defense only adds to the complexity of the system. Therefore, controls need to be applied diligently in order not to impose further opacity on the system. Protection may even need to be applied in areas where control gaps do not appear. The introduction of a new barrier simply creates a new opportunity for interaction. For instance, with the introduction of predictive path capability, even though manual equipment may not be heading for a truck's intended path, its potential direction and speed can project a collision. This can lead to the trucks engaging the emergency stop device, which can result in travel lane breaches where previously they did not exist. Despite the diligence of high protection levels, the success of the system depends on whether it can withstand disruption and bounce back from novel situations. Control systems must move beyond literalism, becoming agile when compressed and stretched to their operating limits. The protection systems (i.e. LiDAR, Radar, emergency stops) designed to insulate people from human limitations (i.e. fatigue, concentration), appears to have introduced its own level of complexity through the reconstruction of the haulage system.

5.5. Reconstructing a 'Simplified' Haulage System

5.5.1. Team Dynamics

When the system is eventually reconstructed, people find themselves feeling out the trucks' operating parameters. A truck's reaction to a situation indicates what the truck is capable of and when it will stop. For example, grader operators work closely to a truck's boundary to observe how the machine will respond. This is a kind of game play often observed in teams, feeling out how far another player can pass or kick the ball. It is often intuitively known, how far players should be located in order to receive the ball. When it comes to machine agents, the approach to replacing human work is rarely conceived with human-centric methods. Therefore, despite the specific training people undertake for their functional role, system supervisors find themselves working out how machine functions will respond in the workplace. This is due to the machine logic being hidden from the user, which claims to protect the vendors' intellectual property and stop the system from being overridden.

The storming phase between mineworkers and machines is where the trade-offs and the frustrations occur on the frontline. Where manual machines could previously communicate directly with a truck driver, now requires a different line of communication. Communication with a driverless truck involves selecting boxes, updating system settings and typing instructions to inform the machine on what needs to be performed next. Moreover, it can also be difficult to get a machine to register what the human is trying to tell it. This is not just for system-based roles, but also the operators who have to interact with driverless haul trucks. Excavators, for example, need to set a loading point with their bucket to identify where the truck needs to reverse to. Operators are also required to press a button on their joystick to authorise awaiting trucks to enter the loading area. Where a truck driver previously reverse into the loading bay, an excavator operator is now required to authorise the trucks' entry through a computer-screen interface.

Through practice, manual equipment operators working with driverless trucks learn what functions a machine can and cannot perform. Often, it can be frustrating for users, who now need to complete tasks that were previously handled by truck drivers. On the other hand, the transfer of agency can be quite positive, allowing excavator operators to choose when a truck comes into the loading area. Overtime, mobile equipment operators learn driverless capability through their interactions with the system, identifying limitations and reactions to various situations. Although a screen interface helps with equipment separation, operators of manual equipment can activate a driverless trucks' proximity alarm. Until operators learn safe distances, manual equipment can frequently stop trucks by not knowing how to interact with them. In addition, a manned haul truck would remain outside another piece of equipment's 50 metre exclusion zone, making contact over the radio and asking for permission prior to entering the work area. As a consequence, manual operators interacting with driverless trucks go through a phase of working out driverless capability before they can begin to perform under these new circumstances.

The benefit of working with machine agents is their relentless repetition of one method. Although there are complexities, the predictive path capability assists people to monitor the trucks' intended haul route. This also increases their level of trust towards driverless trucks. In a manual environment, it can be difficult to determine whether a truck driver will turn left or right. At times, truck drivers do not indicate or leave their indicator engaged, reducing the level of trust towards manually operated equipment. Contrastingly, human operators are given a level of security and control over driverless trucks. Each operator is given an emergency stop device that can stop all driverless trucks within several hundred metres. Once people identify recurring patterns and operating parameters of the trucks, they begin to perform more efficiently. Despite the positive performances observed with driverless trucks, the language and information outputs transform, resulting in a much more complex by-product to learn.

5.5.2. Learning What Driverless Trucks Perform

What was previously controlled locally by truck drivers is now managed by a centralised control system. A work environment where pre-shift briefings, radio announcements, safety meetings and return to works could articulate site-related matters to truck drivers, no longer exist. Alternatively, users are equipped with a standardised fleet management system that operates within specific operating parameters. The benefit of those parameters is that every truck performs each aspect of the cycle the same, yet the downside is they perform nothing else. Whether it is turning a corner, indicating or changing gears, the entire fleet will all perform tasks the same way. Consequently, the same areas of the road are targeted, which results in corners and ramps deteriorating much faster. Since mine supervisors have limited control over the driverless trucks' performance, they begin to adapt local practices within the operating parameters. This can be seen in the installation of speed zones, which prevent trucks from changing gears on ramps and ultimately preserving road conditions for longer. As more capabilities and limitations are learnt, the more supervisors find creative methods of closing the gaps.

If engineers are the only architects of driverless technology, automation may only lock-in systemic ways of mining. Moreover, with multiple customers operating along the same parameters, the impact could be observed more broadly. If the designer is yet to figure out how to automate parts of the cycle, the system leans on ancillary equipment operators, supervisors and manual truck operations to cover the rest. Determining when a truck should leave a loading area is complex, therefore excavator operators are required to inform trucks by pressing a button. In addition, narrow work areas, such as stockyards, can require haul trucks to be operated manually. When it comes to supporting roles, trucks are unable to distinguish the difference in road objects. Therefore, the system relies heavily on mining personnel to verify that the truck's travel path is clear before proceeding. A truck may have identified a windrow, tumble weed or even cattle. Supervisors have learned that reverse objects should be approached with caution, given that driverless trucks have reversed over waste dumps after being cleared to proceed (Department of Mines and Petroleum, 2014). Virtual and physical distinctions can result in trucks attempting to achieve dump locations regardless of context. Therefore, driverless trucks are unable to free themselves of machine literalism, executing specific instructions that are pre-programmed into the machine.

The difficult part about learning what a driverless truck can do, is that the logic behind a decision remains hidden. As a result, supervisors of driverless trucks learn by observing and doing. A supervisor can learn the patterns of a driverless truck by watching the reactions to machine interactions. In addition, people also monitor the assignment engine to compare with the trucks' instructions. Other than observations, the language and labels that are used must be learned in order to understand what the truck is trying to explain. The methods of communications are chosen by the designers of driverless systems, not the users themselves. Whether it is through alarms, beeps, lights and information boxes, they are all structured in unconventional methods that were previously experienced in a manual truck operation. Therefore, the learning process for users is evolutionary, as software systems are upgraded, and new product capabilities are developed. Supervisors will always compare driverless technology to human level performance, leveraging their domain expertise in how mining operations should function. Despite this, artificial intelligence systems like AlphaGo, may even find other methods of hauling that are worth exploring (Etherington, 2017).

5.5.3. Supervising and Working With Driverless Trucks

The problem with working with a pre-programmed machine, is that they are not necessarily team players (Christoffersen & Woods, 2002). However, the WA Mining Industry has so far found driverless technology to be a relatively good ‘team player’. Driverless trucks run hard, play their role and do not complain. Moreover, supervisors feel empowered over the truck fleet, responsible for task allocation and capable of stopping the fleet at any time. The trucks will literally follow every instruction, re-assignment and take longer routes to achieve their objectives. However, it depends on the perspective when evaluating the situation. Although the trucks play their specified role, they also need a lot more support. There are residual tasks that are often unspecified, unpredictable and imbalanced. Supervisors can be undertaking monitoring tasks and simultaneously be confronted with network outages, truck slides and broken-down machines. This can quickly lead to fault-finding exercises in determining what has occurred and why. Monitoring a fleet can involve long periods of inactivity, quickly followed by highly cognitive tasks. Therefore, human improvisations rapidly materialise on the frontline; adapting, testing and playing in order to keep the trucks moving.

Supervisors of driverless equipment are often held accountable for the performance of the machine. If the machine did was it was programmed to do, there is only ever the supervisor who is to blame (McKinnon, 2019). In particular, if the situation was considered foreseeable, then the supervisor is expected to intervene to avoid a negative outcome (National Transportation Safety Board, 2018). It is an interesting perspective when automated systems are not held to the same standard of accountability as supervisors. For example, if a truck’s action resulted in an incident, yet the machine did what it was programmed, then the supervisor is held accountable. Supervisors are expected to monitor and detect failures that are unspecified and unpredictable in nature. Data is often retrospectively analysed to highlight whether a supervisor could have taken control. However, with operating parameters rarely known by the supervisor, they can be left surprised when the machine simply hands back control. Automation surprises have been a phenomenon for quite some time (Sarter et al., 1997). Driverless trucks, for example, can be found driving the longest haul route to the crusher. To supervisors, the action can be leave them amazed as to why the truck chose a longer travel route. What is always not explained, however, is how multiple network outages or obstacle detections influences the system to increase the predicted travel time. Therefore, a faster route is selected in order to get the trucks to their destination sooner. This prioritisation and decision-making process is not always explained without a prolonged analysis of the system. Supervisors are rarely afforded the time to reflect on the actions and insights that justify their marginalised roles in optimising the system.

5.5.4. Navigating Beyond Design Situations

Situations that emerge beyond the design driverless technology requires supervisors to think outside the box. The benefit of driverless haul trucks over self-driving cars is their ability to stop when faced with novel situations. For example, if a survey has not been uploaded for the area, the truck will not enter the area. Moreover, if the communication network is lost, the truck will stop. Self-driving cars, on the other hand, are not afforded the same luxury. The vehicle will hand back control to the driver regardless of if the person is prepared for it (SlashGear, 2017). Navigating these situations in a mining environment is a little different, given that the landscape of the mine is always changing. Therefore, it is usually in the truck restart where the problems arise. For example, a truck detects an object while reversing to a tip edge, however it may not be an object at all. The object could simply be the windrow, with the reverse point being placed behind the windrow (Department of Mines and Petroleum, 2014). The truck would be unaware that the detected object is a windrow and should be the surveyed dump location. Therefore, the truck supervisor navigates this situation by physically verifying the location of the windrow and uploading a new survey. Without this type of adjustment, the truck would attempt to achieve the location if the system was cleared to proceed.

Since novel situations are infrequent, it is not often that recovery skills can be practiced. Monitoring automated systems has been argued to conflict with human cognition (Reason, 1990). Therefore, when humans are needed to intervene, they can react negatively. Despite this, the ability of a human to apply a level of unconstrained thinking to draw from external sources and experiences, reinforces why they remain. Operating parameters will continue to hamstring driverless trucks by design, given that a machine has pre-determined views of the world. While some simulations and games have multiple possible outcomes, all of the physical world's scenarios are unlikely to be computed. This is dependent, of course, on whether someone believes that the physical world is simply a simulation. If that were the case, simulation could simply learn to represent the artefacts of the world, making non-designed situations a thing of the past. However, as previously explained, this is a reductionist view of the world. Therefore, if human-machine systems are going to navigate complexity, many argue that they will have to work better together (Woods & Hollnagel, 2006). A more collaborative approach will have to allow information to flow freely between humans and machines. Currently, the focus appears to be more on replacing drivers to realise an economic value. This approach will ultimately lead to independent systems, which are ignorant of human-centred perspectives (Fridman, 2018). However, if engineers are to overcome complexity, driverless systems will need to become more open sourced and start working with other branches of science. Otherwise, driverless technology could end up in similar situations as other pieces of extended intelligence, becoming solutionist, opaque and bias in light of the customers' needs (Bleicher, 2017; Bolukbasi et al., 2016; Dressel & Farid, 2018).

5.6. Conclusion

Evaluating the approach to haul truck automation highlights limitations of reverse engineering a complex system. If driverless technology is to move beyond reductionism, it needs more than a collection of engineers to be included in its development. Otherwise, its deployment could experience similar practical constraints as other technologies, with an inability to recognise certain objects, incorrectly classify artefacts and predict outcomes based on stereotypes. What appears to be a truck functioning a particular way on the surface, could simply be a reinforcement of conventional practices. Despite the mining industry buying this technology, they are not the custodians of the algorithms, they are merely the users. Therefore, mining companies have effectively handed over their agency and ability to innovate to vendors. Although the technology has reached enough engineering maturity to be deployed in a mining environment, there is far more to human intelligence. Drivers are able to recognise the physical elements in the mine and learn from the interactions that are had with them. Where operations were in direct control through truck drivers, is now managed passively through a centralised control system. The consequences can be observed in variety of settings where artificial intelligence targets data correlations and not the causes. Therefore, to shift the industry paradigm, a diverse range of domain experts and product users need to assist engineers to designs systems beyond narrow and bias views of mining.

This research study highlighted various examples of reductionism in practice in the WA mining industry and the simplification of predicting criminal recidivism, foreseeing areas of crime and classifying objects. The predictive capacity and level of accuracy has been achieved by validating machine performances against the data that was held out for testing. Therefore, as this study suggests, when specialised technology faces non-designed situations, it relies heavily on human supervisors to navigate them. Although technology can appear more intelligent than humans, this assumption and capability is achieved from what the system excludes. As a result, haul truck automation has been no different, with the technology presented as a predictable and more accurate substitution for truck drivers. However, as significant incidents demonstrate, driverless technology has its own set of novel situations to resolve. If the industry is to truly work towards becoming safer and more productive, the underlying causes of incidents and inefficiencies need to be addressed, rather than simply running the system efficiently more unproductive. The industry must push for more open collaboration with users to enable users to establish new methods, ideas and products. More collaboration will enable the industry to move beyond the technological advancements of today and embrace complexity. As a result, the approach can avoid systemic tendencies, opacities and exploitations of inefficiencies that come with replacing truck drivers with machines.

Chapter 6

The Experiences of Mineworkers Interacting With Driverless Trucks: Risk, Trust and Teamwork

This chapter is being considered for publication:

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6.1. Abstract

Driverless haul trucks represent a significant safety transformation for mine site workers in the Western Australian (WA) Mining Industry. Research within the industry is yet to explore the experiences of frontline workers who are mining with this new technology. The aim of the study was to investigate the practical experiences of miners working with driverless trucks to provide a broader evaluation of safety incidents on WA mining sites. A stratified sample of workers, from a WA mine site, were interviewed face-to-face using a mixture of open and close-ended questions. The research study undertook a convergent parallel design approach to develop a comprehensive understanding of various risk perspectives. Interpretive data collected from multiple cases were analysed thematically through cross-case displays. The results indicate new hazards and risks are introduced through automation on mine sites. Despite this, miners developed high levels of trust for technology through predicted pathways, adherence to instructions and exercising diligence when stopping for objects. The driverless trucks were perceived to play their part; however, technology does not assist mineworkers and

engage in team play. The workers' perspectives in this study highlight the introduction of new risks, high levels of trust and the narrow focus of driverless technology.

6.2. Introduction

Driverless haul trucks have been involved in several mine site incidents since 2013 (Department of Mines and Petroleum, 2014). These kind of events are unconventional and are new to the Western Australian (WA) Mining Industry (Department of Mines and Petroleum, 2015a). Although they account for a small number of total incidents across the industry, plans to expand the technology across Australia could see those numbers increase. Incidents involving driverless equipment have not only been observed in the Mining Industry; with self-driving car collisions occurring on public roads across the United States (National Transportation Safety Board, 2017; 2018). Despite recent reports of incidents involving driverless haul trucks, they provide little insight into the experiences of mineworkers working with this technology. However, the experiences of people interfacing with automated systems across high-risk industries does appear to be well known in aviation (Billings, 2018), maritime (de Vries, 2017), manufacturing (Frohm et al., 2006) and the railroad industry (Gschwandtner et al., 2010). Experiences reported through the interactions with automated equipment include automation surprises (De Boer & Dekker, 2017), machine literalism (Billings, 2018) and lack of transparency (Wessel et al., 2019) to name a few. What is most concerning, however, is the fact that automated systems are often evaluated on what they have been programmed to do, not on what they should have been programmed to do (McKinnon, 2019). Such inward thinking will hinder the improvement cycle of human-machine systems, leaving the frontline to continue to make local improvisations to soothe the practical constraints of pre-programmed machines.

Open-cut mining represents a unique and high-risk environment with mine workers performing various tasks with a variety of tools and equipment. Moving haul trucks creates a particular risk, due to the mobility, size and speed of the machine. In addition to this, mining companies are now replacing their truck drivers with automated systems. This substitution represents a transformation in the nature of tasks completed on mine sites, and associated risks, with the integration of human and machine activities. Moreover, there are also specific risks associated with computer interfaces, which are linked to feedback loops and system warnings (Dixon et al., 2007; Parasuraman & Manzey, 2010). Lastly, supervisors and users of automated technology are often the last lines of defense, applying local adaptions to avoid incidents and recover systems from failure (Reason, 1990).

Several studies have made connections to the nature and causes of human-machine breakdowns in an attempt to investigate the effects of automation on human performances. There have been reports that automation can be challenging to track given the lack of transparency in machine interfaces (Sarter & Woods, 1992). More recent studies have explored the effects of the unawareness of machine modes and associated features (Björklund et al., 2006; Feldhütter et al., 2019, August 26-30). Specifically, a lack of mode awareness emerging from an overreliance on automation rather than visual attention. Mode awareness has been argued to be a more complex phenomenon than merely eye-tracking. In addition, there are also links to the level of trust that is extended to automated systems and the reliance that is placed upon them (Botsman, 2017; Körber et al., 2018; Lee & See, 2004).

Despite the extensive amount of human factors research conducted in the aviation industry, there has been little research undertaken in the WA Mining Industry. A Code of Practice (COP) by the Department of Mines and Petroleum (2015a) indicated that there are unique risks associated with automating mobile equipment. Although there is no mention of trust or reliance issues that have been linked to automation (Hoff & Bashir, 2015), the COP does note the risk of human intervention, system overriding, survey mismatches and mode switching. Research examining the attentional demands of automation suggests that monitoring automation can create out-of-the-loop problems for humans (Endsley, 2017). Moreover, a study in automated driving identified that individual trust levels influence how humans monitor the surrounding environment (Körber et al., 2018). Therefore, there is a real need to determine the trust levels of miners and whether attentional demands are leading to out-of-the-loop problems (Department of Mines and Petroleum, 2015b).

There is a significant body of knowledge that evaluates whether automated systems are team players (de Visser, Pak, & Shaw, 2018; Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004; Sarter & Woods, 1997). Team players have been defined as agents that cooperate (sharing, observable, directable) and participate (fluent, coordination) in team play (Christoffersen & Woods, 2002). Within the aviation industry, there is a powerful link between new surprising problems and human-machine breakdowns; for instance, how automated systems managed to get into a particular mode (Sarter & Woods, 1995). The characteristics of a team player are that they must be able to cooperate with driverless trucks and share similar priorities. If automated systems are to be redirected, relative to operational demands, the task can be achieved quite easily. Finally, the effectiveness of feedback and awareness improves team play and minimises the significant problems with human-machine interactions (Sarter & Woods, 1997). The high-risk environment of driving trucks suggests that improving team play is equally important in mining. However, there is still no research conducted on how driverless trucks can become better team players.

The research aimed to explore the practical experiences of mining personnel working with a driverless haulage system. This aim was achieved by facilitating face-to-face interviews with workers using semi-structured questions. The technique enabled the researchers to gather quantitative and qualitative data on the perspectives and lived experiences of worker interactions. Data that was transcribed was analysed using a pattern matching technique, identifying the themes across the sample group to represent the experiences of workers.

6.3. Methodology

6.3.1. Design

The study embraced a convergent parallel design approach to develop a comprehensive understanding of risk perspectives (Creswell & Clark, 2011). Complex reasoning was adopted to accommodate emerging themes inductively and deductively for validation. The process worked back and forth until data saturation was achieved (Creswell & Poth, 2017). The interview data were compared and contrasted for grouping and theme allocation. The combination of quantitative and qualitative methods strengthened the results, quantifying the 'Yes' and 'No' responses with context and explanations from the qualitative data (Creswell, 2014a). The multi-method research design increased the likelihood of developing empirical generalisations about the phenomenon, contextualising the quantitative aspects and measuring the qualitative variables. In an attempt not to over-generalise the population, any inferences were supported with distinct experiences when concluding. This approach preserved the inherent complexity of the perspective by maintaining social context, exploring raw expressions and experiences on the transformation of roles (Miller & Crabtree, 2005).

6.3.2. Participants

The population of the study involved employees and contractors who work with driverless haul trucks. The size of the population was approximately 450 people who performed specific functions and characteristics pertinent to the research. A single-stage sampling procedure provided the investigation with direct access to the participants and the population under study (Teddlie & Tashakkori, 2009). The characteristics of the population were understood to enable stratification to occur. Therefore, the following roles and features identified: control room operators who monitor the performance of the trucks and make decisions via computer interfaces; pit technicians who attend to truck recoveries and system builders who build and verify the virtual mine model; ancillary and haul class operators manually controlling equipment; supervisors of system-based roles and auxiliary equipment operators who check and inspect work; and, the professionals who include the designers and specialist in the function and pre-programming of the trucks. Specific characteristics targeted by random selection may not represent the entire population (Creswell, 2014a). There was saturation by recruiting 25 participants, which represented 5.5% of the operation when validating results.

6.3.3. Data Collection

Semi-structured interviews were digitally recorded and took appropriately 45 minutes to 1.5 hours to complete. Participants were interviewed one-on-one between January 2018 and February 2019. The interviews were conducted on the research mine site and held in a quiet room. Every meeting was digitally recorded and was transcribed verbatim.

During face-to-face interviews, participants were asked whether automating the haul trucks introduced new hazards and risks. Participants that believed new dangers and risks emerged were offered to elaborate on what they were and what contributed to them. Secondly, participants were asked to provide a trust level rating and what underpinned their level of trust. Thirdly, whether the interviewees observed driverless trucks perform something that they did not anticipate. Did their trust level reduce after facing an incident or unanticipated situation? Fourth, did the system inform them adequately of what mode and function the truck is performing. Fifth, are driverless trucks considered team players and do they assist people to perform their daily tasks. Lastly, have mineworkers ever instructed a truck to do something, yet it undertook something different. The set of questions (Table 1) remained consistent for all participants across the stratified sample.

Table 6.

Interview questions specific to risk, trust and teamwork when working with driverless haul trucks

Topic	Question
Risk	– Do you believe new hazards and risks have been introduced through haul truck automation? – What do you think is contributing to incidents involving driverless haul trucks?
Trust	– What rating out of 10 would you say your trust level was towards the driverless trucks? – Have you observed a driverless truck perform something that you did not anticipate? – Did your trust level change after an incident or unanticipated situation? – How confident are you in redirecting or overriding obstacle detections?
Teamwork	– Does the system inform you adequately of what mode or function the driverless truck is performing? – Have you instructed a driverless truck to do one thing, yet it performed something different? – If the driverless trucks were team players, how would you describe them?

6.3.4. Data Analysis

Interview data was uploaded and transcribed into an online database. Interpretive data was collected from multiple cases and analysed through a cross-case display. The display compared the interview responses for patterns and themes when coding abductively (Tashakkori & Teddlie, 2010). A mixed-method analysis provided statistical and analytical generalisations about the phenomenon (Creswell et al., 2011). Descriptive analysis organised and summarised the responses to enhance understanding of worker experiences. The technique was applied to represent natural clusters, grouping and dimensions (Onwuegbuzie & Combs, 2010). Statistical results were, therefore, justified rather than predicted, comparing different perspectives drawn from qualitative and quantitative data (Creswell, 2014b).

Participants rated their understanding of the systems' modes and features, comparing their reasons why with responses that may have been higher. An inclusive design framework calculated statistics from data themes. Therefore, the numerical properties of the results stemmed from the stratified sample taken in the population (Onwuegbuzie & Combs, 2010). Cross-case analysis facilitated the simultaneous analysis of multiple perspectives to avoid being bound by individual contributing factors (Onwuegbuzie & Combs, 2010). Raw data were sorted into groups and did not distinguish between independent and dependent variables (Miles & Huberman, 1994).

Furthermore, to enhance the investigation, this approach enabled the researcher to identify patterns and variables. The variables were compared against the participants' perspectives working with driverless haul trucks (Wainer, 2005). A graphical analysis reported the results and highlighted how they related to the questions, which assisted in presenting the statistical information in visual form. Bar graphs were developed for the visualisation of practical significance and trends in the worker experiences.

6.3.5. Ethical Considerations

The research was approved by the Curtin University Research Ethics Committee (HRE2017-0844). The participants were provided with written information about the study. The researcher undertaking the interviews was an employee on the mine site. Therefore, the researcher informed participants of the researcher's role before commencing discussions. Participants provided written consent to participate in the research and were given the opportunity to choose an alternative location. The interviewees were assured that interviewed records were to be kept confidential, with the participants allowed to cease the interview at any time.

6.4. Results

The findings of the miners' experiences working driverless trucks were synthesised into three themes. Those three themes include; the introduction of new hazards and risks, higher levels of trust for haul trucks and the narrow focus of driverless technology. The headings describe the workers' primary response to the question of their thoughts and personnel experiences.

6.4.1. New Hazards and Risks Introduction Through Automation

6.4.1.1. Hazards and Risks

A majority of participants reported that new hazards and risks had been introduced through automation (see Figure 6.1). Participants explained how it used to be enough to train people how to drive haul trucks. However, since the replacement of truck drivers with driverless trucks, coordinating the truck fleet had become much more complicated. Driverless trucks were said to perform everything that was instructed, yet they would not perform tasks that were not instructed. New hazards, such as complacency, were reported to have emerged in anticipation of a trucks' next move. An expectation that the trucks would repeat the exact performances every single time. However, the participants explained how there are factors outside the design parameters that can influence the trucks' performances. For example, they discussed how truck settings and speed zones can be applied to change the truck's reaction to a situation. Human intervention was said to be required when the technology expected a particular operating environment; requiring roads to be dry and survey information to be accurate. When there was a difference between the virtual model and the physical environment, the participants highlighted that the driverless trucks were limited in how they could respond. As a result, without speed restrictions and accurate survey information in place, trucks could drive full speed in wet weather and reverse over windrows. Therefore, personnel needed to be a step ahead of the system to put controls in place and avoid incidents.

A humans' complacency towards driverless trucks was raised by the participants as a particularly significant hazard. Since automated trucks were considered so 'predictable', the frontline workers had developed a high level of trust. In particular, when participants compared their experiences with manual truck operations. Despite this, participants revealed how high levels of trust drove practices that were not observed in a manual environment. For example, a grader operator that is working head on into the pathway of an oncoming haul truck until it stops, pulling away at the last minute. These practices placed a high dependence on the trucks' lasers, sensors and GPS systems to work, with little consideration that it was controlled by a computer, as illustrated by one participant who stated:

> *You still have to respect the blue light. They are a big machine, no one in them, could be doing 60 km/h. They are not just going to stop on a dime [abruptly].* [P23]

If a vehicle turns in front of a travelling haul truck, it was reported that a driverless truck could not stop in time. The eyes and ears of truck drivers were said to be different from the lasers and sensors that substituted them. Mining personnel monitored a 3D world through a 2D display, which required a high frequency of verifications to validate the virtual model. Participants raised the importance of checks to avoid truck backing through windrows. Virtual mine models needed to be 'real' to prevent trucks penetrating the boundary:

> *Had a truck back through a windrow to get to another windrow behind that, because someone had not surveyed it in. A grade operator has come up and said, 'no, it's all clear'.* [P21]

Now that mine controllers supervise multiple trucks; it was noted by the participants that an enormous amount of responsibility had been placed on a single person to manage numerous trucks. Since there was no longer direct communication with a haul truck, mine controllers were said to rely on computer interfaces. Controllers stated that they set goals for the shift, allocated trucks and redirected the fleet where they were needed. When it came to manually operated equipment, participants highlighted that the machines must be connected to the network to be visible in the system. Vehicles without communications were escorted through the mine, which created escort splits and unintended interactions. Furthermore, participants reported that personnel relied heavily on this technology to recognise their vehicle and rarely observed in-cab displays. In addition, the reliance of personnel drove new methods of managing truck breakdowns. For example, one participant stated that:

> *[Driverless] truck breaks down on a ramp. Truck stops. We put a virtual zone around it…. In the manned world, if that had have happened. Someone would have to stay in the [manual] truck; we would put a barrier behind the truck, we would put cones there, we would probably put a lighting plant there to shine on the truck... We are comfortable with virtual controls, as opposed to hard controls.* [P15]

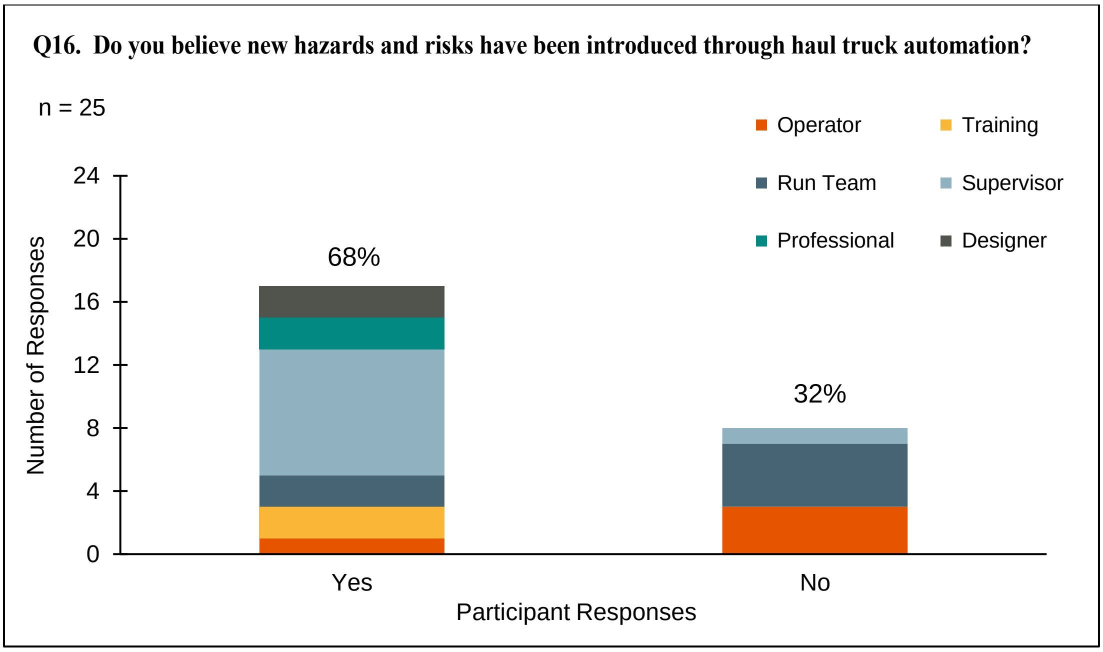
There were situations where personnel reported being unable to create a dump plan without turning off all the exclusion zones. An exclusion zone was said to prevent driverless trucks from driving into a zoned area. Participants highlighted that the problem with zones in dump plans, was that personnel were not turning the zones back on. Personnel tended to rely on sensors that did not always recognise objects. Moreover, the participants noted that people were still learning how to interact with driverless trucks properly. As one participant stated:

In general, I think it is safer, but it's that learning around working with the system properly. I guess, what it does and what it doesn't do. [P25]

Whenever people were interacting with a 400-tonne truck, participants noted that there would always be associated risks. Participants explained how people could still be on the ground refueling and mode changing driverless trucks. If the mode changing process was not followed, participants highlighted that there was a chance that a driverless truck could drive away while someone was nearby. Despite this, when comparing these hazards to manual truck operations, the participants maintained that the risks had been reduced.

Figure 13.

Responses to question whether new hazard and risks have been introduced through haul truck automation



Participants reinforced that the positives of driverless technology far outweighed new hazards and risks. Where priority rule breaches used to be the most common risk, the participants reported them to be now virtually non-existent. Therefore, replacing the truck driver removed typical incident types such as priority rule breaches. As noted by one participant:

> *The amount of incidents we used to have with priority rules breaches with truck on truck. Things like that, that's just disappeared. We don't have it. Pos comms (positive communication) breaches as well.* [P18]

Despite most participants reporting that there were new hazards, there were a small number of participants who stated there were no new hazards. Those participants claimed that removing people simply left nothing to worry about. For example, one of the participants said:

> *I think it's a much safer environment to drive around in, than if there were humans driving around in the trucks. Because you can see exactly where they're going, and you just stay out of their way, basically.* [P5]

Driverless operations were reported to be a lot safer than manual, which was referenced by the improvements in recordable injuries. Participants recalled the hazards and risks that were observed in the driverless operations. The hazardous conditions had elements of human and technology involvement. The primary concerns were the differences in the virtual and physical world, complacency and limited experience with automation, as explained by one participant:

> *… this comes back to knowledge of people in the pit… grader operator didn't look for that windrow being surveyed in and all that sort of stuff. Where if he had a bit more knowledge before that event, he would have known… that windrow is not surveyed in, don't back that truck in there.* [P21]

6.4.1.2. Humans Are Contributing to Driverless Incidents

When asked what is contributing to incidents involving driverless trucks, a majority of the participants reported that it was humans. The events were argued to be a perfect representation of the mining culture embedded in the WA Mining Industry. Participants claimed that people who were so focused on the dirt could quickly look past things and that there was much more detail now required to run a truck operation. Moreover, it was argued that people were not verifying situations in enough depth as described by one participant below:

> *Especially with the truck going through the bund, everyone assumes when that occurred, it was just a little rock that was there that the truck had seen. They didn't go into the in-depth detail to look at it a little bit further and actually really check.* [P2]

Participants explained how personnel must compare the virtual mine model before clearing reverse obstacles, otherwise a truck could reverse into a windrow if the spot point has been misplaced. Another example suggested was when detected objects were cleared from a distance, making it difficult to identify whether there were any objects behind the truck. Participants explained how personnel need to make themselves more aware of their surroundings, including communicating with others to verify and explain what is being observed. The trust extended to the system was described as quite high, with participants highlighting that personnel do not expect that a truck will do something outside of its design parameters.

When frontline personnel perceive that they are being rushed, it was reported that people perform tasks outside of the procedure. The low operating discipline on behalf of the mineworker was claimed by the participants to lead to people not following standards and avoiding ownership. As a result, participants noted that mineworkers have more faith in computer literalism than human cognition, with one participant describing the system as perfect:

> *What I believe is that the system is perfect. We are the ones that slow it down or make it fault. So, human error…* [P18]

Participants reported that personnel become comfortable with what driverless trucks can perform. If people do not look at their in-cab displays, they will not observe truck assignments. When people are not concentrating, it was reported that people tend to rush into tasks and create incidents. These conditions include lapses in judgement or not focusing on the things around them. It was suggested that the inexperience of working with driverless systems had led to actions that were in conflict with the situation. Moreover, as the mining operation expanded, it was reported that more people were brought over from the manual truck operation with less experience. For instance one participant stated:

> *It's just the skill set of operators. A lot of operators have moved around; we are bringing in a lot of other operators at this point in time. They're experienced operators, but not all have autonomy experience.* [P22]

Surveys that do not match the physical mine leave virtual distinctions that the trucks accept as an accurate representation. When people do not respond quickly enough to downpours of rain, trucks can be left operating at full capacity without speed or traction controls (Jamasmie, 2019). Moreover, water cart operators could have applied too much water on the road, creating slippery conditions for a driverless truck. The lack of knowledge with truck capability has led to people removing controls while believing other functions were in place.

It is essential to know how to read and use the information outputted by the system correctly. Some conditions were considered by the participants to be influencing people's actions involving mainly manually operated equipment interacting with the trucks. Without physical demarcation, it is challenging to identify an intersection that exists in the virtual mine model. Unless in-cab displays are observed, there is nothing to indicate intersections exist. Participants explained that this can be confusing when a truck stops for no physical obstruction in the truck's lane.

Participants reported that workers could become comfortable with driverless technology, regardless of what it does. Participants noted that people assumed driverless trucks would always identify them and that this assumption drove relaxed behaviours when in the field. Moreover, in the beginning, participants highlighted that the operation did not have all of their systems and processes in place to support frontline workers. As the technology was evolving and people learning the processes were just being developed. Therefore, the participants explained how the operation relied heavily on the manufacturer to coach personnel on how to interact with the driverless fleet.

6.4.2. High Levels of Trust Developed With Driverless Technology

6.4.2.1. Participant Trust Levels

Participants reported a high level of trust towards the driverless fleet (see Figure 6.2), claiming that if a truck drove somewhere that it was not instructed to go, then it became the person's fault. For example, driverless trucks that parked too far away from the excavator had the loading point placed there by the operator. Furthermore, it was explained that driverless trucks could reverse over rocks or up the dig face when instructed. Driverless trucks were claimed by the participants to be reasonably accurate, which resulted in high levels of trust. This was particularly so when compared to a manual truck environment, with one participant adding that they would rate humans low on a good day. With 12-hour shifts, driverless trucks were reported to perform safely for 12 hours, where truck drivers were not. As one participant suggested:

A man truck might be spot on after his smoko [cigarette break] and his coffee, but 5 hours down the track, he could be thinking about fishing or something like that. An autonomous truck is not thinking about that. [P10]

Trust was increased through the introduction of in-cab displays, which highlighted the haul trucks' travel paths. In addition, frontline personnel could control driverless trucks from their light vehicle. Moreover, driverless trucks were claimed by participants to not drive out of their assigned lane like a manual truck driver. As a result, with blue paths indicating where trucks were travelling, participants trusted that the truck was going to go straight and not veer off in front of them. As time went on, people's trust level appeared to have increased, with the realisation that the driverless trucks were not going to hurt them. The truck would just stop. Despite the potential for truck slides, interviewees reported that driverless haul trucks losing control turned their wheels to the outside windrow to avoid oncoming traffic. It is these sorts of practices and observed vigilance that increased trust as illustrated by one participant who stated:

When you watch them give way to a cow on a haul road… Come to a stop in a space that no way a human could pull a truck up in, safely. And a cow walks across the road in front of it, and the truck drives off in the end. And you go, wow. [P4]

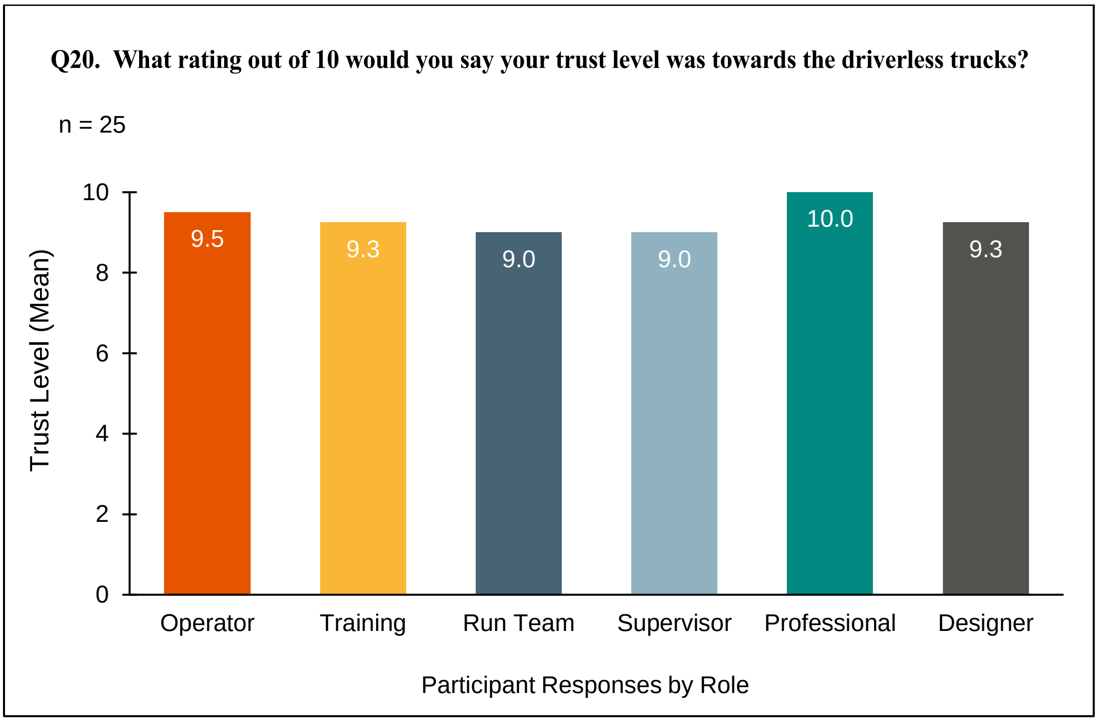
Driverless trucks usually attempt to correct themselves and avoid oncoming traffic. It is these responses that participants observed in the mine. It was also noted that through virtual playbacks, when participants watched truck movements, the machines were never found performing something unsafe. Although personnel may question why a truck is driving from one location to another, one participant claimed that they never observed a truck doing something unpredictable:

I've never seen a truck do anything in an unsafe manner that I couldn't say wasn't predictable… But I've never seen it do something unpredictable. There's always been a reason why it has always done what it has done. [P3]

Participants argued that there was always a reason why a truck performed something or was redirected. They also observed trucks waiting in a queue and then suddenly execute a U-turn to travel to another loading source. It was noted that people might find this action unpredictable. Yet it was suggested that this might be unexpected, but not unpredictable. For example, the assignment engine could simply re-assign a truck elsewhere, with the U-turn lanes already available for the trucks. The more participants observed trucks performances and understood the assignment engine, the more they trusted the system.

Figure 14.

Median trust level out of 10 by role towards the driverless trucks



Participants reported that trust is built through learning what the trucks will and will not perform. Moreover, they explained how personnel must understand the controls and the systems that are in place, particularly how driverless trucks respond to situations. Recognising that it is an algorithm, participants reported that trucks would simply repeat the observable functions. These functions are underpinned by in-cab displays that highlight the intended travel path, which is non-existent in a manual truck operation. Moreover, participants had the sense that trucks would remain in their lane that if a truck touched or slightly breached the path, it would stop. A manual truck was reported to have less certainty, as described by one participant:

> *You don't have the uncertainty of a manned driver, that can go off over windrows, can go bush, can go anywhere, if they wanted to… You know a truck is going to stay in its*

lane, and it's going to travel that path, and if deviates slightly, it's going to stop. [P19]

Driverless trucks had built trust by stopping when they lost communication on the mine site. The fact that the system stops when the situation is 'not right', made participants feel like safety was taken seriously. Moreover, manually operated equipment were said to lose communication and generate an exclusion bubble, which expands a zone that stops trucks until the vehicle has found a safe location. The trucks' safety mechanisms and overall effectiveness underlined the high level of trust realised. In addition, driverless trucks were reported by participants to behave the way a truck is supposed to, responding to situations similar to a truck driver, if not better. Driverless trucks were explained as travelling where they were supposed to and parking where loading units needed them to.

The human factor was argued by participants to have been removed, with priority rules and communication breaches no longer a risk. One of the significant dangers reported was fatigue, where truck indicators were never trusted. Participants noted that they would never drive into the same intersection with a manual haul truck, claiming that it was unknown whether the driver was paying attention. In comparison, the technology had introduced layers of controls to maintain a safe distance between people and haul trucks, including avoidance boundaries and emergency stop devices. However, the participants did note that they would never walk out in front of a truck. With an understanding of what a truck is capable of performing, the only trust issues were highlighted in wet weather. As one participant stated:

> *But, road conditions, weather permitting and all that stuff. Where a dump truck could potentially slide down a ramp into an LV or a car or something, yeah, that's a bit of a different question… If we don't put a zone lock on in time, then stuff can get pretty hairy."* [P12]

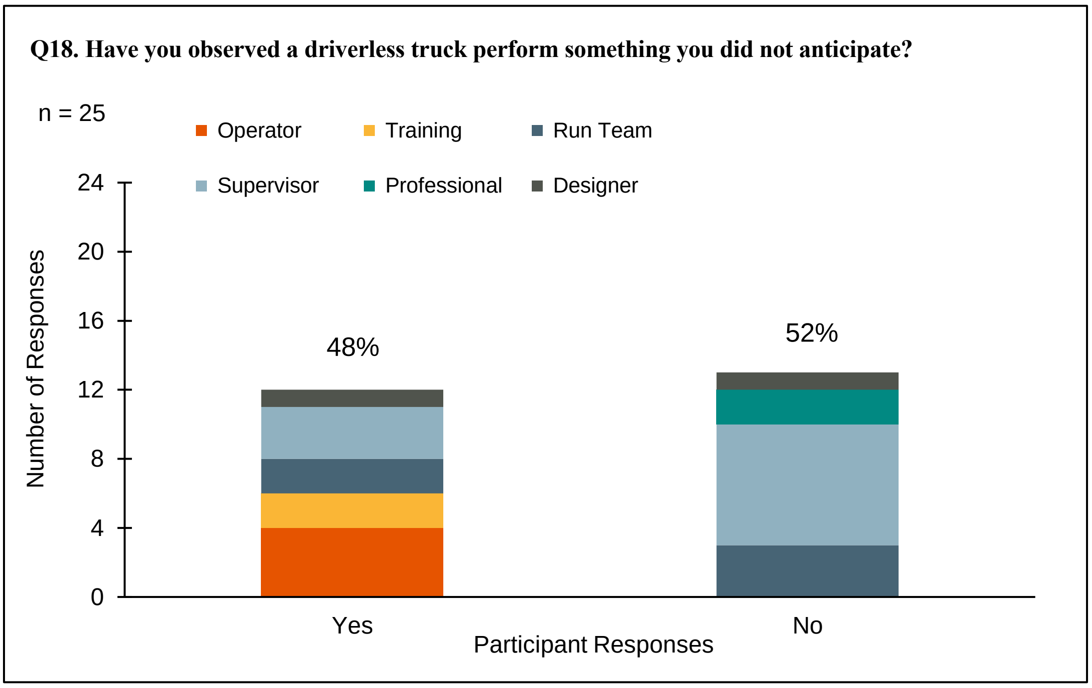
6.4.2.2. Driverless Trucks Performed Unanticipated Tasks

Driverless haul trucks were observed by participants to perform tasks that were not expected (see Figure 6.3). A driverless truck 'wobbling' aggressively side-to-side was one example. Although it can now be explained as a steering fault, at the time, participants were left confused. Driverless trucks can also drive away without explaining its intentions to manually operated equipment. This reinforces the point made earlier by a participant who noted that manual machines could no longer make direct contact with a haul truck driver. On the pit floor, driverless trucks are given the flexibility to generate their pathway to being loaded. For a dozer operator, they can be surprised when a truck arrives behind them without notice, as noted by one participant:

> *All of a sudden, the digger moved to a certain spot and the trucks had to come back in behind me, and I didn't realise… I came out, and this blinkin' thing is right behind me on the dozer, going 'barrrrrrrrrp' (sound of the truck horn).* [P5]

Figure 15.

Responses to whether participants had observed a driverless truck perform something that they did not anticipate



Participants reported that driverless trucks could be found driving the longest haul route to the crusher. Several in-cycle delays on the haul route changed the average time taken, resulting in the trucks making a different way. However, at the time, the mine controller did not understand why this was being performed. Excavator operators have observed empty trucks driving off before loaded trucks as well. It was later found that the empty truck was higher up in the queue. Therefore, the system assigned the empty truck away, despite the other truck being loaded. Driverless trucks have also been observed travelling back to the loading unit with its tray in the air. Without a dump script in place, driverless trucks can drive away without being instructed to lower its tray.

Observing in-cab displays enables the frontline to be more informed of truck performances. The information highlights what a driverless truck is performing and what it is likely to do next. However, some functions are not described unless the designer previously explained it—for example, trucks driving through dust with its horn sounding. Although the algorithms are not visible, the data logs highlight a person's input or mechanical failure. Participants explained how this uncertainty could be answered. Yet, not every role is provided with this level of information. Participants without this level of information learn through observing machine actions:

> *So, you learn how to interact with them… Figure out where the dump spots are, where the digger is loading from, and you just watch your screen to make sure they are going in the path, and you can move out of their way.* [P12]

Most of the truck activities were reported by the participants to be fairly structured. As a result, the trucks would not do much other than what was instructed. It was reported that there are always human decisions underlying why driverless truck do what they do. And, also that there are different reasons why trucks slide out of their lane. Participants identified that birds were being detected as objects, which were leading trucks to engage the emergency brake. What was also surprising to participants, were driverless trucks trying to correct themselves. When faced with a wet road, driverless trucks were noted as making every effort to remain on the centre line. The permission-based control system also enables two trucks to use an interaction at a time, which was never permitted in a manual operation. Despite participants observing practices that they had never seen before, once they had learned the parameters of the system, it answered a lot of unanticipated situations.

6.4.2.3. Trust Levels Did Not Waver After Incidents or Unanticipated Situations

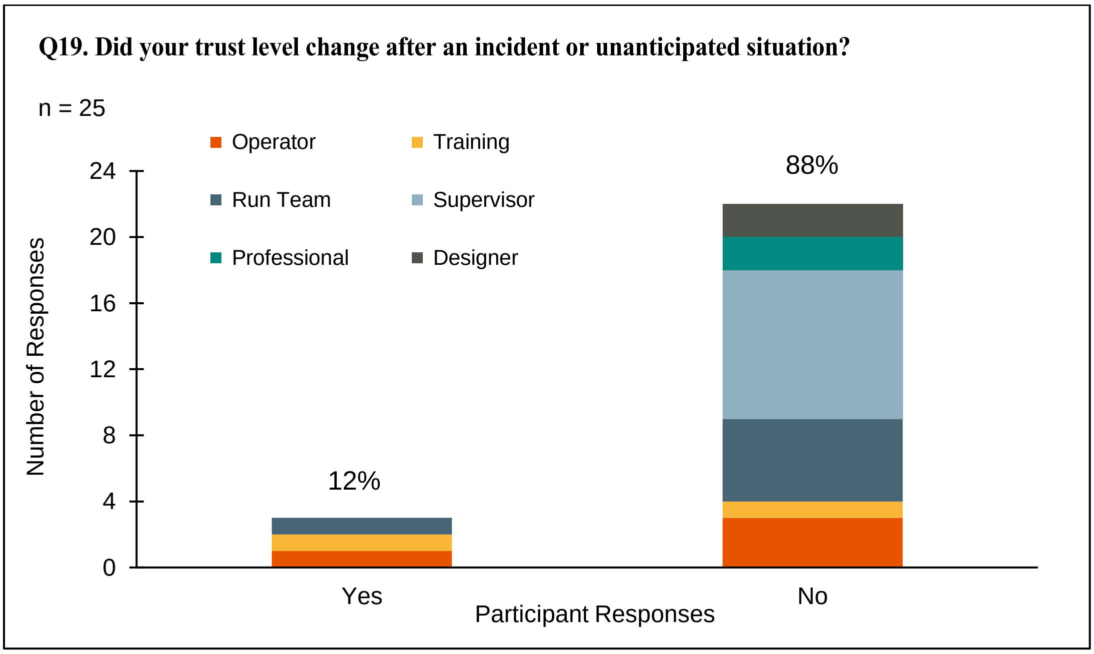
Trust towards driverless trucks never wavered for the majority of participants (see Figure 6.4). The participants reflected on incidents involving driverless trucks and explained how humans had instructed trucks to perform those tasks. Since the truck was only performing what was instructed, participants noted that their trust did not waver after such situations. What was even more profound, was the fact that some participants had increased their level of trust upon having a given situation being explained. As one participant stated:

When I found out it wasn't the truck's fault… it wasn't technology's fault, it was human error. So that just reiterated to me that I still had full trust in the system. [P23]

If the trucks only perform what has been instructed, the logic appears to be relieved of the consequences. As a result, with a person identified as the fault, participants found themselves comfortable with the actions of the computer. However, there were reports of participants becoming warier after being involved in an incident. Not necessarily with the system itself, more towards the clearing of objects and questioning the virtual representation. By developing a basic understanding of the automated trucks safety features, participants were able to build a level of respect for the system. The experience of working long enough with the system establishes a level of knowledge for what a truck will and will not perform. For some participants, it has been a journey of watching the technology evolve overtime and ultimately improve.

Figure 16.

Responses to whether participants' trust level changed after an incident or unanticipated situation.



Trust for a driverless system is reinforced when compared to manual truck operations. Participants reported truck drivers turning in front of them in a light vehicle in manual trucks operations. With people sitting in a truck for long periods, the risk is considered a lot higher. As one participant explained:

> *I've always felt comfortable with them. Because I've had issues where people and trucks have pulled out on me when you least expect it. Because of the predictability of the AHTs [Autonomous Haul Truck], I've never really had those moments.* [P15]

Providing an allocated pathway in the system has meant that participants have avoided similar experiences in manual. For example, when approaching an intersection, the in-cab display indicates the intended path with blue coloured lane. This predictability results in people building trusting the trucks knowing what direction the truck is travelling. Some participants admitted placing too much trust on the system. There was a general belief that a truck is built to keep people safe, with many participants reporting that they had never faced a situation where a driverless truck had performed something they had not anticipated.

6.4.2.4. Personnel Are Informed of What Mode or Function Trucks Perform

When asked when the systems inform personnel of what mode or function trucks are performing, the participants responded favourably (see Figure 6.5). Blue lanes on in-cab displays were reported to indicate that trucks travelling in autonomous mode and their direction. When approaching a driverless truck, the mode lights located on the side of the truck indicated the machine's mode. When combining the visual reference with the virtual mine model, participants noted that personnel could identify what was around a truck and foresee any potential interactions. More in-depth screen displays provided supervisors and run team members with diagnostics details and the performance of the fleet. When mode changing trucks, the lights change colour and flash to indicate the change in modes. Additional real-time information on in-cab displays highlights scripts and zones that can influence the function of the truck. It is in dumping and loading (dynamic) areas where participants experience surprises:

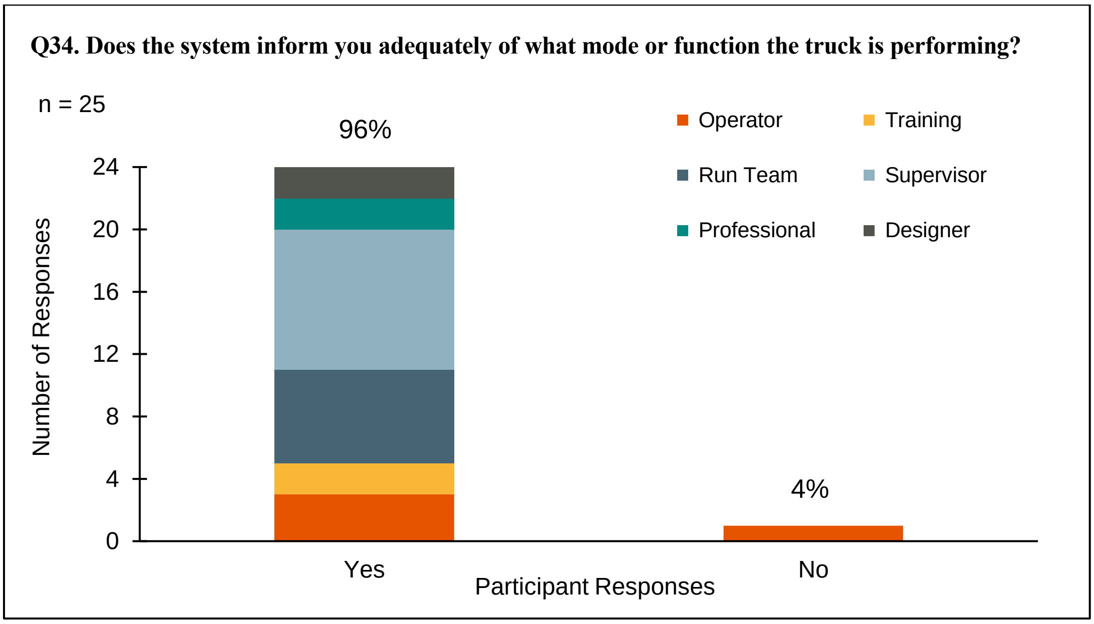
> *Sometimes they drive off by themselves. The controller didn't know what was happening. We put in a delay to have a clean-up, and it just backed itself up the ramp and took off.* [P5]

A dynamic area allows trucks to utilise the space to reverse into a loading bay. On haul roads, participants reported that determining what a truck is performing is relatively clear. The blue light indicates the driverless mode and the blue lane identifies where it is heading. However, when in manual mode, a predicted pathway is not provided, requiring personnel to switch back to conventional priority rules. It was noted that at times mode lights could be challenging to change, which was described as a communication issue that could prove difficult to switch between functions. However, when asked whether the system informs personnel, one participant put it simply:

> *It's blue, flashing blue, it's in autonomous mode. It's lifting its tray, it's dumping, it's backing under the digger, and it's going to get loaded.* [P15]

Figure 17.

Responses to whether the system informs participants of what mode or function a driverless truck is performing



Only one participant reported that the automated system did not adequately inform them. In contrast to observing mode lights or learning the repetitive elements of the haul cycle, it appeared the operator expected some level of feedback on what trucks are performing. The level of detail displayed on in-cab displays is dependent on the role being undertaken, which manual haul class and ancillary equipment do not have. Despite this, there were personnel who considered the information adequate. For run team members, the status page provided additional functional information. As one participant states:

> *It tells you exactly what state the trucks in. Whether its travelling loaded, travelling empty, dumping… spotting at a dump, spotting at a digger, queuing… it tells you exactly what it is doing all the time.* [P24]

There are truck tiles that are coloured green, yellow or red, which indicate the health of the machine. Since the system was reported to log everything, system-based roles can see real-time modes of the entire fleet. The system is said to highlight what needs to be addressed and what is happening in the system. However, this is providing that personnel understand what they are looking to obtain.

The mode lights provide additional meaning, including communication losses that result in mode lights turning green. With the added benefit of a status page, participants reported that they are informed of what part of the cycle each truck is performing. Whether it be travelling empty, loading at source or dumping at the crusher, the information is available. Moreover, if a truck is facing issues such as wheel slippage, the system will highlight that this is occurring. In addition, the system is reported to display mechanical problems and increases in the truck's tyre temperature. When a truck is on delay, the truck icons turn grey to highlight that production is suspended. It was noted that a truck could only be in one of the five aspects of a cycle, which makes it easier to determine what the truck is performing:

> *… yeah because it's in, like travelling, spotting, loading, dumping, you know it's a cycle that it's in. It's only them five or six cycles that it can be in. So, you know which states it's in, and whether its autonomous or in manual mode."* [P23]

The data that indicates how many tonnes are on a truck, inform personnel whether the machine has been loaded. According to the participants, the real risk, however, was whether there was too much information for people to process to remain in-the-loop.

6.4.2.5. Driverless Trucks May Perform Tasks That Were Not Instructed

Participants reported that trucks had performed tasks that were not anticipated (see Figure 6.6.). For instance one participant said:

> *Yes, go the other way, without me seeing. Take a load of waste to the longest waste dump because of me not closing a particular dump off or taking a different route that I didn't want it to.* [P8]

The participants reported that if a truck is instructed to do something, it will just go ahead and do it. Rarely, they argued, has a truck ever performed something that was not expected. A truck was more likely to do nothing than do something that was not instructed. To some participants, driverless trucks are the perfect truck driver:

> *To me, they are the perfect trucky (truck driver)… If it went there, but it was supposed to go there, but I assigned it to go there. It's not the truck's fault; the truck's only doing what it got told to do.* [P13]

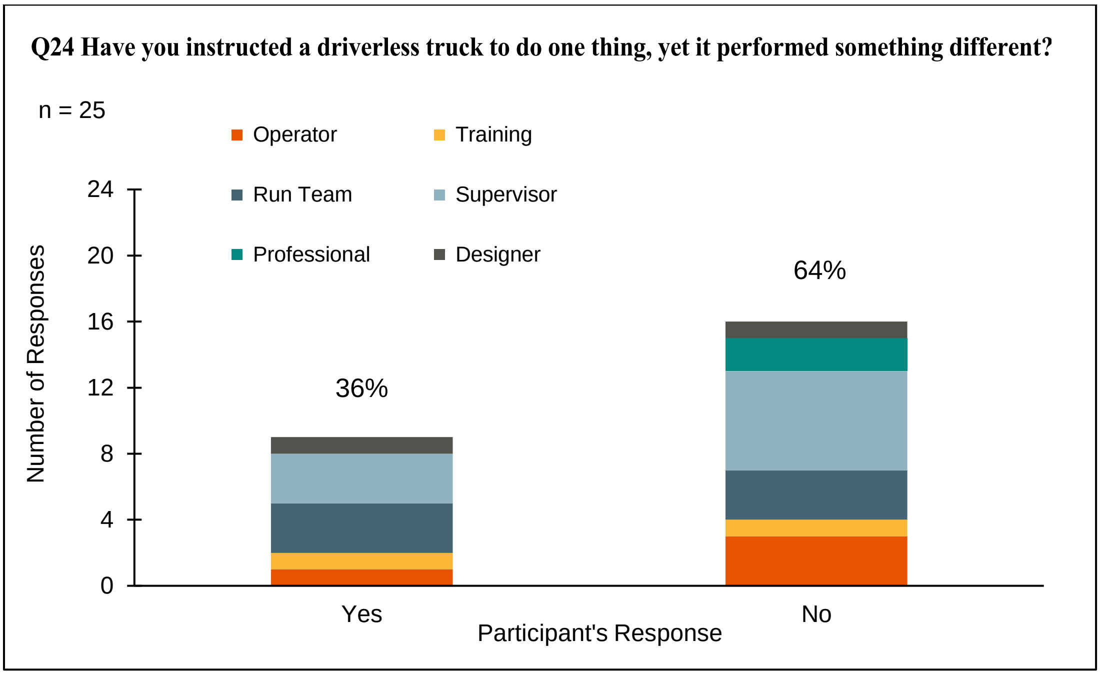
In the participants' experience, if a truck is instructed to do something, it will go ahead and do it. A participant experienced a situation where a truck breached a windrow. It was noted that this occurred when the windrow was detected as an object. To the person clearing that object, there appears to be no obstruction to get to the windrow. However, since reverse locations can be mistakenly placed behind windrows, if cleared, the truck will attempt to reverse over the windrow. There were also other examples experienced in the excavator, where pressing the incorrect button led to trucks parking out on the pit floor. The automated system can be re-assigned to perform a task numerous times; however, if old assignments exist, driverless trucks can be difficult to direct as described by one participant.

> *We sent it out of the fuel bay. We sent it to go to park up in one of the park up bays. Done another loop again, come back around and parked up on the other side and sat there looking at us… It's done it three times before we got it to where we wanted it to go…* [P4]

The participant explained that it was later identified that personnel had previously attempted to instruct a truck to enter the fuel bay. As a result, old assignments existed in the background and were being executed before performing the new instructions. In addition, trucks may hang onto scripts when the crusher light turns red as the truck is reversing into the bay. Trucks have then tipped shortly after being instructed to move forward away from the crusher bay. Participants reported that unanticipated situations could be glitches, rather than a truck performing different tasks. In contrast, trucks that take longer routes for no apparent reason are said to be recalculated routes after multiple stoppages, which increase the average travel time on main thoroughfares. More often than not, however, participants noted that a driverless truck is likely to remain stationary than perform something different.

Figure 18.

Responses to whether participants have instructed a driverless truck to do one thing, yet it had performed something different



6.4.3. Driverless Trucks Play Their Role, Not Necessarily Team Players

6.4.3.1. Team Play

Driverless trucks were described as the workhorse of the operation. To be a team player, however, participants noted that the correct goals and inputs must be provided to enable the system to succeed. These reports highlight how reliant the system currently is on human contributions. When describing whether the trucks are team players, participants explained how much harder they work than truck drivers. Driverless trucks perform what personnel want when they want it. Despite various responses, the majority of participants were positive in how the fleet acted as a unit. Yet, it was expressed that it would be nice if the trucks helped each other out. For example, if an object was already cleared for one truck that information is not passed on. Therefore, the system does not learn from its experiences like truck drivers. Although participants described them as hard-working, the system also showed signs of independence and labelled them as being 'tonne hungry'. Driverless trucks were reported to drive as fast as they could and move as much material as possible:

> *There are no toilet breaks, no meal breaks, no hot seating, no crib breaks. They come in for a bit of fuel once a day, and away they go… They just do what I asked them to do, and they don't talk back.* [P11]

Driverless trucks were also described as performing tasks relatively the same. For example, if a speed or traction zone were put in place, every truck passing that zone would reduce their speed. Given their discipline to controls and instructions, participants highly regarded their ability to play as team players. Participants noted that the trucks followed through with instructions when given to them, grinding away as their key player.

Despite the positives, there were, however, situations where participants observed literalism from the system. Driverless trucks may work hard, yet they focus on moving the dirt. Therefore, despite what is on the daily plan, trucks drive to loading units moving the most material. The driverless system is said to be geared towards utilising the most productive machines. If trucks are not overseen, the system only focuses on moving tonnes. For example one participant said:

> *Like I said, if you give it the options, or if you know how to control the options you give it properly, it will play your game. But, if you let it do whatever it wants it to do, it will play its own game, and it's a production game.* [P20]

Although driverless trucks can move material quickly, some participants highlighted that they have to reign them in. Otherwise, the system will transfer material that personnel do not want to move. The control room aims to move material as per the plan; this can be at odds with how trucks are designed. It was argued that personnel need space to move the fleet freely between sources and destinations. Although they were primarily considered team players, they were not necessarily viewed as the captain. Instead, they fulfilled the role of a half back, who would remain present before and after the game. As personnel learned to work them, participants noted that the relationship was improving. With the intricacies and complexities of such a system, a participant argued that it is bound not to work. If driverless trucks do not receive the right inputs, participants noted that driverless technology could not be expected to perform:

> *Well, it's not the system that changes, there's inputs… If there's a change in the priority, someone has to input that into the system, that's just basic. It's not artificial intelligence, it's just a system that we tell what to do…* [P15]

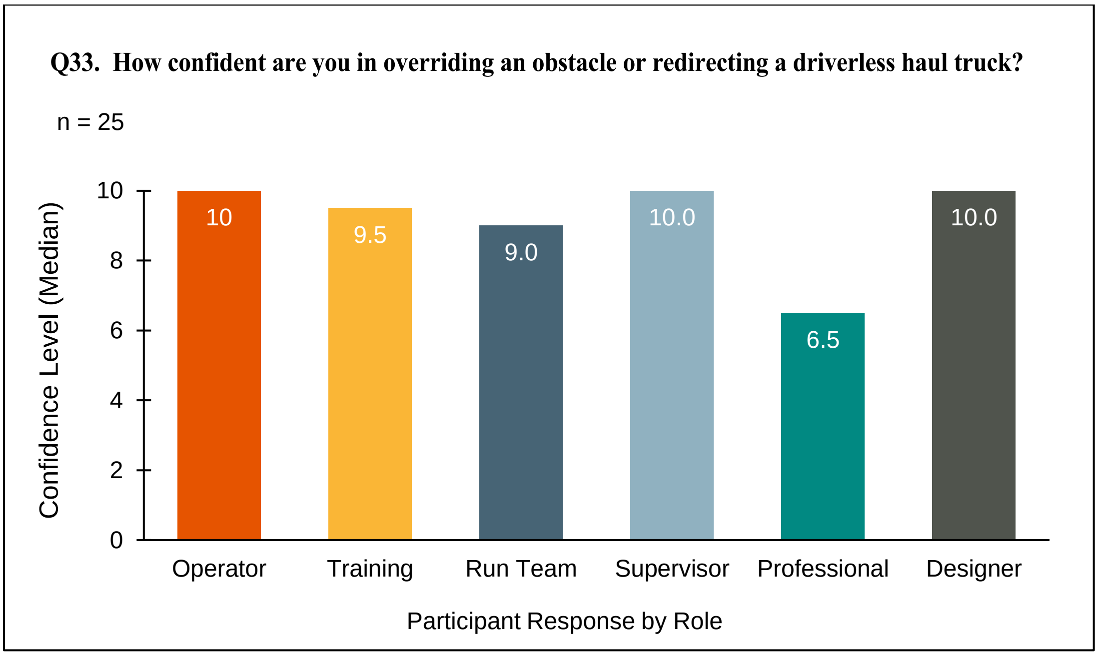
6.4.3.2. Participants confident in redirecting or overriding obstacle detections

Depending on the participants' role, various experiences were shared with redirecting and overriding obstacles. Supervisors and designers were the most confident, given that they both have high levels of knowledge and information (see Figure 6.7). Knowledge is coupled with field time, validating the virtual mine model with what is being observed. Participants reported that specific training is required to direct trucks, which also becomes technical in-cab displays. When it comes to clearing objects, every person was suggested to be capable of performing this. Despite this, some participant experiences tested their level of confidence:

> *The truck picked up the windrow, come up with an obstacle, I cleared the obstacle, and then the truck climbed over the windrow to get to where it was going.* [P23]

Figure 19.

Median confidence level out of 10 overriding obstacles and redirecting driverless trucks



Although there was a high level of confidence across the participants, intervening is highly dependent on whether the foundations are in place—for example, the physical world matching the virtual system. Upon experiencing a situation where a truck breaches the boundary, it appears that participants were far more cautious in their approach. Despite this, participants still recorded a high level of confidence. The main reason for this was the driverless systems' adherence to instructions:

Well, they just do what I ask them to do mate, and they don't talk back, so yeah. [P11]

Since the truck is only performing the instructions given, participants maintained that the trucks were not at fault. The reason why the professionals' confidence level was much lower was purely from a frequency perspective. With the majority of the participants' confidence levels being so high, it could be argued that their trust levels were also high. Given the participants' experiences in some incidents, it was noted that the task must also be performed within strict guidelines. Otherwise, personnel could find themselves experiencing unintended situations.

6.5. Discussion

This study reflects similar experiences of humans interfacing with automated systems in high-risk industries (Billings, 2018; de Vries, 2017; Frohm et al., 2006). Study participants noted that new hazards and risks were presented through the introduction of driverless trucks. Despite this, participants developed a higher level of trust through observing predicted travel, diligent truck reactions and compliance to instructions. However, the high levels of confidence could be linked to the complacency contributing to driverless incidents.

New hazards and risks associated with driverless haul trucks were reported in the interviews. Driverless trucks require communications to operate; however, if those communications are lost, the sudden braking that occurs can cause trucks to slide. Moreover, the mismatches between the virtual model and the real mine resulted in trucks breaching windrows after objects were cleared. This experience reflects the literalism and opacity that comes with automation (Billings, 2018; Wessel et al., 2019). When it came to who was responsible for incidents, participants reported that humans were making the main contributions. The main reason was that the system was considered to be performing what it was instructed to do. A truck reversing over a windrow, it was noted could be cleared by a human to achieve a dump location place behind the windrow. However, the feedback loops and the transparency of the system need to be considered (Dixon et al., 2007; Parasuraman & Manzey, 2010). When verifying reverse objects in the field, there appears to be no obstruction between the truck and the windrow. Yet, it is the windrow that is identified as the object. As a result, the object is cleared, and the truck passes through the windrow. In this scenario, humans are required to check the physical location against the mine model. Since a high level of trust has developed, it appears humans do not anticipate that a truck would reverse over a windrow, even if there were potential mismatches.

A high level of trust had been developed towards driverless trucks by them only performing what was instructed. However, this trust could also lead to a reliance on automated systems (Parasuraman & Riley, 1997). This comparison was made to the manual environment, where it was difficult to determine where a truck driver was heading. When it came to driverless trucks, the intended pathway on in-cab displays provided a level of transparency on the trucks' intentions. Predicted pathways removed a lot of anxiety for smaller equipment operators with manual trucks frequently turning in front of them, which increased their level of confidence. In addition, when dump or load location were set, driverless trucks reversed to that exact location. Manual trucks, in this instance, were reported to present a higher risk of reversing into excavators. More importantly, the additional concentration requirements to drive a truck for 12-hour shift. Despite being involved in incidents and unanticipated situations with driverless trucks, a majority of participants' trust level did not waver. Therefore, the findings highlight that high levels of trust could be maintained if it could be demonstrated that driverless trucks performed what was programmed.

There were driverless observed performing tasks that were not anticipated. However, this was highly dependent on the persons' role and experience, which was realised in the operators' response. An operator has less detailed information on their screen interfaces, whereas supervisors, run team members and professionals have access to diagnostic and assignment engine pages. These roles have the option and time to analyse the background information relating to performance. Therefore, the performance is matched to the mode or script at the time and increased human awareness of automated features (Björklund et al., 2006; Feldhütter et al., 2019, August 26-30). There were, however, participants in those roles that were surprised by automation. Predominately, their experience was to do with algorithms and fleet management, which has featured in surprises in the past (De Boer & Dekker, 2017). These results highlight that in-cab display information for operators could be improved, with additional explanations and training in the algorithms influencing the assignment engine. Participants reported that the system informs personnel of what mode or function a truck is performing, which is in stark contrast to other industry experiences (Feldhütter et al., 2019; Sarter & Woods, 1995). More specifically, the participants alluded to the mode lights located on the side of the truck. In addition, the blue lanes highlighted the truck's intended haul route reinforced that the truck is in an automated mode. Despite haul routes, there were operators surprised by the movements of driverless trucks in the loading area. Automation enables the trucks to generate a path, which can shift from one side to the other, depending on the location of the excavator. This situation had resulted in increased proximity detections due to operators being surprised by the trucks' presence. Operators are driven to observe their in-cab display more frequently to monitor the truck lane generation. This practice was a learned skill that was developed to avoid interactions and remain in-the-loop.

Driverless trucks were reported to perform something that had not been instructed rarely. Participants argued that the trucks are likely to do nothing than follow instructions. This response also underpins why a high level of trust has been extended to the system. In addition, there is no debate on whether the decision is an appropriate one, merely performing the task anyway. Participants reported that although trucks may deliver something that was not instructed, there are usually additional assignments or influencing algorithms in the background. This was highlighted in the fuel bay and more extended haul route examples when participants elaborated on what they had observed. Since driverless trucks were considered the workhorses and mostly team players, the trucks performed instructions when personnel wanted it, when they wanted it. Yet, when participants reflected on whether the trucks were team players, it was noted that they do not assist others in performing their tasks. In particular, when one truck had an object cleared safely, 5 minutes later, another truck could identify the same object. Although the trucks play their role and work hard, the experience reveals the narrow focus on automation to perform nothing else (Christoffersen & Woods, 2002; Klein et al., 2004). There was confidence in redirecting or overriding obstacles detected by driverless trucks. In particular, participants knew that despite what they performed; the trucks would only work within the confines of their parameters. Despite the belief that the trucks would never do something unsafe, the fact virtual and physical distinctions exist presented actual risks that any instruction could be taken literally (Billings, 2018). The difference means that although a person physically observes the edge of the windrow, the virtual system reference point may be further back. Therefore, the truck could perform activities based on the virtual mine model, not the physical representation, resulting in unintended consequences.

6.6. Conclusion

The research highlights the perspectives of mineworkers surrounding risk, trust and teamwork. New hazards and risk factors were introduced through automation, including virtual-physical world distinctions, communication losses and operator complacency. Humans were considered to be contributing to workplace incidents, which was explained by the belief that driverless trucks only perform what has been instructed. Therefore, despite the introduction of new hazards and risks, a high level of trust has developed with driverless technology. High confidence was underpinned by predictable haul routes, adherence to instructions and diligence for stopping for small objects. More importantly, the trust did not waiver after participants had been involved in a driverless truck incident. The driverless trucks were considered team players concerning the execution of their role. However, when it came to assisting other teammates, the participants reported that the technology simply remains focused on its purpose. As a result, the system does not engage in team play to work as a team to resolve localised problems. The localised problems created situations where personnel needed to override or redirect the driverless fleet. Despite the confidence of participants in executing those adapting, human intervention has contributed to incidents involving driverless haul trucks. The response did not intend to result in unintended situations; however, the experiences of the participants have highlighted the consequences of introducing automation. Mineworker experiences demonstrate the presence of new hazards and risks, as the dynamic of the human-machine relationship unfolds in trust and teamwork.

Chapter 7

From Truck Driver to Systems Engineer: Transforming the Miners' Contribution

This chapter is being considered for publication:

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7.1. Abstract

Driverless haul trucks represent a significant role transformation for mine site workers in the Western Australian (WA) Mining Industry. Research within the industry is yet to explore the experiences of frontline workers transitioning to driverless truck operations. The study aimed to investigate the role transformation of mineworkers, their residual workloads and local adaptions when working with automated systems. A sample of 25 employees, from a WA mine site, were interviewed face-to-face on site using a mixture of open and close-ended questions. A comprehensive understanding of the risk perspectives was developed through a convergent parallel research design. Multiple cases were analysed thematically through cross-case displays and utilised complex reasoning to accommodate the emerging themes. Participants reported the introduction of new roles, while conventional roles were redefined. The residual work reported included building virtual mine models, clearing detected objects and calling trucks into the loading area. The study's findings suggested that although employee truck driving had been drastically reduced, new technology and computer-based skills were being developed. The results confirm that haul truck automation transforms mining roles, with residual tasks that require local adaptions to overcome non-designed situations.

7.2. Introduction

The introduction of automated technology marks the beginning of the replacement of truck drivers for machines. This alternative approach intends to substitute driving activities that have been reversed engineered into a computer. Engineering maturity has enabled mining haul trucks to drive from A to B, which appears on the surface to be performing the task like a truck driver. What is not always visible are the inputs and local adaptions that make driverless performances possible. Local adaptions fulfilled by residual roles aid the technology through non-designed situations. Despite recent reports of mineworkers removed from the mining operation, there are still routine and adaptive tasks performed to make driverless technology a reality. Therefore, there is a real need to understand the transformation of roles, functions and skills required to complete tasks post-automation.

Driverless technology requires numerous data inputs to perform, with goals and fleet allocations determined at the start of a shift. Not only must the technology be pre-programmed to perform truck driving tasks, but the system-based role must also provide instructions on what material is to be moved. Material movement includes the tonnes required from each load unit and associated destinations. For this to occur, the driverless system requires a virtual mine model to be in operation. Driverless trucks need these data points to compare incoming LiDAR, radar and GPS data with the virtual model. The mining model contains travel lanes, intersections, active mining areas, exclusion areas and speed zones. These digital aspects must be computer generated and designed by new formed roles, which then physically verify data in the field. Once the model is available, the driverless trucks can operate within that model, providing it has loading sources and associated dump locations. From there, the system can generate truck assignments between those locations. Within the cycle, a truck may be confronted with an object in the lane, which requires a human to clear. Those objects can be centre dividers that are not surveyed, wildlife, spillage or vehicles that have lost communication. Trucks may also lose connection, which requires the machine to be recovered by mine personnel. Once the haul truck arrives at the loading source, the excavator must call the truck into a loading bay designated by the operator. The operator must then press a button when the truck is fully loaded. The driverless machine can then travel at full speed unless restricted otherwise by the speed zones. For example, a speed zone may be in place near potholes or slippery roads conditions from a downpour of rain. These are just some examples of the types of inputs, which locally adapt to the changes and complexities in the practical constraints of a mining environment.

Through the substitution of personal work for a machine, research has investigated the repercussions of residual tasks on humans. Leftover jobs are often unspecified and require human supervisors to overcome the situation (Dekker & Woods, 2002). Furthermore, automated systems can provide little feedback on what is happening and rarely offer a safe way forward (Reason, 1990). Therefore, not only is the operator suddenly reintroduced back into the control loop, they must determine how to safely proceed within the confines of the system's design (Banks & Stanton, 2016). Automation may not even hand back control, functioning beyond the parameters that requires the operator to take control (Endsley, 2019). Therefore, double-binds can emerge, where operators may intervene to create an incident, or fail to intervene to allow an incident to occur (Dekker, 2003). The operator is therefore, monitoring the performance of the system, with skills in performing designed tasks; yet developing improvised skills only in times of malfunction.

More recent studies analysed the role of humans in self-driving cars (Fridman, 2018; Wessel et al., 2019), yet these findings are vastly different from a haul truck with no safety driver. Despite recent guidance and warnings surrounding driverless haul truck technology, there is little understanding of the transformation of support roles (Department of Mines and Petroleum, 2014; 2015). The original assumption was that the replacement removed the human contribution (Glover, 2016). However, when comparing residual human tasks across various high-risk industries, it is clear that human tasks and skills continue to play a significant role (de Visser et al., 2018; Lewis et al., 2018). Those skills include computer interfaces and data outputs to monitor the performance of the system (Sarter et al., 2007). For the mining industry, this represents a significant shift for operators who may never have used a computer before. In addition to learning new skills, existing conventional techniques can diminish overtime (Billings, 2018; Bravo Orellana, 2015). These techniques can include driving haul trucks or operating an excavator without an in-cab display. Therefore, it is evident that there is a need to explore the roles and skills changes that may be transforming the human contribution.

Research in aviation and manufacturing have analysed residual tasks post-automation. Remaining duties include activities that designers are yet to automate. As a result, they are rarely conceived and developed with humans in mind (Reason, 1990). Human-centred approaches have advocated in designing human tasks that are leftover (Billings, 2018; Fridman, 2018). Automation design adopts skills and attributes from multiple disciplines, promoting the interests of humans in a joint system approach. What occurs, in reality, is that the machine becomes the primary focus—optimising the pre-conceived ideas and efficiencies of the designers' one-best method, thus limiting exploration, cooperation and learning capabilities (Giacomin, 2015). The workload can, therefore, be a residual set of tasks that are short and intensive, followed by long periods of inactivity (Ferris et al., 2010). After periods without activity, suddenly people are reintroduced to recover the system from failure. Research is yet to explore these experiences in a driverless truck operation, given that driverless technology is in early development in the mining industry.

The purpose of this research was to explore the role transformation of mine workers through the introduction of driverless technology. Face-to-face interviews were conducted on the mine site using semi-structured questions. The quantitative and qualitative aspects of the issues enabled the researcher to gather the perspectives and lived experiences on the mine site. Data from the interviews were transcribed and analysed individually, then synthesised in to themes to represent the participant views of the transformations.

7.3. Methodology

7.3.1. Design

A convergent parallel research design was used to develop a comprehensive understanding of different risk perspectives (Creswell & Clark, 2011). Multiple reasoning accommodated theory inductively for emerging themes and deductively for testing and validation. The process worked back and forth until data saturation and research significance were achieved (Creswell & Poth, 2017). The interview data were compared and contrasted for grouping and allocation of themes. Quantitative and qualitative methods were mixed to strengthen results by quantifying 'Yes' and 'No' responses. Quantified data was supported by the context and explanations contained in the qualitative data (Creswell, 2014a). The multi-method research approach increased the likelihood of making empirical generalisations about the phenomenon, measuring qualitative variables and contextualising the quantitative aspects. The research did not attempt to over-generalise the population, therefore supporting each inference with distinct experience when concluding. This approach preserves the inherent complexity of each lesson learned by maintaining social context, with the raw expressions and perspectives on the transformation of roles (Miller & Crabtree, 2005).

7.3.2. Participants

The population of the study involved employees and contractors who worked with driverless haul trucks. The size of the population was approximately 450 people who performed specific functions and characteristics pertinent to the research. A single-stage sampling procedure provided the investigation with direct access to the participants and the population under study (Teddlie & Tashakkori, 2009). The characteristics of the population were understood to enable stratification to occur. Therefore, the following roles and features were identified: control room operators who monitor the performance of the trucks and make decisions via computer interfaces; pit technicians who attend to truck recoveries and system builders who build and verify the virtual mine model; ancillary and haul class operators manually controlling equipment; supervisors of system-based roles and auxiliary equipment operators who check and inspect work; and, the professionals who include the designers and specialists in the function and pre-programming of the trucks. Specific characteristics targeted by a random selection may not represent the entire population (Creswell, 2014a). Data saturation was achieved at 25 participants, which represented 5.5% of the operation when validating results.

7.3.3. Data Collection

Interviews were digitally recorded on audiotape and took appropriately 45 minutes to 1.5 hours to complete. The duration depended on whether the participant elaborated on their experience relating to each question. Participants participated in interviews between January 2018 and February 2019. The interviews were conducted on the mine site itself and were held within a quiet room. Each meeting was digitally recorded and transcribed by one of the researchers verbatim.

During face-to-face interviews participants were asked to describe their role and whether it changed through automation. Participants elaborated on how it changed and what activities needed to be completed. Moreover, each participant was provided with questions surrounding the workload of support roles, remedial actions, interpretation of system information and understanding of the systems' modes and features. To understand local adaptions participants were asked whether they had confronted situations beyond procedures. Furthermore, the participants were asked how people remained in the loop with what was happening and their decision-making to determine whether to intervene or not when something did not seem correct. The set of questions (Table 1) remained consistent for all participants across the stratified sample.

Table 7.

Interview questions to role changes, workload and adaptions when working with driverless trucks

Topic	Question
Role transformation	– How would you describe your role in the driverless operation? – Did your role change through the introduction of driverless trucks? – Have your skills changed or diminished through the introduction of driverless trucks?
Residual workload	– How would you describe the workload of system-based roles that support the driverless operation? – Are there activities that need to be complete because the driverless system is limited in what it can do? – Have you ever misinterpreted information that was given to you by the driverless system?
Local adaptions	– Have you ever been faced a situation that required you to think outside of a process or procedure? – How do you remain in the loop with what is happening in the driverless system? – How do you determine when to intervene or not when something doesn't seem right?

7.3.4. Data Analysis

Interview data was uploaded and transcribed into an online database. Interpretive data collected from multiple cases was analysed through a cross-case display. The display compared the interview responses for patterns and themes when coding abductively (Tashakkori & Teddlie, 2010). A mixed-method analysis provided statistical and analytical generalisations about the phenomenon (Creswell et al., 2011). Descriptive analysis organised and summarised the responses to enhance understanding of worker experiences. The technique was applied to represent natural clusters, grouping and dimensions (Onwuegbuzie & Combs, 2010). Statistical results were, therefore justified rather than predicted, comparing different perspectives drawn from qualitative and quantitative data (Creswell, 2014b).

Participants rated their understanding of the systems' modes and features, to enable comparing their explanations as to why their responses may have been higher. An inclusive design framework calculated statistics from the emerging themes. Therefore, the numerical properties of the results stemmed from the stratified sample taken from the population (Onwuegbuzie & Combs, 2010). Cross-case analysis facilitated the simultaneous analysis of multiple perspectives to avoid being bound by individual factors (Onwuegbuzie & Combs, 2010). The raw data was sorted into groups and did not distinguish between independent and dependent variables (Miles & Huberman, 1994).

To enhance the investigation, this approach enabled the researcher to identify patterns and themes. These were compared against the participants' perspectives working with driverless haul trucks (Wainer, 2005). A graphical analysis reported the results and highlighted how they related to the questions, which assisted in presenting the statistical information in visual form. Bar graphs were developed for the visualisation of practical significance and trends in the workers' experiences.

7.3.5. Ethical Considerations

The Curtin University Research Ethics Committee (HRE2017-0844) approved the study to be undertaken. The participants were all provided with written and verbal information about the study. Participants provided written consent to participate in the research and were given the opportunity to choose the interview location. The interviewees were assured that interview records were kept confidential, with the participants able to stop the interview at any time.

7.4. Results

The findings of mineworkers' roles transformations were synthesised under three main headings. Those three headings include: role changes through the introduction of automation; the residual workload; and, the local adaptions that occur to assist driverless trucks in non-designed situations. These headings capture the workers' primary response to their experiences with automation and changes to their work

7.4.1. Role Changes Through the Introduction of Automation

7.4.1.1. Role Description

Participants' role descriptions ranged from loading trucks to monitoring the performance of the automated system. Professionals developed reports from the system to analyse truck performances. The analysts work attempts to understand truck cycles and associated delays. The information was used to educate the operation on how to optimise the automated system. Training roles described their position when upskilling operators to transition from manual to driverless truck operations. Upskilling involved teaching the additional layers and processes associated with automation. For example, setting a loading location and then how to direct a truck into the bay. People were taught how to react to a situation and how driverless systems were likely to respond. All the activities described were involved with automation:

> *Quite a lot more involvement with the trucks from an autonomous standpoint, for a digger driver. You've got to put in spot points. Make sure you've got one called all the time. Make sure you're always thinking three or four trucks ahead as to where the truck is going to be…* [P4]

The most challenging component of this was explained to be the shift in responsibility. In particular, the operational and spatial awareness to be successful in those changes. An excavator operator, for instance, previously loaded trucks, maintained the bench and pulled batters. The introduction of driverless technology, however, introduced additional buttons and screens to interface with the driverless trucks. When it came to controlling the fleet, participants highlighted how they closely monitored the fleet to ensure machines performed as expected. The assignments were monitored to ensure the fleet was cycling through the loading units as explained by one participant:

> *Mainly just watching the trucks. So just making sure that they're doing what they are supposed to be doing. Their assignments, their cycling through the diggers correctly, going to the correct dumps. Those sorts of things, yeah.* [P7]

Mine controllers described their role as directing the fleet across the mine in the most efficient way possible—the trucks were controlled from a central location, which managed 25 machines for every control room operator. In comparison, machine operators were in charge of a single area. As a controller, one person could be responsible for multiples areas at any one time. Therefore, maintaining positive communication was described as a crucial step since truck drivers were removed. The daily plan, compliance, production, safety, and emerging issues all need to be managed. When breakdowns occurred, the fleet was to swap around to maintain operations and be completed manually. Controllers utilised field-based personnel to provide physical dump locations, including the validation of the virtual mine model to suite the physical mine, as one participant confirmed:

> *All your processes, you got to ensure your onto your builders and make sure you've got somewhere for the trucks to go. The system at the start is pretty overwhelming; it's really complicated. But once you sort of figure it all out, it's pretty simple.* [P9]

Participants described how automation forced improvements in road compliance. Road compliance involved maintaining road standards, intersections and windrows. Additional technology layers require design standards to reflect the mine model. Therefore virtual models that do not reflect the physical world create risks and extra work for humans. Where a manual truck traditionally drove around road spillage, driverless systems identify the spillage as an object. However, the participants stated that this practice increased compliance, as those conditions were unlikely to be raised by truck drivers. Production technicians attend to objects that are identified in the field since driverless trucks are unable to classify objects. The role monitors and supervises truck cycles, mode changing machines and undertaking tasks that automation cannot perform:

> *Mode changing, manning them up when we had to go manned, to take them to the workshop, clearing obstacles. If we had to do manual tips, or refuelling... Taking care of the trucks, while not being in the truck.* [P11]

Participants reported that wheel dozer operators keep the dumps pushed and the loading floor clean for driverless trucks. Areas around the crusher are maintained to remove built-up material that could be identified as an object. Despite a virtual model, physical dividers exist for separation and protection in the mine. More importantly, to prevent manually operated equipment from cutting corners and colliding with other machines. Supervisors monitor the performance of the truck system and oversee the mine plan to ensure the operation is meeting site targets. Since a large workforce remains, a significant portion of the supervisor's work is verifying the work that operators perform. Some tasks need to be allocated to people to provide an environment for automation to operate. As a result, verifications are frequent, and operators supervised to validate the entire system. Not only do supervisors oversee the work, but they also authorise to control trucks and build virtual models, playing a role in every discipline to ensure people have the tools and information they need. As one participant who was also a supervisor stated:

> *I do quite a bit of running around to make sure that people are getting the knowledge they need and helping them to perform their role properly*. [P20]

The supervisor role was described as being a role between every function and included communicating inside the control room and having a close connection to the pit. The pit was described as being heavily reliant on decisions made in the control room. Field roles required that the virtual mine model to be built and maintained. Therefore, as explained by one participant system-based duties are critical to running a driverless operation:

> *Without our role, the trucks don't run. So, we build all the road networks, all the dumps, get them into the digger and park ups, that sort of thing… We got to update surveys, make sure the trucks can do their thing.* [P23]

The participants stated that the most crucial task is making sure the virtual mine matches up to the physical mine. It is in identifying hazards or situations that could damage trucks or put personnel in danger. Therefore, new roles monitor and compare the model to validate against physical intersections, corners, ramps and dump locations.

7.4.1.2. New and Transformed Roles

Participant's explained how new roles were explicitly designed for automation, while others were transformed (see Figure 7.1). Those roles included analysts and system-based roles, while conventional roles were upskilled with new interfaces. Analysts taught themselves how to get into the system to understand automation. The data is analysed while replaying the actions of the machine. What has changed is the quality of data that comes with automation. Everything a driverless truck performs is recorded and stored somewhere in the system, much more than a manual haul truck. Therefore, there is more to analyse and understand the technology-based layers. Similar experiences were shared with excavator operators, with far more involvement in how trucks enter the loading area. For example on participant stated:

> *Now you've got to put in your spot points, make sure you've got one called all the time. Make sure you are always planning 3 or 4 trucks as to where the trucks have to be and where it's gotta go… looking at floor conditions, bench conditions… yeah, it's quite involved.* [P4]

The most challenging component described by participants was developing peoples' spatial awareness. Participants described having to think a lot more about their tasks. The trucks may be automated, yet they require humans to provide additional instructions in certain situations. This required manual equipment operators to learn how to plan for upcoming machines and how to coordinate them safely. For instance one participant stated:

> *Yeah, you've got to plan where you want those trucks to a certain degree, but you just hang your bucket there, and the trucks come. With autonomy, you know, you've got to progress your spot point, you've always got to be putting where you are going to put the trucks.* [P4]

In a manual truck operation, truck drivers would reverse themselves based on the excavator's position. However, now trucks are driverless; the excavator operator needs to physically identify where they would like trucks to be loaded. Excavator operators described this move as a positive step, enabling them to take responsibility for loading the trucks. Participants expressed that this enables them to know exactly where the trucks are going to travel:

> *Previously, Betty could back over one part, and John could back over another part. There was an element of doubt sometimes where they were going to go. But now you know exactly where they are going to go with the lanes and stuff that is generated on the screens.* [P5]

Participants described how the floor conditions must be kept smooth in driverless operation. If floors are rough, the obstacle detection system will identify objects and stop short of the excavator. The positive is that there is far more data available through in-cab displays. However, the operators had to learn how to observe and interpret the information displayed on the screen. The screen provides information and functions that allows operators to control the fleet. Participants explained how comfortable they had become now that they had been empowered to manage the fleet. Driverless trucks that end up in the wrong loading position were explained to be the operators' fault, now that automation followed the instructions given by the operator. The screen also provided information about what trucks were doing and when they were coming. Operators could identify a loading location before trucks even arrived, which did not exist in manual truck operations:

> *Whereas, with a trucky [slang for truck driver], well he is sort of stopping there, he's waiting, you know. 'Oh, where do you want me to go?' And you're like come on get*

under the bucket here; this is where I want you. No more of that, you don't wait for the trucky, you tell the trucky exactly what you want him to do. [P6]

For participants who previously drove a truck, they explained how they were either trained in other equipment or upskilled in system-based roles. Therefore, their experiences were vastly different depending on where the participants transitioned from. Participants were taught how to operate other machines with in-cab displays, developing the virtual mine model and controlling the fleet:

So, I was just driving trucks before. Very manual. It was physically driving the truck, refuelling and doing all the tasks that are involved with that. And then yeah, now it's just like sitting behind a computer, more technical based, keeping the fleet online, those types of things... [P7]

Despite the transition, some participants believed similar mining principles still applied in automation. They reported there were also fewer people to manage within the operation, therefore managing crib breaks and hot seating arrangements had reduced. However, participants noted that driverless systems were far more labour intensive than manual trucks. Where a manual operator would drive around broken-down trucks, driverless trucks would stop and wait. In addition, if a driverless system lost communication, it needed to be manually recovered and relocated to a safe location. These were the types of additional practices learnt. More importantly, some of the roles in the manual operation were described as reasonably simple in comparison. Moving from operating equipment in a manual to driverless vehicle meant the introduction of computer-based tasks and practices. As a result, if personnel moved into a system-based role, there were more changes involved, as noted by one participant:

Loading trucks like in the autonomous world, because you then became the truck driver as well the load unit operator… And in the sense of pit tech (technician), yeah, we didn't require those in the manned world. So, it was a new skill, new role. [P11]

Participants described how there were more aspects to consider. For instance, mode changing a truck and recovering it manually when it broke down. Operators also had to be mindful where the machines were driving, given that the system could not determine the type of terrain. Therefore, load unit operators were responsible for guiding driverless trucks into their loading position. Participants highlighted how new starters initially began driving haul trucks. Since there were no trucks drivers, operators needed to be upskilled initially on more complex machinery. In addition to learning equipment functions, they also had to learn how to interact with the driverless trucks. Despite this, driverless trucks were described to be more predictable in what they performed, with lanes indicating the direction of a machine. Participants involved in the early stages explained how they had to learn the system prior to developing safety procedures and inductions:

> *Number one I had to learn the system. Number two, then I had to go and start writing procedures, processes and inductions for autonomous operations… Because we actually had upgrades every, you know, twice/ three times a year… so, therefore, it changed processes and the way we actually operated. So, it did actually change the way I moved around, well part of my tasks within autonomy.* [P13]

Participants reported how training documents were needed to evolve with the operation. Despite the manufacturer offering a system, the site developed their own ways of working. With software and functionality, upgrades came with better safety and engineering controls. When the system was upgraded, the processes needed to be changed. Therefore, the practices required a shift in the way the mine site operated. When the procedures established the standard, those practices eventually stabilised. However, automation had introduced levels of complexity within existing processes. In manual truck operations supervisors relied heavily on the control room. With automation, people began to monitor the activity much more closely:

> *Manned relied a lot on control in Perth to run the trucks and run the system. And we just kind of overseen what they were doing and contacting them. Whereas now with autonomy, we can actually see for ourselves what's going on, where the trucks are going, where the dig units are. And we can help assist them with it.* [P9]

Participants explained how supervisors previously managed a lot of operator change-out arrangements. The task is now limited to excavator operators, with the people who remain. For supervisors leading the operation, participants described how there was not a lot of change for them. Primarily their role was to supervise people doing the work, so unless they were actively participating in tasks, automation did not change a whole lot for supervision. However, they still had to drive vehicles amongst driverless trucks and follow all the new processes introduced. Before the final development, supervisors were far more involved until the residual roles evolved. As one participant confirmed:

It definitely changed. In the beginning it was more around problem-solving and sorting and understanding the system. And then of course, as the system grew and as we grew as a mine site, it went more to the supervision of the people and delegating those other roles to the actual people that were doing it. [P19]

As the system matured, it was reported that supervisors were performing similar tasks—for example, pre-shift briefings, daily meetings and workplace inspections. Depending on what tasks people performed, some adjustments were made in the way the tasks were executed. Grader drivers, for instance, needed to change the way they maintained the road. Participants highlighted how graders no longer took control of their entire route; they had to work in smaller sections to work in with the trucks. Similarly, with dozer operators working on the pit floor, operators needed to work around the machines, rather than automation working around them. Therefore, for a supervisor, it was more about verifying that these tasks were performed correctly. Furthermore, there was more to confirm in a driverless operation, including load plans, survey lines and speed zones. Supervisors needed to adapt and plan their work through the system. As one participant explained:

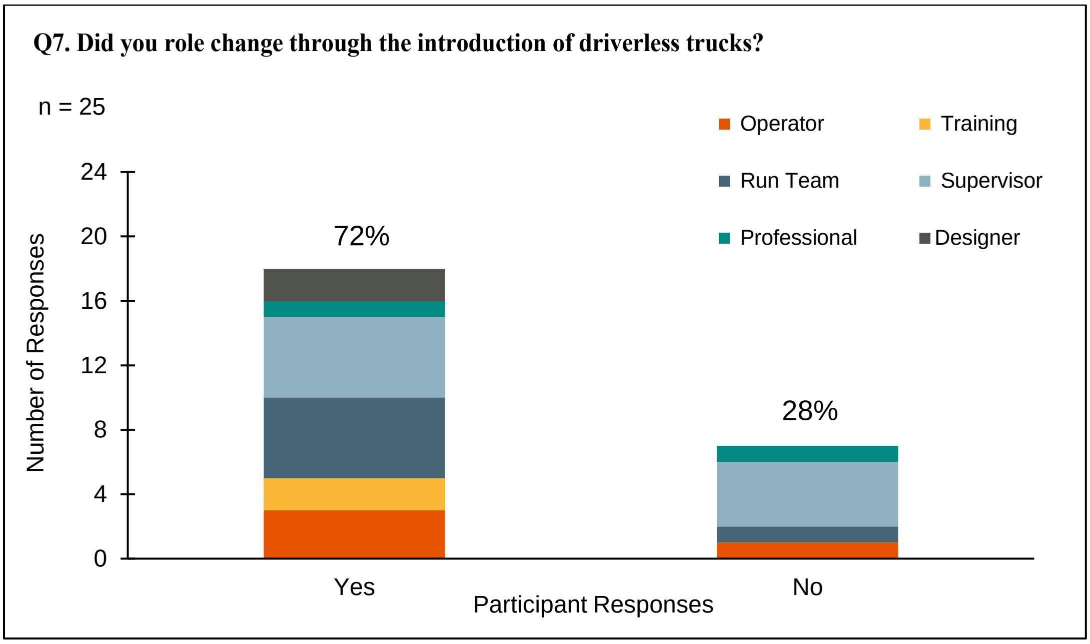
… you now have a lot more visibility. So, you can see a lot more without having to do the k's [kilometres] in the pit… You don't have to be running back and forward all the time. You know you still got to do your physical inspections, but you just don't have to be doing it 24/ 7… [P16]

Participants frequently described their role as being the eyes and ears for the operation. Despite trucks stopping if there was something wrong, the automated system was not capable of identifying potholes or wet roads. Personnel had to intervene to slow the trucks down by putting speed zones in place. The control room required in-field personnel to advise them of environmental conditions:

So that's the big change. Don't let the truck just do their thing… They might run through potholes. Like for example, now it's raining. The roads are absolutely buggered, but they will just go flat out until something breaks. [P23]

Figure 20.

Responses to whether participants' role change through the introduction of driverless haul trucks



The fact that people are dealing with the technology was described to be a significant change. Personnel needed to trust a computer, as well as their colleagues. The actions people make also impact on the decisions that are made by the machine. For example, anything that computer is instructed to do, the trucks will perform. In contrast, a human was explained to question a lot more of the decision makings. Yet, the machines fitted with additional perception and object detection. Therefore, some people now validate those systems to ensure they are working—the system design tailored for people who like to be in control. The entire mine can be observed, including lanes and speeds within the mine. Most importantly, how to interact with a truck with no driver was a learnt skill.

7.4.1.3. New Technology and Computer-Based skills

Participants explained how the introduction of driverless haul trucks increased their skills (see Figure 7.2). The base level of operational understanding remained, while automation took it to a whole new level:

> *The way I look at it is you know; this is the next level for operators. It's how they can use their current skill level and integrate it with a new technology.* [P2]

Participants reported how people that applied the system were the ones who were more comfortable; they also worked in the system. The ability to interface effectively with automation was explained as one of the differences. There was no doubt that some participants created and or learnt new skills. Personnel now had to observe visual displays to monitor the virtual system. Some operators needed to manipulate loading points and where they wanted the truck to go. The most challenging part was noted as the physical world not always being represented in the virtual model. Therefore, skills were developed to observe the screen and visualise where the person wanted to position the truck. Work areas may be tight, yet the operator must be able to get trucks into narrow areas. Driverless systems were said to need more room to maneuver; yet the adaptive skills were difficult to teach. As one participant described:

> *So, you've got to be able to imagine how you're going to get the truck in there and manipulate sometimes your spot points and all that sort of stuff to try and get the truck to come in and do what you need it to do. So it's definitely created another skill because you've got to think outside the square sometimes, you've got to load the truck where you wouldn't usually load a truck, or how you wouldn't usually load a truck, but to get a truck loaded you will just deal with what you've got to get it in there.* [P4]

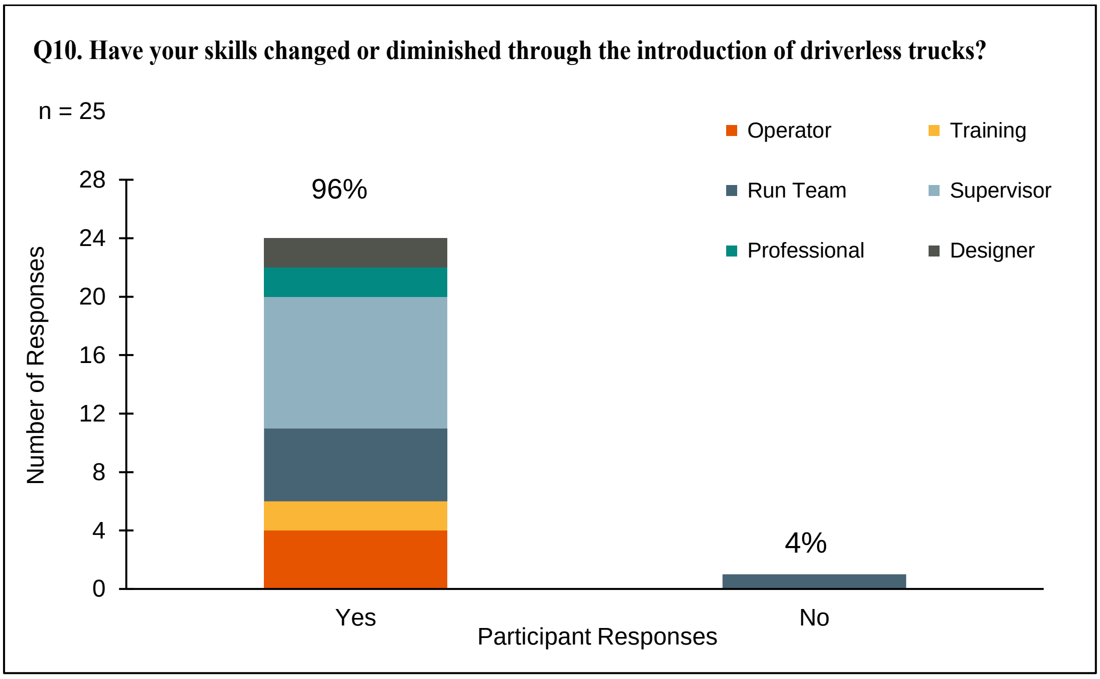
Operators also explained how they needed to be thinking ahead of the game. The skill is in changing boundary lines to give driverless trucks more space to operate. As a result, the excavator operator can avoid getting stuck in a corner and start to plan where they are moving to next. Forward-thinking developing skills and working with the technology skills were considered important. Participants explained how personnel must want to be good at learning technology. Those who do not wish to excel simply are not interested, nor are they effective. People were reported to need time to understand how to interact with the technology. Participants did note, however, that frontline workers soon became reliant on technology. Reliance was claimed to remove some of the abilities to excavate without a screen. In addition, the tolerances for loading a truck narrowed, where operators were more cautious with truck drivers behind the wheel. While dig patterns and wall compliance remained unchanged, it was the interface with the truck fleet where transformations occurred. Described as a learning curve in interfacing with computers and planning further ahead:

> *Yeah… changed dramatically. Like I said before I'm a basic guy, but you know learning these computer things I'm like wow… man, I didn't even lift up a pencil, I didn't even know how to lift up a pencil and write on a piece of paper when I was at school… For*

me, the autonomous side has sort of taught me you know how to be like a, what do you call those things? Not like a Pac-Man, Techno man! [P6]

Figure 21.

Responses to whether participants' skills had changed or diminished through the introduction of driverless haul trucks



Learning how to interact with driverless haul trucks increased peoples' confidence in the use of the technology. Participants highlighted how they had purchased new technology on the back of learning screen interfaces at work. The participants stated that by learning the system and implementing their adaptions they refined their skills and improved their performance. Technology was viewed to have opened new pathways and methods of thinking. As one participant said:

Well, you know in my mining career I've never worked with screens before, everything has been eyeball. Use your eyeballs, and those are the screens you use. But you know, getting to know how to use the screens and how to use the system properly. I think that's the main thing, hey, the system. [P6]

Driving haul trucks was described as monotonous and unchallenging. More importantly they highlighted little problem-solving aspects to the role. Supervising a driverless fleet in the control room was seen to offer controllers the opportunity to develop new methods of hauling.

Conventional techniques such as refueling a truck were considered by the participants to take a little longer than it had previously, however the skill was yet to diminish. For personnel already in the control room, participants explained how the fundamental skills were relatively the same. Automation simply added another layer onto their routine, with an emphasis on positive communication. A truck driver would previously enter a delay if the truck broke down—however, a control room operator now manages this aspect. The layer of automation in the mine site had introduced new skills in fleet management. The fleet management system taught people how to enhance truck performances through the virtual mine model. In particular, how speed zones and lane designs could impact on a truck's reaction. Computer interfaces inside light vehicles allow the system-based role to learn how to use a computer. The more people used this system, the more they learnt. With the ability to lift computer skills, personnel developed knowledge of how to reduce and increase truck speed. Moreover, there are simultaneous activities needed to be completed at the same time. More importantly, learning what the trucks can and cannot perform, while understanding the boundaries in a safe environment was considered important:

> *One thing about autonomous is that it introduces new skills. It affects everybody in the pit and actually affects everybody as a whole… It affects water cart operators, affects every machine operator in the field; it affects all your mine controllers. Now it introduces new roles, your pit operator competency, you got your field builder, you got you, system builder, you got your autonomous mine controller…* [P13]

New roles learn how to mode change a truck and interact with them safely in the pit—learning how to survey and verify high walls. System-based roles are creating virtual environments that are important to the operation. Physically mapping the mine site digitally and mapped to coordinates. If the virtual environment does not match the actual mine, then risks can emerge. Therefore, these new system-based roles were described as the cog in the wheel for the operation:

> *So, here you've got one person who is the driver of 30 trucks. And I think that takes a skill, because not only are you monitoring those trucks and you're assigning them… you gotta [have to] monitor their health as well too, because if a truck stops, you don't have a trucky calling up [asking for assistance]….* [P13]

Computer interface alert system-based roles also influenced the skills of the workers, as these interfaces did not exist in a manual truck operation. Every role has been touched by automation, whether it is multiple screens in the control room or small interfaces in cabs. Supervisors are taught how to mode change and recover trucks when they lose communications, how to build a virtual dump model, a lane network and implement hazard zones. The system was described as a large computer game that participants needed to understand. Instead of driving around and physically observing things, the system allows people to look at the area through a device. Participants described learning how to use a tool that enabled personnel to be more efficient and plan what they wanted to do next.

7.4.2. Residual Workload

7.4.2.1. Workload Bunching

The workload of residual tasks can be short and intensive, followed by long period of inactivity. If a driverless truck breaks down or identifies an object, people must respond immediately. The workload compounds with machines queuing when a broken-down truck is not cleared. Balance comes with keeping on top of clearing objects, validating and surveying dumps. Core operational activities are part of routine tasks, planning work based on what is happening. For system-based roles, this means driving around the site, following trucks and improving their cycle times and changing lane angles to increase truck speed and monitoring the way truck turns a corner. At times, the workload is described as high stress, with constant interruptions and breakdowns. From a users' perspective, since there is much going on at one point and system-based roles need to be across it:

> *Previously for a manned operation you wouldn't, you have 40 trucks drivers that can think about it and do it yourself. You've got one controller, on average, looking after 25 trucks, with one builder. Planning all the work for those 25 trucks, as well. So, it's constant just churn; it doesn't stop; it's relentless…* [P2]

When a driverless truck loses communications it immediately stops. There is a lot of interaction and intervention to keep the operation moving. Controllers, for example, have to intervene when something happens. Whether it is an obstacle detection or a close interaction with a light vehicle. Moreover, a driverless truck may also lose its assignment, which can also compound issues. Particularly when there is production pressure to deliver outcomes for the business with high expectations on Key Performance Indicators (KPIs). Participants explained how it is not a job that people can do for a long duration. On average personnel fulfil such a role for two to three years at most. People are moved around every couple of days, which reduces their internal stress levels. Some people were described as to be able to handle such a workload, while others were considered to have a lower tolerance:

> *Some people can handle it better than others, but you got to try and keep that balance right for them as well. Otherwise, people just get frustrated and get burn out, make mistakes. There's this whole other piece that we have to consider now, which we never did before.* [P2]

Participants highlighted how the control room no longer has people in the cab to witness activities unfold. Therefore, local adaptions by truck drivers to avoid situations are no longer there. The workload in responding to those needs now reside with system-based roles. For example, if a machine broke down on a section of road, a manual machine would use an alternative route. However, with automation, the driverless fleet would continue to use that same pathway and wait behind the broken-down truck. Manually operated equipment could also navigate around the truck, because automation is unable to perform this function. With set planned routes in the system assignment, driverless trucks are unable to react to emerging situations. As one participant explains:

> *What can tend to happen there… if a scenario like that is unfolding and it's not identified soon enough, suddenly is potentially a simple solution or recovery, suddenly compounds and becomes bigger and bigger and bigger.* [P3]

The intensity to resolve driverless truck issues can be quite high. For example, when the physical environment is not overly stable with rough roads and low network coverage. When the situation is unstable system-based roles can always be recovering trucks. Furthermore, dump spaces need to be allocated to the fleet evenly across the mine. The workload can increase to rebuild dumps, surveying and modifying the dump plans. The high workload follows extended periods of inactivity:

> *Short intensive moments. Like so you'll have a lot of not a lot. Then you will have a whole lot of outages… there will be bloody trucks falling off the thing [network] everywhere that you gotta [have to] go fix… get trucks and put them back into manual mode and move them out of areas and stuff like that. It's very sporadic.* [P4]

The work of the excavator operator was described as one of the most straightforward tasks on site. The role was explained as dull in comparison to system-based roles and functions, particularly when the excavator was benching, and there were a limited amount of trucks presenting. When operating the dozer, participants found it challenging to avoid machines while trying to perform their work. In preventing driverless truck interactions, a grading task was stated as taking up to three or four times longer when maintaining the road where driverless trucks travel. Participants explained how the control room should always be busy and that there is data retention or tasks to follow up on with maintenance when the system is running smoothly. Despite this, there appears to be only two people designated for the entire haulage fleet:

> *So, it is a busy thing, and I think a lot of people forget you've taken away the thirty truck drivers and left one person in charge now.* [P8]

A higher workload was noted as taking away employees' attention from what personnel needed to focus on. Participants described how by merely looking at the virtual mine model; participants can determine how their day is likely to unfold. When the excavators are in tight areas or drop cuts, the system-based workload is going to be high. Close areas do not flow as the automated system needs space to reverse trucks under the loading unit. As illustrated by one participant, setting the goals in a group of excavators and haul trucks can be difficult, taking approximately an hour to complete:

> *If nothing happens in an hour, all your processes, all your dumps are fine, all your dig units just miraculously go. It would be really good, but it never happens in a drop cut, it never happens in a reverse drop cut, there's a lot of cleanups, there's not a lot of room there, so you are mucking around with builders. The trucks are stuck, and you can't get cusps. So yeah there's a lot of workload in situations like that.* [P9]

The driverless system was described as being designed for opened spaces, with big dumps and short runs. In those situations, it is more effective than manual operation. Although communication with field-based roles is crucial, calling people by phone and using messaging applications was reported as common practice. The control room not only managed the in-field interfaces, but also communicated with plant control. These roles became the voice for the system in and advise others where the material is heading:

> *Yeah, you can have hours where you don't stop... Being on the radio, talking on communicator, talking to maintenance, talking to supervisors and all that. Then you*

might have four hours flat out and then nothing. Ha-ha. So, it really does fluctuate a lot [for a controller]. *[P9]*

Participants noted that it depends on the conditions. There might be perfect conditions with a limited number of detected obstacles. Whether there is a full crew, or the team is short of people for the shift. Therefore, with the balance of potential obstacles and road conditions, the workload can differ:

One shift you could be recovering trucks, clearing obstacles none stop, and you are just getting calls for two-ways both of them don't stop all night. Then other nights when the system is running well, and the roads are maintained well; spillage is low. You could be cruising around, waiting for something to happen. [P11]

The workload was described by the participants as moving from one extreme to the other. System-based roles could also fulfil simultaneous activities, including hot seating, calling trucks into maintenance bays or covering breaks. While it was described to be balanced a majority of the time, it is the intense moments that increased the cognitive workload. Those moments appear to all come at once as illustrated by one participant:

Like yesterday, at one stage we had the scraper broken down and 100 metres, couple hundred metres up the ramp we had a dump truck broken down. Then another 150 metres we had another dump truck broken down. We are trying to build bunds behind the dump trucks that are broken down on the ramps and get the Mine 5s and 6s, with the maintenance guys to come and fix them. [P12]

The main activities were described as including the verification of dumps, travel lanes and speed zones. More importantly, was the role of following the trucks around the mine and ensuring they were optimising the cycle. When the cycle was efficient, there were limited abnormal reactions to situations. Participants reported how this is rarely the case, despite the workload balance improving. The problem is that if one of the variables is taken out of the equation humans must intervene. For example, if a dump is full, the truck cannot think for itself in terms of where it needs to go. Therefore, the workload increases for system-based roles to provide a new location. If a truck stops for an obstacle and is not cleared, the oncoming machines will sit behind the truck and wait. When the system is running smoothly, the workforce is calm. However, when workloads increase from disruption, the situation becomes tense. The health events, truck stoppages, network loses, and truck recoveries all come at once.

7.4.2.2. *Executing Tasks That Driverless Trucks Cannot Perform*

There were several tasks stated to be performed that were a by-product of automation (see Figure 7.3). Personnel must take surveys of the real mine site and upload them into the mine model. The task drives the physical parameter of the area with a mobile machine. Despite the development of LiDAR technology to gather this data, it is not there yet. The trucks also need to be recovered after losing communications or breaking down, manually driven out of the haul road.

Road obstacles detected within the lane must be visually inspected before clearing. Moreover, since the trucks do not retain that information, the operator can return to the same location moments later. Since the driverless system has improved, the residual work overtime was argued by the participants to have improved. However, with the operation expanding, the driverless fleet was moving into areas designed for a manual truck operation. The spaces were tighter and developed on smaller fleet classes. Therefore, the participants claimed that they needed to assist driverless trucks more through those areas:

> *A lot of the newer areas we're going into were designed for told me whereas a lot of the areas we originally moved into were designed for manned fleets and they're even designed for manned fleets of a smaller truck class. So that was constantly causing issues.* [P3]

There also several tasks that personnel would like to perform, yet they are restricted. They are undertaking maintenance on roads reduced due to surveys, interactions and obstacles it can create. When it comes to loading a truck, a virtual spot must be placed by the excavator with the bucket. The system accepts that spot if it is within the survey boundary. Excavator operators need to press a button on the joystick to authorise the truck to enter the mining area. The location is commonly used twice before the operator needs to reset the spot as they move along the bench. When leaving the excavator, there are settings and adaptions put in place:

> *I have to slow them down because of the floor conditions. It can't recognise that there are big bumps in the floor and it just goes charging through. Generally, I use the system on office selection. I will use preferences when I am in tight areas.* [P5]

The participants explained how it was not only individual tasks that the trucks could not perform, but it was also coordinating their movements. At times the fleet needed to be locked to a particular area, otherwise, the logic would direct trucks to the excavator moving the most tonnes. It was described as a highly manual task to assist the system. Therefore, goals were introduced into the system to determine where trucks were allocated. The dumps will also go full, whereas, in the manual operation, this would not be the case. Therefore, mine personnel did not have to re-plan an area and shut the dumps off to resurvey the model. The trucks were then moved around to accommodate the work, which required personnel to think more ahead. For example one participant stated:

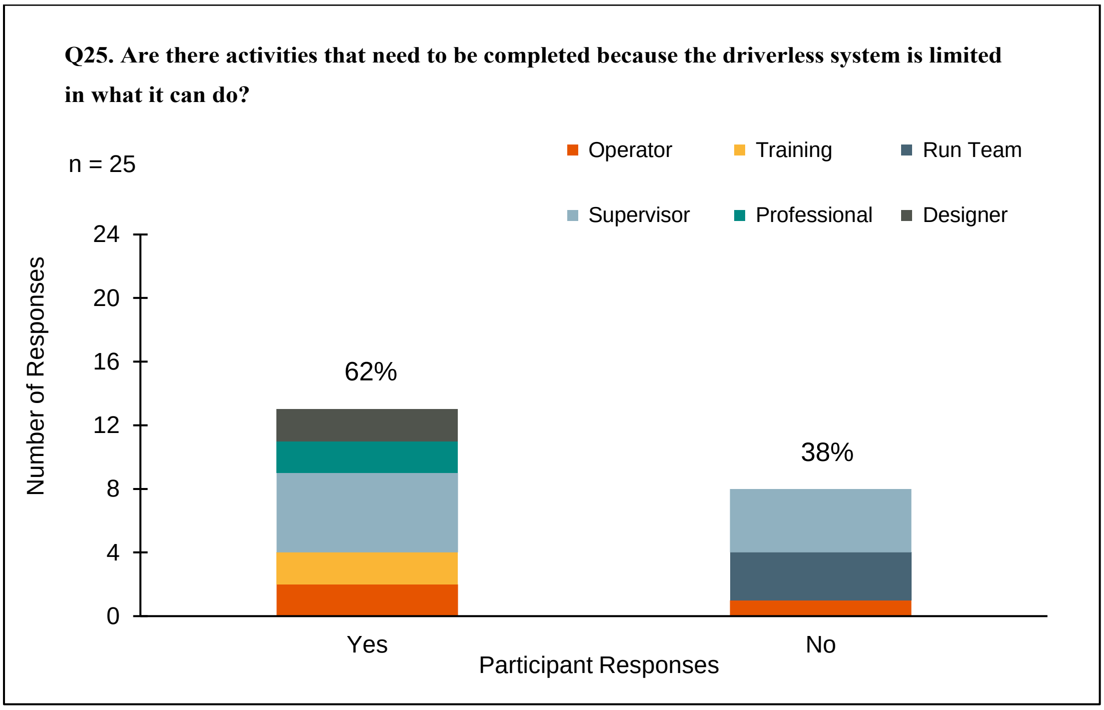
> *We do a lot of surveying and verifying of the real world. The autonomous truck, they could do a lot of the surveying as well, I sort of like having the human intervention and ownership of the area. We have to go and physically or virtually clear a non-obstacle.* [P11]

The participants believed that there was a suitable level of human-machine interaction. However, participants noted that there was a lot of remedial work. For example, a truck may fail to tip on a waste a dump truck multiple times, which requires the dozer to push more material. This practice can result in weak spots, yet the dozer operator needs to keep pushing. Participants described how they needed to think outside of the box for the trucks:

> *I guess we are the eyes for them, and the brains for them. Because they just do what we tell them to. You gotta [have to] be pretty onto it [aware]… Monitoring where they are going, make sure the trucks with high grade are going high-grade dumps or crushers. And the trucks with waste are obviously going to waste dumps.* [P12]

Figure 22.

Responses to whether there are tasks participants need to be completed because the driverless system is limited in what it can do



Participants highlighted that the system was not perfect from the beginning. Participants explained it would be nice to identify objects and classify them appropriately, instead of waiting for a person to clear the object. Moreover, the trucks are yet to identify potholes; therefore, personnel must put in speed zones in hazardous areas. Participants believed automation could be more intelligent, rather than merely travelling quickly back to a digger only to queue. Therefore, the system could be a lot smarter and limit the workload on personnel. Other examples were discussed, such as trucks being unable to lower their tray, with the truck's tray getting stuck on the windrow. Despite these limitations, the focus can soon turn to the people supervising, whether they are planning and enabling the trucks to perform. Since the system requires more room to maneuver, the system is limited in tight spaces. When comparing them to manual operations where there was no need for human intervention.

7.4.2.3. Interpretation of System Information

The participants described how mine personnel may misinterpret the information outputs from the driverless system (see Figure 7.4). Operators may interpret some warnings and codes in a particular way. However, more detailed analysis was usually said to be provided by engineering, mainly when they are the designers of the codes. The design in practice can create situations that are not reflective of the intended design. As a result, video footage and snapshots are taken by people to compare the outputs with actions. There is diagnostic information presented to display fault codes, which must be interpreted by the personnel supervising the system. Without the background information, the users can be left confused about what the truck is trying to tell them. Depending on the person's role, they may have access to diagnostic information. Therefore, they rely upon in-cab interfaces or system-based personnel. Some of the indications are even more passive, with a change in lane colour or truck function:

> *So, you get an obstacle; the lanes go green. You may not read that this is happening or take notice. You may misinterpret it or be prompted by control. You might also be in the body boundary and be in its lane. Sometimes people don't know they're in the lane, and the truck won't come back.* [P4]

The participants explained how there are other examples where trucks do not reverse into position because it is already in a loading sequence. The excavator operator presses the send button and the truck backs under the excavator. Operators must also learn what the lanes colours represent. For example, if a truck does not reverse into position and the lane colour is blue, it means that the digger bucket is blocking the lane. The in-cab display may also indicate that a truck is 10 minutes away. However, the truck does not arrive when the system stated it would be on the screen. There may be specific errors or messages that operators do not understand; therefore, personnel are required to read maintenance manuals to understand the data:

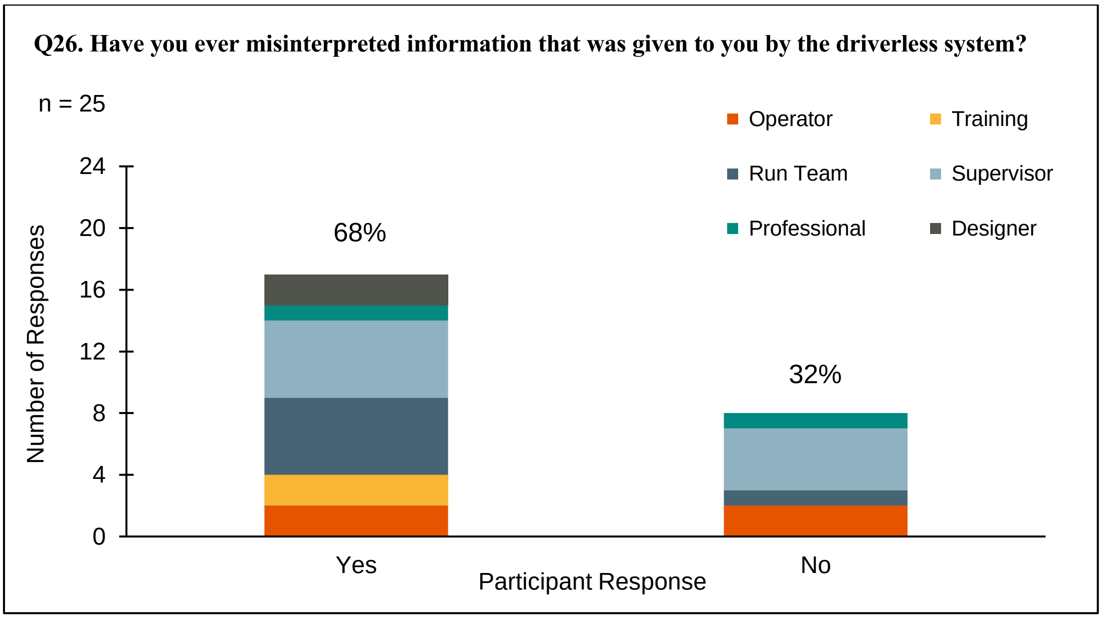
> *There is some information there that doesn't make sense. You are troubleshooting, you might troubleshoot it three or four times, and all of sudden it works. I've had instances where I can't figure out why the trucks are doing what they are meant to be doing, and all of a sudden worked. And I can't even explain it.* [P9]

Participants explained how, at times, driverless trucks do not know where to go. A truck that is stationary with a green tile, with no information to highlight the issue. Participants described these situations as errors in the details outputted that do not make any sense. Therefore, personnel troubleshoot it by pressing stop/ play and the truck drives away. There were also instances where the system highlighted that a truck was in operation, yet it was reversing back to the loading bay. Deadlocks could occur in the loading area, despite no additional instructions given by the digger operator:

> *So, I suppose like when you are looking at what you are seeing, like the information you are receiving, you can't explain why it is doing it… Sometimes in a dig unit and all that you can have a truck on your screen but it's not actually there.* [P9]

Figure 23.

Responses to question whether people had misinterpreted the information given to participants by the driverless system



Despite some of the information or glitches that are unable to be interpreted, participants believed the information was always accurate. Everything that is presented on screens to operators is available in real-time. The labels, acronyms and the types of data were noted by participants to be understood once they understood them. However, in the beginning, the language is new and highlights terms that have little meaning:

> *Like the new people that come over, you'll hear: 'Can you power cycle that truck?' Which is basically can you turn that truck on and off again. They like to use stuff like that.* [P11]

Participants explained that there are help pages available to personnel to interpret system information. Moreover, the predicted pathways of the trucks were stated by participants to be accurate. For example, if the blue lanes indicate that the truck is going straight through the interaction, the truck always travels straight. However, it was noted by participants that misinformation can be provided, such as updated survey files or the system is not transmitting the positions of equipment. Road lanes can be observed on the right-hand side of the screen, yet the paths are actually on the left-hand side. Therefore, it is not necessarily a misinterpretation of information, but more the fact that the correct information needed to be displayed to operators. Designers label the codes used with terms that personnel do not always understand:

> *Not in autonomous run mode. What does that mean?... Unload assignment request. So, no one knows what that means, and it (the driverless truck) just sits there in red (red tile).* [P14]

Participants in system-based roles explained how it takes time to learn the systems' information outputs. Once those terms are understood, personnel can start to determine what the system is attempting to explain. The understanding of the information was argued by participants to be underpinned by experience, attaching the reference or warning to a specific meaning from previous interactions.

7.4.3. Local Adaptions

7.4.3.1. Situations Emerge Outside of Processes and Procedures

In the initial stages of driverless truck development, the participants spoke of situations the technology had never faced before (see Figure 7.5). In particular, when an operation first attempted drop cuts, participants described them as a 'nightmare'. Because the space was so tight, the trucks could not turn around and reverse back to the excavator. Without the trucks being able to reverse to the loading point, the trucks were unable to be correctly loaded. This phenomenon according to the participants forced excavator operators to adapt and change their techniques. In addition, the system functionality needed to be adjusted to accommodate the mining environment. Design criterion were created by operations for engineers to design the system to match the environment and work more effectively. Upgrades allowed the trucks to perform in tighter spaces and allow trucks to reverse back to the excavator:

Early on, it was a lot of manual intervention to do that before. You know, you'd have a builder focused on that the whole time. Just sitting there, tweaking the lanes or moving the spot point or just doing a whole pile of manual click work to make that happen. And that gets pretty onerous when you are doing that for 12 hours, consistently. [P2]

The practical experiences faced by the participants since the implementation have enabled the technology to evolve. Participants reported that this is where a lot of the improvements came from; working through the pain points. Participants explained how operators were consistently confronted with novel situations. The structured processes were designed for operators to broadly cover scenarios, however they also had to embrace the dynamic and fluid environment of mining. The scenarios faced may not be the same every single time as explained by one participant:

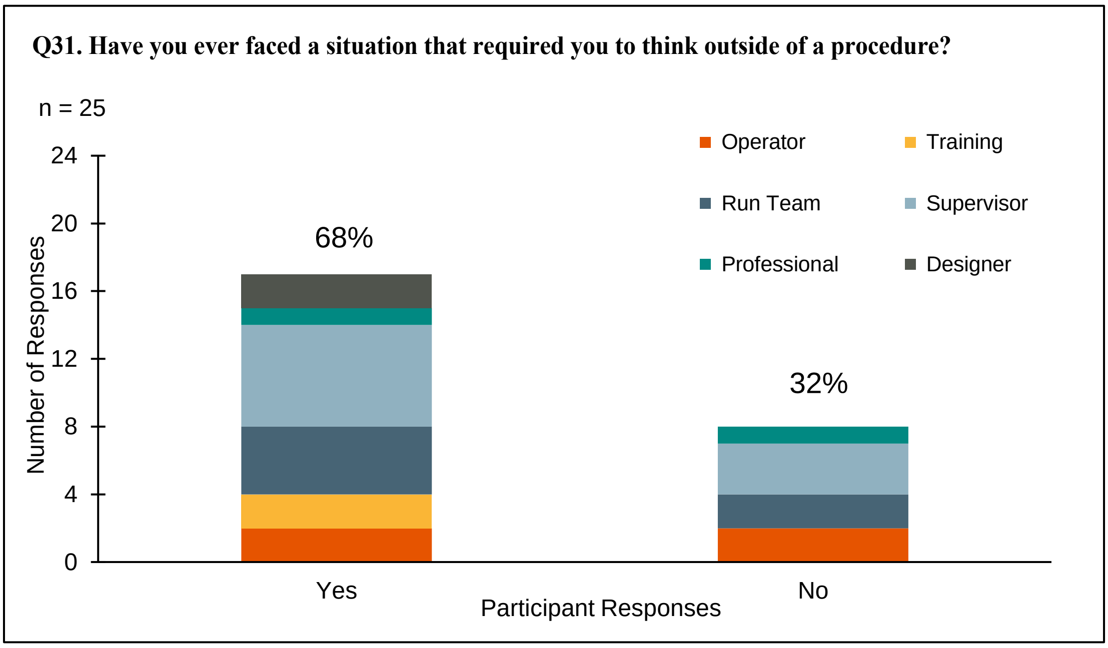
You get variations of that scenario. That's the situations when I say constantly. It is how to match the scenario and slightly modify your response but following the process in principle. Depending on what is happening and where the truck has stopped. They may have to get a little bit creative within the area to resolve the issue. [P3]

Participants noted that mining procedures were re-written in the early stages every day of the week. What was executed by people, in the beginning, would not be sensible in the future. The operation was said to be continuously improving upon safety; with productivity reported as having to think creatively when troubleshooting trucks. For example, a truck may remain stationary, and the system-based roles unable to move the truck. Therefore, they had to figure out why the truck was not moving and work through a process of elimination. There was no manual or instruction for unique situations that arise. Therefore, the participants reported adapting their experiences in those situations:

Or you have to do silly things like override it to sit on the correct lane, or you know. Or it could be as in-depth as… getting a power cycle for the truck to reset. Kind of what was, system-wise was happening on that truck… Outside the box like it happens all the time. I can't really say one thing. [P7]

Figure 24.

Responses to question whether participants had ever faced a situation that required them to think outside of a procedure



Since personnel were adapting in novel situations, there were reports of inconsistencies across the shift. The participants argued that every shift should perform the same tasks. The differences were explained by participants to be as simple as handing back the control of a truck. A chain of command informs the personnel controlling the fleet that the mine is safe for driverless equipment. Participants noted that for an operator, there was not a lot of adaption to be made outside of the available functions. Although it was noted that some operators have the flexibility to play within the parameters, for example, selecting what side the trucks should reverse to the excavator. Therefore, it was explained that operators usually lean on system-based roles for technology support. More importantly, when attempting to recover the truck from a situation, they use learned functions to influence truck performances as illustrated by one participant:

> *... there's definitely a few tricks you can do here and there to get trucks out of situations that wouldn't be like textbook… you might not have lanes to get a truck out, but you can still... plan-exit-forward or reverse a truck. So, you can actually deal with an issue with the truck and get rid of it without the input of anyone else.* [P9]

The participants explained how vital was the ability to think creatively to overcome these challenges, particularly given that if automation is to be successful, the trucks need to keep moving. Therefore, if a truck faces a situation that it cannot overcome, it is the operator who is troubleshooting the cause. Participants described it as something they were getting better at but challenging to teach. In the early stages, participants described how there were many situations where standards were still being developed and a minimal number of mine personnel understood driverless technology. As time progressed more processes and systems were developed by professionals for the personnel. The gaps were covered, and personnel began to know how to perform those tasks. Over time, as situations emerged, the systems for working with machines to prevent incidents from occurring evolved:

> *That's the thing with autonomous the processes have been developed because of things. To prevent that happening against we have developed those processes. Activities outside of the processes eventually become the structured process.* [P23]

Participants explained how the processes also attempted to cater to the masses. Therefore, arguing that a set of fixed methods would never cover for all situations. As a result, there would be times where personnel needed to provide a level of adaption to suit the scenario.

7.4.3.2. Remaining In-The-Loop With the System

Participants reported that there are opportunities to assist personnel in understanding what the trucks are performing. Different roles also have separate displays. Where a system-based position may have an in-depth assignment engine display, an operator of a machine has far less. Therefore, according to the participants, operators are not necessarily informed by the system of what function the truck is performing. Operators simply have the lanes displayed and identify the mode light function. For example, if a truck performs a U-turn, the operator will not receive information on why the truck performs the task. Additionally, if a truck stops, a machine operator will not be informed of why. There could be various reasons why it stopped, including obstacle detections or loss of communication.

> *They don't have any feedback point currently to understand some of those things. I think that's where our next generation of software for in-cab displays will start to change. We want to be able to give the operators a level of detail and understanding so they can see some of the stuff. And potentially engage at a certain level.* [P2]

Remaining in the loop appeared to depend on the level of visibility in the system. Without a computer-screen interface, it can be challenging to determine what the truck will do next, unless personnel understand the pattern of the truck cycle. For example, a person may intuitively know what the next step is in the sequence. However, the surprising component of this is when the truck performs something different. A driverless truck, for instance, may turn around while waiting in queue to be loaded. Participants explained how this comes down to visual displays in the field and understanding the basics of mining:

> *The truck's travelling it's either full, or it's empty, it's queuing or its spotting, loading or tipping. I think if you were new to mining and didn't really understand the basic cycle of a truck. Even if you didn't know what each element was called, then you may think it is unpredictable behaviour.* [P3]

Participants described how driverless trucks can only perform tasks within the cycle sequence. Actions are not completed without the correct instructions from the system, indicating that the information is available somewhere in the system. A truck cannot physically move without a valid lane to drive on. Therefore, rather than being informed, the truck's actions are observed to determine what cycle the truck is performing. This knowledge, however, depends on the persons' experience and role. There were participants who grappled with the interfaces to know what was happening. For example one participant stated:

> *I struggle with those pages that tell you where the truck has been and where it is coming from the loading unit and process. What dump it's going and how it is going and where it's going. I think those pages are fairly technical. For a digger operator (their type of interface) it's fine, it's basic.* [P4]

For simpler interfaces in manually operated equipment, the screen is described by participants as straightforward. Operators can observe the lanes coming towards them and the colour changes as it gets closer. Operators without technical displays seek guidance from system-based roles to inform them of truck performances. Those roles relay messages to enable operators to remain in the loop. For example, a request may be made over the radio to determine why a truck is not reversing. A controller may advise operators to move their bucket out of the way when it is detected as an object. The experiences of control room operators can be much different, particularly given that they now supervise up to 25 trucks.

Yes, you may be looking at one truck on this side but then like 20 seconds later you're back at the side... like it's constantly flicking between the two, because of your screens... I literally have two screens, and then I'm looking at both at the same time (to remain in-the-loop). [P7]

The participants explained how they do not disconnect from the situation; instead, they direct their attention to where they are needed. For example, if the flow of the daily plan changes and the excavator is moving locations. Monitoring the screens and scanning the situations is a way of staying in touch. Despite being actively involved in a task, participants who worked in the control room utilised their peripheral vision to observe any abnormalities. Furthermore, the radio calls enable personnel to hear what is happening and get an indication of what is coming next:

I listen to my two-way [radio]. That's a big indication… like with the trucks you can watch and observe, so that's how you stay in the loop thereby watching that. But if you're not told what's going on, you can only do what you can do then. [P8]

Radio communications were noted by participants to provide essential information. The difficulty, however, was in predicting what the system will do next. After truck tips, for example, the system generates its assignment based on the goals provided. If the truck is heading in the wrong direction, it gives system-based roles minimal time to redirect the fleet. A controller may also decide to lower the production of an excavator to avoid trucks favouring one machine over another. Despite the indication of the current function and listening to the radio, the system was reported not to indicate what driverless trucks will do next. However, in terms of what a truck is currently performing, it was stated to be reasonably straightforward as explained by one participant:

The trucks are doing what they are supposed to do—the lane colours and what not you know where's its going. You know where it is turning. I think it generates itself. You can tell by the lane colours. It's just being familiar with the truck. [P3]

There are other signals outside of the system that participants use to remain in-the-loop, including identifying the material type they are carrying and through pre-shift briefings. The material type indicates whether the truck is going to a waste dump or crusher. The system also can send messages between personnel or inform them of a site-wide stop. If there is an emergency, an alert is presented on the screen to indicate that operation is to cease. Participants described how detailed information was provided to system-based roles through in-cab displays, yet remained limited for operators:

> *I'd say you are not really informed unless you have a client (technical screen) in the car at all. You'll have dump spots close on you for no apparent reason. Dumps close, dump reopen and that. I'd say there's no feedback in that sense.* [P12]

According to the participants, the technical displays provide more information on what is happening, which is different from the predicted pathways provided to operators on every in-cab display. There are several travel progress monitoring pages to enable personnel to monitor the performance of the trucks. These progress monitoring pages tell people where the truck is going and where it has been. The status page provides haul routes for all trucks and is monitored by operators to determine where it was loaded. A yellow route path indicates the truck's destination. Furthermore, the viewing options provide travel pathways and are continuously monitored for performance issues:

> *Let's say if I'm driving around, I see a truck stop. I'll bring up the autonomy status page. Boom I'll click on the truck. Why is that truck stopped? What is it doing? That information is fed to me immediately. So, I know what's going on with it. It's having a comms [communication] loss; it'll turn green and go in a minute. It's crapped out [stuck] it's not going to move, so I know we have to recover it. So constantly using all that data on the monitor to tell me what's going on in any one point.* [P21]

The in-cab displays are used by personnel to determine what is happening. The status page highlights whether the trucks are in operation or on delay. Radio communication is used by people to provide additional context to the status of the machines. Therefore, participants emphasised using various means to remain in the loop.

7.4.3.3. Human Intervention

There are various diagnostic tools that driverless trucks use to self-analyse functional issues. The self-analysis assists personnel to understand the health of the machine. Despite the sensors located on driverless trucks, personnel are still required to intervene when the trucks face novel situations. From a diagnostic point, if a truck appears to be performing not as intended, personnel monitor the system in the back and dial into the truck live. The actions are observed and evaluated to the required design, attempting to understand what is influencing the actions.

For more immediate effects, participants described not trying to intervene unless someone was at risk. Participants explained that personnel do not have to intervene unless the truck does something beyond what it is programmed to do. Therefore, in the event of an emergency, personnel are provided with an emergency stop device. The device enables people to stop the fleet when activating the device.

> *The AHT [Autonomous Haul Truck], for whatever reason, hadn't identified as a potential risk at the time. Maybe it is a situation where the AHT had and based on what the individual piece of equipment was doing it didn't believe it would interact with it or it may have already performing the necessary steps to avoid the situation. However, as a reactionary measure, I would have hit the emergency stop.* [P3]

Participants reported that when a driverless truck is observed stationary with their tray in the air intervention is required by personnel to put the truck back into operation. Despite the control room attempting to send a script to recover the truck, the truck will remain unresponsive. The truck mode is changed to manual and driven to a safe location. When it comes to deciding whether to intervene, participants describe that it comes down to chronic unease. If a situation does not look right, the participants explained the feeling they had to intervene. When asked what indications participants look for, they pointed to their experiences that reinforce their confidence in taking control.

> *I've made some stupid calls; I've called up and asked what that truck doing is. It's alright it's just doing this. It's about being proactive; if something is not right, you react to it. Whether you call control or press the emergency stop and have a discussion with control.* [P4]

From an excavator point of view, if I don't see anything, I don't like I'm up against them straight away to get it fixed or ask them why—some a driven by data, while others explain using their instincts when deciding whether to intervene. For example, if a truck is bouncing over a rough floor, participants revealed that the truck's speed is reduced by the operators to avoid truck damage and false overloads. Personnel intervene by placing speed zones across the loading floor. Participants argued that people must take ownership when working with driverless trucks:

We are the eyes and ears for it, like I tell everybody. So, don't be afraid to question it if it's not right. Fix it. Chronic unease. If it doesn't feel right, then it's probably not right. [P4]

There were reports from the participants of choosing to intervene when identifying incorrect lane colours or trucks not moving. The control room is called by operators to analyse the diagnostic page and determine what has occurred. Participants highlight making calls when they believe it is not safe enough to operate. Trucks may be shut down by the control room to reboot the system. Additionally, driverless trucks observed travelling over rough ground are stopped by personnel until the road surface has improved. Participants explained how system-roles monitor the actions of the trucks when determining to intervene, particularly in comparing settings to the conditions:

I was at the top of a waste dump putting in a centre island. That's when I saw the truck; it got sent away because all the dump spots were full and I saw that it was about to go down the ramp. I checked my screen, saw that there was a zone on it, zone had 42 k's (kilometers an hour), so I tried getting a hold of mine control. Couldn't in time so I [emergency stopped] it. Called control and told them the situation. And yeah got the speed limit on the way down. [P12]

The participant explained how the settings did not accommodate a loaded truck descending the ramp. Although speed zones would be in place heading away from a loading unit, it is usually not in place heading away from a dumping area. When safety is the primary issue, people intervene. However, when it comes to the assignment engine, personnel avoid intervening and re-assigning trucks where possible. The reason is that the cycles can be interrupted and lead to more trucks bunching. Participants described instances where there is no choice but to intervene such as when excavators go down:

Sometimes, that's not feasible... sometimes this digger will have four trucks and the trucks are still wanting to go back there, and I don't want any more trucks to go back there so I'll hard assign them away. [P7]

When the assignment engine chooses to send a bunch of trucks to one excavator and not another, there will be personnel who intervene. Participants described wanting to avoid incidents and prevent harmful situations from occurring, in particular, if they observed a potential interaction with a person in the field: As noted by one participant:

I'll just stop that truck. "Can you please move out of the lane?" And then we'll be able to proceed with you know... preventing something before it happens. That's the duty of care I guess your operators... like you want to look after them they look after you, they help you out, they clear obstacles, they do everything that we need them to do so do the same for them. [P8]

If a truck is broken down in the middle of the road, it was explained how personnel intervene to send them manually to another load unit. Since the trucks cannot drive around one another, a person needs to intervene to build a virtual lane to allow trucks to overtake. Participants noted that it can be challenging to intervene since there is so much going on. Unless a truck is observed getting into an awkward situation, it is unlikely that people will have the opportunity to intervene:

If I had of been watching a truck go over the edge, I could have intervened with my [emergency stop]. When I saw it just go over the windrow, we could have [emergency stopped] it. That would have intervened with that truck, and we would have stopped the truck, and it wouldn't have gone over the edge. [P23]

Participants also described witnessing trucks reversing into a paddock dump with the wheels spinning. In those clear cases, participants highlighted that people would intervene. They added that there is no real science behind the intervention, other than intervening when there are flames, or there is smoke coming from the truck. It is, however, a different scenario than in a manual operation. Rather than contacting the driver, the truck is emergency stopped, or system-based roles stop the truck:

Other incidents where a truck was trying to back through a windrow, and you could see it trying to get through the windrow. A water cart spotted it and was like copy mine control this truck is trying to get through the windrow. He should have just [emergency stopped] it. So, it's fairly obvious if there's something going on, hit you're [emergency stop] and call mine control. [P11]

The participants reported that there are people who are afraid to intervene and activate the emergency stop device. With experience and time comes the confidence to take over control. There are instances where rocks can fall behind the wheel. Where a truck could not identify that a large rock was caught under the tire participants highlighted that they would intervene.

Limitations also include pedestrians on the pit floor and trucks entering the loading area. The fact that someone is at risk triggers personnel to intervene.

> *Same goes if there was someone on the floor for whatever reason. A person, I wouldn't hesitate to use my [emergency stop] straight away to stop a truck. Anything like that. Anywhere where you think it is going to hurt somebody I just wouldn't even hesitate.* [P15]

The in-cab displays also allow people to foresee potential interactions of safety incidents. Also, if a person identifies a truck going to an area where it should not be, a person will intervene. As soon as a truck stops or performs a task that is inconsistent with its script, personnel intervene. There have been instances where a truck is cleared by personnel to proceed, yet it does not drive away. Personnel must intervene to send the truck a further instruction as to where it must travel to. Whether a truck is backing up to a tip head and a person is unsure whether it is going too far unless the person had a full display they would not know. A technical display provides people with an in-depth understanding of the where it is going to stop, how much further and what speed it is doing. It was explained by participants how experience in observing truck performances underpins whether people will intervene:

> *I think with experience watching everything constantly; you know that you don't have to intervene. I've never intervened other than an a-stop, wet road or escort. I think its experience, being showed and taught what to do. And wanting to know the system. If you don't want to know the system, you are not going to know what to look for.* [P14]

Participants stated that mine personnel need to be more proactive. Currently, it was noted, that people are reactive and wait for something to happen. For example, rather than intervene in a situation, they wait until the driverless truck needs assistance. Field participants ring system-based roles to ask them for me details behind a truck's performance, to increase their understanding. There were contrasting views amongst the participants as to n whether personnel should intervene or not, or only intervene when a truck steps out of its parameters. For example, a truck may have lost communications or breach its travel lane and stopped. Personnel will dial into the truck and change the mode to manual. Participants explained that people learn by making mistakes, developing the necessary skills to intervene with the technology. If something does not look right, people are encouraged to stop a truck, as explained by one participant:

Having the trust of the operators as well if they see something that's not right, they say it. And this is another big one, and I guess this is all to do with training and confidence. What each role does, knowing when the time is right to make a change. [P25]

Participants explain how people in the field are the eyes that identify situations. Despite a central control room that monitors truck performances through the screen, control room operators cannot observe everything. The more eyes that are looking for novel situations, the less likely personnel will miss safety issues. Positive communication was stated to amongst the participants be key in contacting a person to check on circumstances and deciding whether to intervene. Participants explained how easy it is to get distracted with operational duties. When everyone has different priorities, personnel can overlook driverless truck activities. Unless there are potholes in the road and no controls in place to slow trucks down, people allow trucks to operate independently. Driverless trucks can be stopped, placing speed zones over the area and letting them go again. This intervention has occurred previously during escorts, with the vehicle being escorted not visible in the system. If a breach in the escort vehicles occurs, it was explained by participants how people intervene to stop the truck from interacting with a vehicle with fewer safety layers in place.

7.5. Discussion

The roles described by the participants highlight the residual positions introduced through the replacement of truck drivers. Conventional roles were upskilled by trainers for relevant employees to learn how to interface with a machine. The transformation of functions highlights the activities that are yet to be automated. Also, it underpins the capability of humans to examine, monitor and modify processes that cannot be executed by automation (Miller & Parasuraman, 2007). The new roles are included in the run team and consist of builders and technicians. The builders design and maintain the virtual mine model, while the technicians monitor truck cycles, mode change trucks and recover them from non-designed situations. While there were new roles introduced, conventional roles were transformed by technology to accommodate the introduction of automation. Excavator operators explained now owning the load plan, which required them to identify a loading point, set reverse location preferences and instruct the truck on when it is suitably loaded. An in-cab display highlighted travel lanes, arrival times and system messages to interface with while continuing routine tasks. Therefore, there were additional tasks and activities to monitor introduced through automation, which reflects the cognitive demands of monitoring computer systems (Wickens, 2008).

The most significant transformation was found in participants who previously drove trucks and transitioned to system-based roles. Where driving a truck was described as being quite monotonous, the new position was actively involved in operational tasks. A system-based role promotes to a higher level supervisory control, which passively receives information and intervenes when required (Stanton et al., 2001). People are not known to be effective passive information receivers; they need to acquire, interpret and respond to data. Researchers have pointed out that people are not overly skillful in responding to this data (Endsley, 2017). Despite this, every role in the operation now interfaces with a computer screen and engages with the automated system. Participants had to learn how to interact safely with driverless trucks and determine their operating parameters. More importantly, routines previously undertaken by manual equipment were forced by automation to change. Graders were required to reduce their road maintenance footprint and excavators needed to manage trucks in the loading area. Equipment practices also shifted, which required dozers to be mindful of their boundary to avoid interacting with oncoming trucks. Although there are studies of skills degenerating due to automation, participants described gaining new skills in addition to conventional capabilities (Bravo Orellana, 2015).

The new skills developed by the participants included computer-related techniques and interfacing with driverless trucks. New techniques that were involved included interpreting system information, instructing automated trucks and nimble handling of buttons and levers. Participants also increased their understanding of the computerised system's functionality. They discovered how a driverless system performs within its system limitations. The system influenced the participants to think further ahead than they would of previously, otherwise they could find themselves unable to respond quickly enough to novel situations. Automation increased participant problem-solving skills, enabling them to utilise technology to overcome conventional limitations. There was an added benefit in being able to control the truck fleet, with automation introducing the capability to reduce speed and increase traction controls. Also, the introduction of modes increased the ability of participants to change truck modes and functionality. Personnel were learning how to build and maintain virtual mine models, which was described by participants to have significant implications on operations. These skills enabled people to plan and become more efficient.

Participants described supervising driverless trucks as creating work that was short and intensive. This experience reflected similar experiences observed by researchers across various industries, where the workload becomes more bunched (Billings, 2018). Following short and intense moments that can be cognitively demanding for humans, there can be long periods of inactivity (Li et al., 2014). Long periods of inactivity can strain the attention of people supervising the system. The sudden reintroduction into the control loop can be challenging to navigate, particularly when participants shared the management of multiple trucks in various pits. Despite the confidence of participants in monitoring an entire truck fleet, the passive roles appear to be far removed from pit operations. Therefore, it was reported by the participants how vital field personnel are in being the ‘eyes and the ears’ for the driverless trucks. These roles play a crucial role in soothing disruptions with local adaptions to avoid sharp increases in workload. Residual tasks can be routine, as well as reactive in helping automated trucks navigate complex situations.

Novel situations were faced by the participants that required them to think outside the box. Processes and procedures were reported by participants to evolve as the operation learnt more about the technology. Local adaptions included situations where a truck does not respond to requests, or the truck needs to be recovered by personnel from a location. Participants described the systems of work as a general guideline for interacting with the fleet, with instructions on how automation works by design. However, it is up to the human supervising the system in how that process is adapted. Therefore, participants described intervening in driverless truck activities when situations did not appear to be correct. There were no real signs other than drawing from previous experiences. It was necessary, however, that participants remained in the loop with what was happening. Participants highlighted how this was dependent on the person’s screen interface. Personnel with less technical displays were less informed of truck assignments and underlying zones influencing truck function. The participants shared how they would rather have more information than less on what a truck is performing. However, this can be difficult to achieve, particularly when designers are trying to provide personnel with information relevant to their role (Salas et al., 2010). Moreover, achieving this objective without inundating them with non-essential details that do not know how to interpret may be difficult (Endsley, 2016).

7.6. Conclusion

The study results highlight the role transformations that have occurred through truck automation on a mine site. Mineworkers transitioned into new roles or had new technology-based interfaces included. The role descriptions were to support the driverless operation by giving the system direction on where to haul and assisting them through non-designed situations. Conventional roles were fitted with computer screen interfaces and learnt how to interact with automated systems. There were additional tasks learnt, including how to perform surveys and interpret system information. Automated tasks boosted the repertoire of skills and capabilities in computerised systems. Everyday activities such as driving trucks remain; however, it is only in occasional instances when trucks need to be recovered manually by personnel. Therefore, the automation of driverless trucks enhances capabilities rather than diminish traditional techniques. Leftover workloads supervising driverless systems were reported to be short-intensive, which left periods of inactivity. Despite other activities being able to be completed, supporting roles can suddenly introduce people to situations that are novel and complex. The human role remains to apply unconstrained thinking to recover from non-designed situations. This exposure has evolved the problem-solving aspects of frontline personnel and influenced their ability to think further ahead. The transformation of roles from the participants' experiences appears positive, with the ability to operate a computer and learning more about how automated systems operate.

Chapter 8

Discussion

8.1. Background

The aim of this study was to evaluate driverless haul incidents on a Western Australian mine site. The research was underpinned by a mixed methodology, which sought to investigate the contributing factors that lead to a loss of control. A convergent parallel design with a multi-faceted approach was adopted. Firstly, the incidents involving driverless haul trucks were explored quantitatively (i.e. predictors). Secondly, one-on-one interviews with mineworkers were conducted and analysed to examine the experiences of working with driverless technology (i.e. perspectives). Thirdly, both streams were merged together to draw inferences about the phenomenon. Quantitative findings revealed a new risk profile, driven by new and transformed hazards. Thus, the results of the quantitative findings were contextualised by asking research participants: about the contributing incidents involving driverless trucks; the new hazards and risks were being introduced through automation; and the situations when a human was needed to intervene. Mixed method analyses were undertaken to transform the data to make statistical and analytical generalisations. This chapter discusses and summarises the key findings in relation to previously published literature, outlining how the findings integrate into existing knowledge and what remains unknown for future research.

8.2. Discussion of Main Findings

8.2.1. Emerging Hazards and Unconventional Mining Techniques

Determining whether new hazards and risks emerged required a broad analysis of the incidents involving driverless haul trucks. Therefore, the analysis of incidents involving manual and driverless haul trucks was undertaken to represent this new emergence, to the extent in which these new hazards were contributing to workplace incidents. In this research, the manual truck operation recorded 566 individual haul truck incidents, while the driverless truck operation recorded 432 incidents between the 1st of October 2013 and the 30th June 2018.

Road conditions were one of the most frequent hazards associated with driverless truck incidents; 116 (26.9%) incidents were reported between FY14 and FY18, while in manual truck operations 140 (24.7%) driver awareness hazards associated with incidents were recorded. While the frequency of road conditions hazards associated with driverless technology were linked to public reports and Code of Practice (COP) (Department of Mines and Petroleum, 2015a; Jamasmie, 2019), there were few findings noted in the published literature. However, this hazard has been identified in the motor vehicle industry, with technology being developed to detect road surface wetness (Abdi´c et al., 2016).

However, the findings in the motor vehicle industry are not directly comparable given the environment and control aspect at the time of the incident. The incidents involving driverless haul trucks were under automated control rather than human control. Based on the analysis, the hazard became more predominant under automated control, given that the technology was unable to identify wet surfaces or presents of rain. The hazard type was substantially more than under manual control, which recorded 32 (5.7%) road condition hazards associated with haul truck incidents. Nevertheless, the results were congruent with those of Department of Mines and Petroleum (2015a), who highlighted that mobile automated systems can introduced hazards beyond those found in conventional mining techniques.

Combining quantitative incident data (Chapter 4) with qualitative perspectives on hazards (Chapter 6), a more in-depth understanding of the risks could be achieved. Consistent with the research undertaken in other industries (Dekker, 2014), that technology changes the processes it is designed to substitute or replace. In this instance, the process changes created new hazards. A majority of mineworkers (68%) reported the existence of new hazards and risks, which supports current literature and quantitative findings. The study sample included a cross-section of the workforce that fulfilled various positions to provide perspectives and experiences. There was no published literature on the perspectives of mineworkers surrounding driverless technology hazards. This is due to the technology being relatively new to the mining industry. Nevertheless, as the self-driving technology matures, there will be further opportunities to research the experiences of mineworkers interacting with driverless technology.

All mine sites are set to benefit from understanding the types of incidents and hazards that can exist through automation that were identified through the mine site research findings. The guidelines in the Code of Practice for safe moile autonomous mining in Western Australia, stated that the safety challenges are dealt with in the planning cycle to implement strategies that are engineering controls and above (Department of Mines and Petroleum, 2015a). Mineworkers were constantly adapting their working strategies to protect themselves from hazards, which was consistent with the literature on computerised cockpits (S. Dekker, 2014). Overall, the hazards and unconventionl techniques arose from the substitution of the truck driver for a machine. The real impact of the hazards appears to be hidden under layers of human adaption, with speed zones, clearing obstacles and adjusting virtual models to keep the wheels moving. In light of this, when situations go wrong, the human is considered responsible since the truck only performed what was instructed to do. This study found that humans were performing various residual tasks to bridge the contextual gap (Pettersen & Schulman, 2016). In summary, the findings from this research highlight the opportunity to update risk profiles to manage the emergence of new hazards. More importantly, they show the need to build driverless systems that are more open and collaborative with the people that work with them, therefore the adaption can assist automation to navigate non-designed situations and avoid failure causes being directed at humans.

8.2.2. Theoretical Viewpoints of Driverless Technology

The epistomology of automation has been one of reductionism. Reductionism had already applied practical constraints on the ability recognise dark faces (Buolamwini & Gebrum, 2018), classify reptiles correctly (Athalye et al., 2018) and determine appropriate areas of policing (Brantingham, Valasik, & Mohler, 2018). Therefore, it was important to understand how reductionism was influencing the approach to automation in the Western Australian mining industry. In this study, the techniques driving the most progress were explored, to uncover the predictive capacity that makes artificial intelligence to appear more intelligent than humans.

The reductionist approach aims to understand each individual component of the haulage cycle within the system. Reductionism attempted to distinguish between what the haul trucks had and what it did, achieveing simplicity from what was excluded. The approach distinguished between what mineworkers and driverless trucks performed as well. This was evident in the perspectives of mineworkers, who reported to undertake specific functions while driverless trucks performed their own. This functional allocation in an engineered system resonates with the findings in the literature (de Winter & Dodou, 2011; Dekker & Woods, 2002; Woods & Hollnagel, 2006) and the residual task being performed by the mineworkers.

The findings were comparable to other high-risk industries who have introduced automated systems. It appears that the Western Australian mine site in this study had deployed technology that was designed for a specific optimisations problem. Based on mineworker reports, the participants described the automated system as being '*tonne hungry*', which meant that the system was soley focused on moving material. This was supported by literature that described automated systems as following a narrow set of instructions (Reason, 1990), with little regard for operational context. The findings were consistent with studies surrounding artificial intelligence (Buolamwini & Gebrum, 2018; Eykholt et al., 2017), which revealed that expert systems eventually confronted situations beyond their design. For the Western Australian mining indsutry, the incident data highlighted the impact of this in driverless trucks being unabled to classify objects and in reducing their speed during inclement weather. This limitations resulted in a number of driverless haul truck incidents.

Comparing the approach to automation and mineworker experiences, a more comprehensive understanding of the strengths and limitations of designing human-machines systems were reached. Reflective of the current research (de Visser, Pak, & Shaw, 2018), the introduction of independent systems appear to ignore the implications on human factors and the pyschological elements of their users. Mineworkers reported misinterpreting information that was given to them by the driverless system, including limited information explaining what a truck was performing. This is consistent with research pertaining to limited feedback loops in automated systems that do not always keep people aware of what is happening (Endsley, 2016). Moreover, the situation was compounded when driverless trucks were able to identify a hazard, however they could not provide a safe way forward. This in turn related to the perspectives of a mineworker, who reported that they frequently needed to think outside of procedures to understand what was occurring to be able to continue work.

The study from this mine site highlighted the limitation of reverse engineering a haulage system as the technology needed more than a collection of engineers to move beyond reductionism (Hamada & Saito, 2018). The deployment has experienced similar practical constraints as other technologies, with an inability to recognise certain objects (Teichman et al., 2011), incorrectly classifying artefacts (Athalye et al. 2018) and unable to predict outcomes based on historical data (Brantingham, 2018). As this study explained, when driverless technology faced a non-designed situation, it relied heavily on mineworkers to overcome them. Mineworkers reported participating in tasks that driverless technology was unable to perform. Although the technology appeared to be more intelligent than truck drivers, the technology faces its own novel situations to resolve. If the industry is to truly work towards becoming safer and more productive, the underlying causes of incidents need to be addressed. This study found that theoretical viewpoints are creating the non-designed situations that were placed outside of the technology's parameters (see Department of Mines and Petroleum, 2014b). In addition to being more flexible, automated systems were found to be more transparent and explainable. This study found the participants considered driverless technology to be transparent with regards to modes and features, however there was little explanation of why driverless trucks perform particular tasks. In summary, the findings from this research highlight the need to promote more user-centred devices in automated haul trucks, including more feedback on actions, logical codes and options for a way forward in the part of the design.

8.2.3. System Processes and Non-Designed Situations

System processes are manual tasks that engineers were yet to figure out how to automate (Caterpillar Global Mining, 2019). With the replacement of truck drivers, a set of activities remained and was allocated to mineworkers to perform. The processes were based on how to work the engineered system, which participants reported to not consider non-designed situations. This study outlined how system processes were developed to support haul truck automation and whether mineworkers were equipped to improvise in non-designed situations.

Mineworkers reported that the system's processes were developed on the practical learnings in deploying driverless technology. Participants reported developing processes to assist personnel to avoid incidents happening again. Processes in automated systems are the by-products of engineering and this is reflected in the literature (Billings, 2018; Reason, 1990). With designers unable to plan for every contingency, automated systems draw upon humans for unconstrained and adaptive thinking (Endsley, 2019). Mineworkers confirmed this when being drawn into recover driverless trucks from a situation and provide the machine with instructions on what to do next.

The research was directly comparable with other high-risk industries because the processes were all leftover tasks. It appears the mining industry, in this research, was replicating similar human factor lessons of the past. Mineworker interviews described their workload when supervising machines to be short intensive moments, quickly followed by periods of inactivity. This was reflective of studies highlighting the workload bunching that occur (Perrow, 1999), with an influx of requests when the failure rates are high (Endsley, 2017). These demands for human input has been argued to be an error inducing mode of operation (Reason, 1990), which was observed in driverless truck incidents. When mineworkers were introduced to clear reverse objects, they were suddenly confronted with a cognitive task to interpret data and identify whether it was an object or a windrow. When this coordination failed, driverless trucks were cleared to reverse over windrows.

Cross-referencing the system's processes, workplace incidents and mineworker experiences, enabled meta-inferences to strengthen the results in determining whether processes equipped mineworkers to improvise. The findings were consistent with the research standardising methods on the predictive capacity of the designer that assumes centralising the most basic steps guides people to the safest outcome (Dekker, 2019). Mineworkers reported that the processes were designed to cater for the masses and are general in nature. Therefore, participants described applying their own techniques to the situation. Similarly, the literature highlighted the proviso to follow written instructions, yet improvise when operational requirements demand it (Dekker, 2003). This was explained by participants to occur in loading areas where mineworkers were manipulating cusps and redesigning lanes to get trucks into tight areas. In turn the processes needed to leverage the problem solving aspect of human intelligence (Lake et al., 2016), rather than debate deviations from central procedures and contrasting individual experiences (Dekker, 2010).

Nonetheless, utilising processes as a recipe for mineworkers stands to demoncratise the system enough for people to improvise. Guidelines state that processes should be based on the prevention and mitigation strategies in relation to hazards (Department of Mines and Petroleum, 2015a); with additional information on how to perform the task. Mineworkers actively utilised standards as a reference in variations of a particular situations. If mineworkers shared and captured the adaptions to processes in a novel situation, the systems' overall effectiveness would improve. The majority of participants (68%) faced situations that required them to think outside of a process and the intervention was often for safety related reasons. Studies suggest that intervention which avoids failure is seen as a mark of expertise (Reason, 1990), while the omission is a sign of being out-of-the-loop (Endsley & Kiris, 1995). In addition to practicing the skills that justify mineworkers marginalised existence, formal processes can be scarcely inadequate to handle goal conflicts of design and application (Xu et al., 2007). This research found that mineworkers were utilising system processes, however the application of their own level of adaption was consistent with other studies (Pettersen & Schulman, 2016). In summary, the processes were developed based on technical limitations of automation, however they needed to be developed with humans in mind, including collaboration, problem-solving and flexibility to ease the tension on the frontline (Billings, 2018).

8.2.4. Human Adaptive Behaviours in Unanticipated Situations

Adaptive behaviours in the driverless operation were stopping trucks from interactions, slowing trucks down over rough roads and implementing zones with wet conditions. Mineworkers were interviewed to understand human intervention and the unanticipated situations they faced. This research highlighted mineworkers applying localised controls to assist haul trucks in situations that were beyond, however they were also surprised by some of the actions of driverless trucks.

The comprehension of what mode or function a driverless truck was performing was quite high as 96% of the participants stated that the system informs them adequately of what mode or function the truck was performing. The main reason for this response was the mode light that was located on the side of the truck (Department of Mines and Petroleum, 2015a), while others with technical displays could observe current function in the system. However, the unanticipated situations came with the fleet management system, where driverless trucks were observed driving the longest haul route. In addition, mineworkers without technical displays reported trucks performing tasks that they did not understand. Therefore, the transparency of the system played a significant role in whether mineworkers observed an unanticipated situation (Department of Mines and Petroleum, 2015c).

The results were comparable to aviation when automation performs surprising events in a mining environment. Mineworkers face unanticipated situations without assignment engine information or limited knowledge in machine logic. These unanticipated situations that arise from automation functions reflect the findings of the literature (Woods & Sarter, 1998), with mineworkers explaining how driverless trucks will turn around at the loading area without explaining the reasons why to manual equipment operators. As a result, mineworkers would intervene to redirect the driverless truck or activate their emergency stop device. The findings were consistent with studies exploring human adaptive behaviours, which highlighted the more humans are promoted to a higher level of supervisory control, the more they are removed from the immediate process (Stanton et al., 2005). For the mining industry, this means that mineworkers are no longer actively involved in driving trucks, reducing the knowledge of how haul trucks perform.

The experiences of mineworkers compared to driverless truck incidents revealed that people were surprised by the actions of driverless haul trucks. Those responses ranged from mode changing trucks, placing speed zones down and attempting to give the system another assignment. Consist with studies surrounding automation surprises (De Boer & Dekker, 2017; Rankin, et al., 2016), mineworkers were attempting to make sense of the function from feedback loops and how they framed the problem. Moreover, in one of the studies, the unanticipated situation had little impact on the trust towards automation (De Boer & Dekker, 2017). These findings were consistent with mineworkers, who explained how their trust did not waiver after being involved in unanticipated situations. Yet, this was inconsistent with algorithm aversion literature (Dietvorst et al., 2015), which described people being unable to trust automation after performing errors. In stark contrast, participants described how driverless trucks only performed what was expected, and that the logic for its actions could be explained. Therefore, a higher level of trust had developed between mineworkers and driverless haul trucks.

Nonetheless, the high level of trust towards automation can lead to a reliance on the technology. This concern was not only raised by the participants, the phenomenon has been well understood in human factors research (Körber et al., 2018; Lee & See, 2004; Wickens et al., 2015). Mineworkers reported that reliance on the technology had contributed to driverless truck incidents. Participants explained how personnel perceive trucks to do no wrong, and if they instruct a truck to perform something that it will not do anything unsafe. However, this perception resulted in clearing objects without verifying the conditions around the truck. Therefore, trucks contacted stockpiles, tipped on red lights at the crusher and reverse through windrows. In addition, the reliance drove practices such as a grader working towards a driverless truck, before moving out of the way at the last minute. Overall, the unanticipated situations depended on in-cab displays and knowledge about the system. Whether the person understood what was happening or not influenced their classification of the situation and in turn local adaption. Studies have found that a double-bind exists in whether people should intervene or not when things go wrong (Dekker, 2003). Unfortunately, the local adaptions often occur unnoticed, which give the appearance that the system is performing as intended. It is only when incidents occur do local human adaptions in unintended situations really begin to draw appropriate attention. This study found that participants described humans contributing to driverless haul trucks incidents. However, as participants shared experiences of working with the system, the interactions between them became far more complex. The findings highlight unanticipated situations linked to in-cab displays and automation knowledge and whether local intervention occurs depends on whether it posed a safety risk or potential for truck damage.

8.2.5. Risk Profile Changes and Risk Strategies

The mine site's risk profile changes were not only specific to haulage; they extended to all mining processes and the equipment that supported them. The mining regulator noted this in their guidance surrounding the safe use of mobile autonomous equipment (Department of Mines and Petroleum, 2015a) Clean-up machines, for example, posed an interaction risk to the dozer operator cleaning up the loading area. Therefore, the hazards types identified in the study are a loss of control that could lead to significant human injury or harm. The results also reflect the hazards and risks that were identified by the Department of Mines and Petroleum (2014b). In this study, the risk profile changes were represented by the hazards that were removed, transformed or introduced in association with haul truck incidents.

Substituting truck drivers for an automated machine progressively removed human factor hazard types and replace them with technology hazards. There were 140 (24.7%) driver awareness hazards associated with manual truck incidents, while there were 47 (10.9%) road obstacles and 38 (8.8%) communications losses associated with driverless truck incidents. There is no driverless truck incident research to compare other than the incidents reported by the regulator and in the media (Department of Mines and Petroleum, 2014, 2015c; Department of Mines Industry Regulation and Safety, n.d.; Jamasmie, 2019; McKinnon, 2019). The incidents and pathways to failure reported in these releases resonate with the findings of this study. In particular, the heavy downpour of rain creating slippery road conditions and the loss of communication posing collision risks.

Although the findings are directly comparable given that they occurred on Western Australian mine sites, they are only a small sample in comparison. Based on the quantitative data, 69.7% (301) of the incidents involving driverless trucks were new, while the other 30.3% (131) existed in manual truck operations but had transformed. The new hazards were occurring more frequently than the transformed hazards. Nevertheless, the findings were consistent with the (Department of Mines and Petroleum, 2015a), which stated that unconventional mining techniques introduced hazards not normally encountered on a mine site, despite the direct benefits of removing human exposures of driving.

Descriptive statistics were combined with mineworker interviews to provide a more thorough understanding of the risk profile changes. Mineworkers reported feeling safer in a driverless truck environment than they did with manual truck drivers. Feeling safer may explain why humans have a reasonably high trust level towards automation in the literature (De Boer & Dekker, 2017). However, as controlled as driverless technology might be on a mine site, its application on public roads has resulted in claims where product developers are turning off detection systems (National Highway Traffic Safety Board, 2018; Wakabayashi, 2018). The same safety devices designed to protect people are yet to distinguish between objects (Teichman et al., 2011), therefore leading to frequent and sudden stoppages. These public reports reflect the experiences of mineworkers who described driverless trucks detecting wildlife, tumbleweed and lose material. What was previously non-existent under manual control, quickly turned into a hazard that caused trucks to breach their lane. This experience would be compounded in a public environment, highlighting the practical constraints of driverless technology and the new challenges it can create.

The incidents and hazards outline in the study, compared with the literature and mineworker experiences, highlight how existing hazards are transformed and new hazards introduced, the range of hazards and their descriptions profile, the conditions that contributed to incidents involving driverless trucks. Manual haul trucks incidents when compared to contrast the shift in the most frequent hazards as the technology was introduced. If the WA mining industry was encouraged to explore the hazard transformation, it would allow for improved safety strategies that reflect the risk. Overall, from FY14 through to FY18, 262 (46%) manual truck hazards were removed through automation, with the other 304 (53.7%) changing shape after automation. In addition, there were 301 (69.7%) new types of hazards introduced. Some of the examples provided by Department of Mines and Petroleum (2015a) were consistent with the findings from the analysis. It is recommended that the Code of Practice is updated to reflect these additional hazards that were revealed on a WA mine site. The findings of this study highlighted the need to understand new risks to promote risk strategies that suit a digitally enhanced operation. Risk strategies should also accommodate the human factors highlighted in this research, which demonstrated the need to develop human-centred technology and enable mineworkers to interact with technology safely.

8.3. Implications of Main Findings

The findings reported in this thesis uncover the complexities of introducing driverless technology into a mining operation. Nevertheless, the results of this multi-faceted design revealed the implications on the industry in practice. These implications relate to both the design of driverless technology and the operational controls in its application. The findings point out where further research is required, particularly where attention is needed as driverless haul truck technology evolves.

8.3.1. Code of Practice

As this study commenced, a Code of Practice (COP) in the safe use of mobile autonomous equipment in Western Australia was released. The COP provided practical guidance for mining operators to achieve their safety obligations. It also focused on the unique risk profiles emerging from mobile autonomous systems in Western Australia. On a global level, the International Organisation for Standardisation (ISO) has developed safety requirements for autonomous and semi-autonomous machines for earth-moving equipment in mining operations. While these requirements relate to autonomous mining equipment and indicate potential risks, this study provides nearly 1,000 incidents to compare against risk assessments, which in turn assists in the improvement cycle (i.e. Plan, Do, Check Act [PDCA]) on empirical evidence obtained from a Western Australian mine site.

The recurring themes and findings during the research related to the importance of standards for both designers and operation, and the collaboration between them in designing the system for the people who apply the system (Woods & Hollnagel, 2006). The implications are in the analysis of the safety incidents, which highlighted the new hazards and risks. By combining incident data with mineworker experiences, the study illustrated the significance of human factors in driverless truck operations. Therefore, safety standards can be more reflective of the human-machine system haulage operations have now become (de Visser, 2018)

8.3.2. Risk Profiles

The shift in risk profiles are driven by the new opportunities that cause harm and the change of the agents that create them. For example, unidentified objects never used to be a problem as the local adaptions of truck drivers enabled them to maneuver around them. However, with the substitution of truck drivers for technology that is yet to classify objects, quickly illuminate situations and deal effectively with conditions that were not present before unidentified objects are a problem. The benefit of a risk profile that has been developed on real-world examples, is that practical constraints challenge the design propositions that often come with new technology. Previous to the watercart incident, mineworkers did not believe that a driverless haul truck would be unresponsive to impeding collision with a manual water truck (Department of Mines and Petroleum, 2015c). Therefore, the application of the technology reveals the systems' response to various situations and conditions. The challenge, however, is that when the technology is upgraded and improved, there will be new situations that emerge among humans and machines (Klein et al., 2004).

The chi-square test perform on the sample data compared the difference between the expected and observed data. The expected data included incidents involving manual haul trucks on the mine site, while the observed data included driverless truck incidents. The test expected to identify 566 incidents involving haul trucks, however the results found 432. The numerator minus the count of what was expected had been squared, the calculation found a high X^2 value of 31.724. The p-value equaled 0, which meant that the incident rates between the two groups were statistically significant ($p<0.05$).

Throughout the study, mineworkers shared experiences of facing situations that had never encountered before. Despite a new risk profile being revealed in this study, eventually there will be additional complexities that emerge. Therefore, the study focused on the theoretical viewpoints that underpin artificial intelligence, highlighting the reductionist approaches that are high influencing the emergence of new risks.

8.3.3. Safe Systems of Work

The systems of work designed for driverless technology has largely been based on what was technically possible to engineer. The residual tasks were by-products that could not be automated. What this research has shown, however, is how the processes were not always reflective of the scenario that mineworkers had faced. Therefore, there were significant adaptions undertaken to practically enable driverless trucks to perform. Despite this, the mineworkers claim that the processes were a good guide for performing routine work. Participants noted that the processes described how to work with the automated system (i.e. mode change, lock a truck), however the processes had no insight into how the technology worked (i.e. what inputs define a detected object, what does a truck actually 'see'). The breakdowns highlighted in this research demonstrate the opportunities for improvement, which can assist mining operators in how they designed their safety systems.

The study found that the safe systems of work were developed on the back of workplace incidents. Therefore, the incidents play a major role in developing safer systems of work. From this, the implications of the research identified residual tasks and roles that need more transparency in how driverless systems function. This will enable safe systems of work to improve as the planning cycle reflects on the mineworkers that are adapting to the gaps in automation limitations.

8.3.4. Design Improvement Based on Risk

Improving the design based on the findings in this report has implications for how driverless systems operate. For example, equipment operators are not given feedback loops to support the automated truck through non-designed situations. Despite the COP and ISO safety standards, there is little user experience guidelines that form the design (Department of Mines and Petroleum, 2015a; International Organization for Standardization, 2019). Predominately, this is left to the designer; however the mining operators need to make the technology works. In addition, the results of safety arise from the interactions and functionality of the system. This was observed in the clearance of objects with no distinction in what the technology was identifying. Therefore, the design aspect to accommodate mineworkers has significant implications on safety.

A repetitive theme arising in the research was the acceptance of the design and the blame directed to the artefacts that surround the technology. For example, the downpour of rain (Jamasmie, 2019) and the loss of communication that was ‘no fault’ of the system (McKinnon, 2019). From this, the research has attempted to change the mindset in the design. A mindset that accepts that outside influences will occur, and the system must become more adaptive to those situations. Learning how to navigate slippery road conditions and trucks that lose communications is paramount to designing a system that evolves from the risks in real-world applications, rather than simply dismissing them.

8.3.5. Diversification in Driverless Technology Design

The divarication in driverless technology design implicates the current approach to automation. At the present time, a range of engineers reverse-engineer what is known about human truck driving and utilise technological advancement to design the system. However, what the literature had shown, is how limited involvement other fields have had in driverless technology development (Buolamwini & Gebrum, 2018; Lum & Isaac, 2016; Skeem & Lowenkamp, 2016). The argument has turned into a technical problem, rather than challenging conventional engineering techniques. The technology is application is transforming the mining practices, therefore the methods that surround artificial intelligence should be challenged as well. For example, rather than simply reverse engineer the system based on historical data, finding out what psychology, human factors, complexity theory and sociology bring to the table. As this research explained, without the diversity of thought, the Western Australian mining industry could experience the same constraints as other industries and create significant safety issues that led them to automation (Department of Mines and Petroleum, 2015b).

Recurring themes identified during mineworker interviews revealed mixed results about machine interfaces. On one hand, the mode lights and assignment engine information were considered effective in informing operators of truck modes and functions. However, on another, the codes and alerts that are generated are cryptic to their users. Mineworkers explained how international phone calls were needed to be made to engineers for the engineers to explain what they meant. This is one example of the design centralisations that often occur with little regard for the user. The implications of the research findings highlight the perspectives of mineworkers and designing from a user perspective, which has never been uncovered before.

8.3.6. Mineworker Experiences Improving User Experience

During the study, the mineworkers shared their experiences and demonstrated the phenomenon they face on a routine basis. For example, pointing out codes that present on in-cab displays and working with driverless trucks that are unresponsive to their instructions. Transitioning from a manual haul truck environment to a driverless operation highlighted a number of tasks that were adjusted. For example, where a haul truck previously self-spotted into to be loaded, this now required an excavator operator to identify a spot point by pressing a button while their bucket was hanging over the location. In addition, the excavator operator was responsible for authorising the truck to entering the loading area and to instruct the machine when to leave. This example highlights the important of the user experiences; from pressing buttons, to the process flows, to the screen functions and information displayed. The breakdown between the user and the interface resulted in a number of safety incidents, including clearing reverse objects that enabled a truck to reverse over a waste dump. This research has identified that the mindset has to change to understand how the user interfaces and interpret the information (Christoffersen & Woods, 2002). Taking the appropriate steps to be guided by the mineworkers' perspectives has significant implications on user experiences.

The importance of mineworkers' experiences was in the perspective of the participants. This means that despite the best intentions of the design, how the user interprets the processes, mode lights, alerting systems, codes, phrases and functions, ultimately determines how the worker will respond. Therefore, the insights from this research has implications for the design in considering how mineworkers would behave or react to a situation, therein avoiding incidents or creating them. The final chapter provides key conclusions from the research and makes relevant recommendations moving forwards.

Chapter 9

Conclusions and Recommendations

9.1. Introduction

The aim of this study was to evaluate driverless haul truck incidents on a mine site by describing the factors that led to a loss of control. The aim was achieved by analysing 998 driverless truck incidents to determine the root causes of haul truck incidents. A stratified sample of 25 mineworkers were interviewed to explore their perspectives and experiences working with driverless technology. Field observations were also conducted to observe workplace practices and identify operator behaviours.

9.2. Conclusions

9.2.1. Conclusions on Emerging Hazards

The first research objective was to describe the hazards that have emerged through the introduction of unconventional mining techniques and the extent risk profile changes have contributed to workplace incidents. The conclusions on the emergence hazards were related to the analysis of incident involving haul trucks on a mine site. The analysis highlighted the emergence of new and transformed truck hazards by exploring individual factors leading to a loss of control. Contributing factors comparisons between manual and driverless truck incidents identified the changes in the pathways to failure. The comparison revealed the presents of new types of hazards that were linked to the introduction of automated technology.

The emergence of new hazards included road obstacles; communication losses; non-surveyed material; zone locking; non-site aware equipment; light vehicle interactions; technology breakdowns; full dump spots; icon spins; truck assignments; machine bubbles; survey mismatches; spot points behind material; and rotating technology. Of the 432 incidents involving driverless haul trucks, 69.7% of the associated hazards did not exist in a manual truck operation, while the remaining 30.3% existed in the manual truck operation, however the way in which a driverless truck interacted with the hazard (i.e. road conditions) resulted in different outcomes.

Interviews with mineworkers confirmed the introduction of new hazards and risks. 68% of participants reported the presents of new hazards, supported with qualitative data on the experiences managing those hazards. Mineworkers found that driverless trucks performed exactly what they were instructed, however this resulted in operators becoming complacent and relying heavily on technology systems. As a consequence, reverse obstacles were cleared without verifying the accuracy of virtual boundaries due to high confidence in the system. There were similarities in other participant reports of emerging hazards, including truck communication losses and road conditions, which supported the insights from the incident analysis on associated hazards.

9.2.2. Conclusions on Theoretical Viewpoints

The second research objective was to explain the theoretical viewpoints of a system that is influencing the company's approach to haul truck automation and the relationship emerging between the components that make up the performance of a complex system. Conclusions were that artificial intelligence as a whole offers a promising route to a sustainable future for the Western Australian Mining Industry. This study contended that the success of haul truck automation hinges on the ability of the technology to embody the complexity of the world around it. The theory and methods of automating a haulage system is one of reductionism. Reductionism has already faced practical constraints in its ability to recognise dark faces, classify reptiles accurately, identify areas for policing and evaluate whether criminals will reoffend. Mining has observed its own set of constraints, with an inability to classify road obstacles and detect the presents of rain. Therefore, the limitations of the technology in real world applications are contributing to incidents involving driverless haul trucks.

In theory, a simplified system represents a number of components that work seamlessly together to load, haul and dump. Reductionism distinguishes between what the system has and what it does, achieving simplicity from what it excludes. The simplification rests on the assumption that components operate independently, without non-linear interactions disrupting the flow of the cycle. Once the system has been simplified to its most basic steps, haul truck activities are analysed to determine the contributions of truck drivers. However, the ability of a human to analyse and adapt to a novel situations makes reverse engineering truck driver contributions very difficult.

Engineering a haulage system attempts to reverse engineer what activities manual haul trucks perform. The method combines the understanding of the haulage cycle with what is known about the human mind and brain. Expert systems require specific training data in order to program the execution of certain activities. More often than not, the training data from the users themselves, with the technology simply replicating the knowledge contained with the facts and statistics. As a result, driverless trucks are limited to the data sources they are collected, coupled with the intricate knowledge of the activities undertaken by truck drivers.

When a driverless haul truck systems is reconstructed based on the theoretical viewpoints of a system, the practical constraints begin to emerge. Through practice, human supervisors and manual equipment operators learn the functions that a machine can and cannot perform. The consequences of replacing truck drivers with a machine challenges the theories that underpin a simplified system. Although the system appears to be straightforward with the re-allocation of tasks to either human or machine, the design is based on the designers' imagination in how the interactions will unfold. Therefore, when driverless technology has faced non-designed situations, such as a down pour of rain, it relies heavily on human supervisors to intervene to overcome the situation. Overcoming the complex requires more open sourced technology to begin working with other branches of science. Otherwise, the future of driverless technology could experience similar situations as other extended intelligence, becoming solutionist, opaque and bias in light of customer requirements.

9.2.3. Conclusions on System Processes

The third objective was to outline how the processes designed to support haul truck automation and determine if operators are equipped to improvise in non-designed situations. The process are instructions that enable people and machines to work together. Those instructions are underpinned by the designers' imagination of operational practices. Practices can include mode changing a truck and the sequence of steps required to execute the task. Whether the sequences of steps unfold along predictable lines is questionable. The engineered component of the process foresees driverless trucks responding to a person's request to mode change, for example. Since designers are unable to plan for every contingency, the technology calls upon humans to solve localised problems. Therefore, when conflicts emerge between the design and real world application, the human must think outside of the ‘designed’ process to enable the truck to respond.

Human supervisors were not always equipped to improve during non-designed situations. Mineworkers participating in interviews noted that the processes they used were adopted from previous learnings from incidents. As a result, participants described that overtime the functionality and capability of the driverless system was learnt, which required processes to be updated to reflect actual practices. Moreover, when the system was upgraded, those practices must also be updated to support new system functionalities. Processes were said to be designed to broadly cover scenarios, leaving mineworkers to embrace the dynamic and fluid environment of mining. As a result, 68% of the participants reported facing situations that required them to think outside of the procedures to resolve the situation.

Despite processes being developed for interactions and activities by design. There was no playbook for novel situations. Therefore, participants described drawing from their previous experiences and knowledge of the system to recover from the situation. The success of the intervention depended on whether human supervisors avoided an incident. Since formal processes does not cover every scenario, there were other cues participants used to remain in-the-loop with the system. It was these localised indications, such as mode lights, in-cab displays, system alarms, that either contributed to, or enabled people to avoid workplace incidents. System processes only supported mineworkers half way, with a complex relationship and different lines of communication evolving between mineworkers and the automated system.

9.2.4. Conclusions on Human Adaptive Behaviours

The fourth object was to determine if there were adaptive behaviours managing unanticipated machine performances and how operators decide to intervene or not when the system appears to be performing beyond design. Undoubtedly, there were adaptive behaviours managing unanticipated situations, which were evident in the incident analysis and interview data. In particular, those situations were visible in those cases where mineworkers were clearing objects or attempting to instruct the truck to perform what was expected. More importantly, mineworkers were surprised by what the machine was performing and what route the driverless system has chosen.

There were mixed views across the participants on whether they had observed the truck perform something that was not anticipated (Yes = 48%, No = 52%). During the interview process, the response depended on whether a technical display was available to the person at the time. Technical in-cab displays provided the assignment engine data to explain current functions or whether a re-assignment had occurred. For manual equipment operators, for example, their in-cab display was basic and simply provided the intended pathway of surrounding haul trucks. Therefore, when a truck performed a U-turn or had lost network communications, manual equipment operators described being unaware of what was occurring at the time. This condition influenced whether people decided whether to intervene or not during situations that were considered beyond the design.

Mineworkers reported utilising information available to them at the time along with their experience when choosing to intervene with a haul truck. Since system-based roles were far more equipped with information to handle the situation, manual equipment operators often resorted to emergency stop devices or contacting system-based roles over the radio. The relationship between personnel in the office and in the field was critical, given that any mismatches between the virtual and physical world could cause an incident. The main trigger for participant intervention was stated to be safety. If the situation is deemed unsafe, the emergency stop device would be activated. However, as the incident analysis had shown, the situation that is being faced is not always clear, particularly when attempting to interpret system outputs, alarms and visual cues being presented by the system.

9.2.5. Conclusions on Risk Profile Changes

The fifth and final object was to provide an in-depth understand of the changes to a mine site's risk profile through the introduction of haul truck automation. Furthermore, recommend strategies to control new risks that have emerged. The risk profile changes were observed through the changes in the types of haul truck incidents that were occurring. Driver injuries were the most common incidents in manual truck operations (n = 136), while lane breaches were predominant in driverless (n = 190). These changes were driven by the emergence of new and transformed hazards. With the removal of people from behind the wheel, driver injuries ceased to occur. In contrast, with the limitations of driverless technology, lane breaches had increased. Lane breaches were being driven roads conditions and losses of communications. Therefore, as the site began replacing more truck drivers with automated haul trucks, the profile shifted towards unconventional risk types.

Although 30.3% of haul truck hazards remained on the mine site, those hazards were transformed. Transformed in the way the haul truck interacted with the hazard. For example, the same road conditions present in manual as there were in driverless operations. However, since the technology was unable to detect the presents of rain or identify wet road conditions, those hazards caused many more truck-related incidents. As a result, the mine site needed to change their processes to adjust from teaching truck drivers how to navigate wet roads to installing speed zones for driverless trucks. Analysing this risk transformation highlighted the need for the mine site to develop new risk strategies to assist in the management of unconventional hazards.

The strategies for managing new risks should be evolved around the introduction of unconventional risks. The analysis provided an in-depth understand of the incidents and hazards that need to be managed. Despite the efforts to design processes based on the engineered system, practical experiences from mineworkers highlighted the need to continuously accommodate real world application. To be sustainable, the recommendations reached beyond risk management, to inform the design of driverless haul truck systems. If the Western Australian Mining Industry cannot quickly learn and adapt to the lessons of early adopts of driverless technology, there is a real possibility that the unconventional risks will be left unaddressed.

9.2.6. Conclusions on Research Aim

The aim of the research was to evaluate driverless haul truck incidents on a mine site by describing the factors that led to a loss of control. The analysis evaluated driverless truck incidents by analysing incident investigation descriptions to determine what had occurred. This method enabled the researcher to determine the causal pathways and uncover what had contributed to each incident. The contributing factors were compared across both driverless and manual truck incidents identify emerging themes and trends.

The evaluation of driverless incidents found that driverless haul truck incidents were dissimilar from manual truck incidents. Divergence was found in how the technology managed different situations or how the design created new possibilities for failure. For example, wet and slippery road conditions existed in a manual operation, however the driverless technology was unable to detect the presence of rain. Therefore, trucks were sliding out of lane more frequently in driverless operations due to the limitations of identifying wet roads and automatically adjusting truck speed. Contrastingly, a loss of network was a new contributing factor that was leading to driverless trucks breaching lane. The introduction of remote operations developed a reliance on network communications to maintain truck operations. When network communications were lost, driverless trucks activated their emergency braking system, which inadvertently caused the machines to lose control. The analysis of driverless truck incidents, such as lane breaches and object detection, highlighted technology-centric factors such as loss of communication and road obstacles that were contributing to losses of control.

Triangulation of incidents with mineworker interviews and work processes underpinned the incident analysis. Mineworker interviews provided further context in terms of what was leading to a loss of control. Interview responses found that mineworkers believed that new hazards and risks were introduced, and that humans were contributing to driverless truck incidents. However, although a majority of participants suggested humans were contributing to incidents, the incidents data highlighted a far more complex phenomenon that was emerging. In particular, the clearance of reverse obstacles that had led to trucks breaching windrows. Participants described the need to carefully check survey lines before clearing a reverse obstacles, as driverless truck will simply drive over an edge in order to achieve the dump location. Since this was a known limitation, there was no expectation of the driverless truck system to apply additional logic (i.e. there is an edge there, do not drive over it). Therefore, mineworkers were expected to understand the design limitations and apply the adaptions that enable trucks to perform what operations intended. When there was a breakdown between mineworkers and the system, participants explored the ‘who’ and not the ‘what’ when describing what was leading to a loss of control. The analysis, in contrast, described the condition such as survey mismatches as the hazard, rather than highlighting the fact that a mineworker did not verify the survey before clearing a reverse object.

The research aim was achieved by analysing 998 incidents of a four year period. This timeframe represented the transition from manual to driverless control, performing under the same conditions and operating in the same pits. 432 of those incidents were in the driverless operation, while 566 were recorded in the manual operation. Despite the reduction in the frequency of incidents, the types of events were transforming. Thus, the analysis needed to highlight the new types of incidents that were emerging. Although mineworkers held varying views on what ‘contributed’ to a loss of control, the incident analysis highlighted empirical evidence on the conditions that were present, while experiences of mineworkers provided another perspectives from frontline workers.

9.3. Recommendations

From the conclusions related to the research aim and objectives, a number of recommendations are made. The recommendations refer to changes that need to be implemented to assist the Western Australian mining industry to deploy sustainably driverless technology.

9.3.1. Recommendation 1 – Review the Code of Practice

The Western Australian Code of Practice for safe mobile autonomous mining in Western Australia, should be updated to reflect the hazards and risk controls required associated with the findings of this report. Providing the Western Australian mining industry with practical guidance on hazards and controls can enable mining operators–deploying driverless technology, to update their risk profiles and safe systems of work.

9.3.2. Recommendation 2 – Update Risk Profiles

Mining operators that have deployed driverless technology, or are planning to deploy driverless technology, should include the hazards and risks identified in this report into their risk assessments. The addition of the new and transformed truck hazards will provide mining operators with the opportunity to control new risks and develop safe systems of work.

9.3.3. Recommendation 3 – Develop Safe Systems of Work for Driverless Technology

Safe systems of work are recommended to accommodate these new risks and leverage the insights from mineworker interviews. In particular, the feedback loops and instructions provided to mineworkers in managing daily routines and unanticipated situations. The Department of Mines, Industry Regulation and Safety and mining operators should develop Safe Systems of Work (SSOW) based on the findings of this report. The SSOW should accommodate the hazards and risk associated with driverless trucks, including the residual tasks that are created for humans with the limitations of the technology. In addition, the SSOW should reflect the findings of mineworker experiences and ensure the processes are centred with the user in mind.

9.3.4. Recommendation 4 – Improving Driverless Safety Systems Based on Risks

Product designers and manufacturers should consider the hazards and risks that have been reported to improve the driverless systems performance. More specifically, if there are technical limitations with reverse engineering human capabilities in driverless trucks; for example, the detection of rain, then the users should be engaged further in how humans can assist the driverless system. For instance, if a downpour of rain occurs, there needs to be appropriate mechanisms to alerts operators of the detection of rain.

9.3.5. Recommendation 5 – Diversify Establish Methods in Driverless Technology

The development of technology should diversify the science and engineering techniques included in the development. A wide range of fields of expertise should be engaged to collaborate on how the technology can become more user-centred and engage more in solving operational problems. Specialists in the fields of teamwork, psychology, complexity and ergonomists can assist product developers to effectively integrate the technology with people in a mining operation.

9.3.6. Recommendation 6 – Utilise Mineworker Experiences in Automated System Developments

The research identified a participant perception that the driverless trucks can do no wrong. Any mistake was perceived to be the truck doing “what it was designed to do”. Driverless trucks are not adaptive; it is the human that is adapting. If humans did not adapt to the complexity and the ‘non-designed situations’ the operation would never move. Therefore, the experiences of mineworkers in applying the driverless truck system should be considered in future developments of driverless technology. Mineworker experiences provide a unique perspective in how automated technology performs in real world applications. The perspectives can assist in improve the users’ experience, including feedback loops, in-cab display indications and meaning of codes to assist mineworkers to safely interact with automated haul trucks.

9.3.7. Recommendation 7 – Further Research into Driverless Haul Truck Incidents

Further research is required into incidents involving driverless haul trucks. The study provided a sample from a single mine site in WA. Conducting further research on other mine sites will enhance the WA Mining Industry's knowledge surrounding driverless technology and the types of incidents that can occur. More importantly, understand the different functionalities of products, their limitations and associated risks with their implementation into the mining industry. Despite theoretical risk assessments that can be undertaken, analysing the hazards and incidents in real world applications provides empirical evidence on how the system in adapting in the environment that it is being deployed. The risk controls recommended in this study should also be evaluated frequently to accommodate future system upgrades and the addition of driverless functionalities.

9.4. Thesis Summary

Over the past seven years, driverless haul truck incidents in the Western Australian mining industry have been widely reported (Department of Mines and Petroleum, 2014, 2015b; Jamasmie, 2019; McKinnon, 2019). Beyond a Code of Practice provided by the Department of Mines, Industry Regulation and Safety (Department of Mines and Petroleum, 2015a), there have not been any studies into the contributing factors leading to these incidents. The regulator warned the industry that mobile autonomous equipment could introduce hazardous situations not normally encountered on a mine site. This research has revealed those hazardous situations, including the perspectives of mineworkers who have experienced those interactions firsthand.

Advocates for driverless technology suggest that automation eliminates safety risk when drivers are removed from behind the wheel. This is based on the assumption that there are no longer mineworkers remaining in the mine and that driverless trucks do not interact with human beings. This thesis argues that this is certainly not the case. Transformations in the mine site's risk profile demonstrated that automation did not eliminate safety risk yet simply changed its risk types. Although new risks had emerged, significant progress was made in removing human exposure to truck driving hazards. The results were evident in the removal of 136 driver injuries that had occurred over a four-year period in the manual truck operation. This achievement marks significant progress for the industry, yet the increase in unconventional incidents involving driverless haul trucks needs attention.

Early adopters of driverless technology have experienced a transformation in their operations. The evaluation of driverless incidents has highlighted this, with new risk profiles, unconventional mining techniques and workers adapting to new technology. A focus on developing safer systems of work, which includes working towards a more transparent and collaborative system, could introduce new insights into the way driverless technology is developed. To make this occur, mineworkers should be considered the centre of the design in real-world applications. Mineworker adaptions in making the connection between pre-programmed design, and the operational requirements, impact of the types of uncontrolled situations that are being observed. While driverless technology is not considered a combined system with mineworkers, the mining industry will not overcome the complexities of a human-machine system.

The research has shown the benefits of conducting a mixed methodology in evaluating driverless haul truck incidents on a mine site. The convergent parallel design developed a comprehensive understanding of the various predictors and perspectives of the risk. The aim was to evaluate incidents by describing the factors that led to a loss of control. The evaluation provides an in-depth understanding of the unconventional hazards that are contributing to coordination breakdowns between mineworkers and automated machines. Utilising a multi-faceted design, this thesis significant contributes to navigating the future deployment of driverless technology and improving the safety aspects of its practical design. The research also contributed to new knowledge about the types of incidents and hazards that are associated with driverless technology. Given that this mine site was one of the first of its kind, the implications of this study offers the entire mining industry a head start on managing the associated safety risks. Rather than relying on theoretical assumptions in how a mining operation is likely to respond, the industry can now utilise a four-year study with a detailed analysis of incidents, coupled with the actual experiences of mineworkers interacting with driverless systems. The opportunity, of course, is now integrating these lessons and insights into an industry that is already accelerating.

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Appendix I

Ethics Approval

Curtin University

Office of Research and Development

GPO Box U1987
Perth Western Australia 6845

Telephone +61 8 9266 7863
Facsimile +61 8 9266 3793
Web research.curtin.edu.au

05-Dec-2017

Name: Janis Jansz
Department/School: Department of Health, Safety and Environment
Email: J.Jansz@curtin.edu.au

Dear Janis Jansz

RE: Ethics Office approval
Approval number: HRE2017-0844

Thank you for submitting your application to the Human Research Ethics Office for the project **An evaluation of driverless haul trucks on a mine site: a mixed methodology**.

Your application was reviewed through the Curtin University Low risk review process.

The review outcome is: **Approved**.

Your proposal meets the requirements described in the National Health and Medical Research Council's (NHMRC) *National Statement on Ethical Conduct in Human Research (2007)*.

Approval is granted for a period of one year from **05-Dec-2017** to **04-Dec-2018**. Continuation of approval will be granted on an annual basis following submission of an annual report.

Personnel authorised to work on this project:

Name	Role
Pascoe, Todd	Student
Jansz, Janis	CI
McGough, Shirley	Co-Inv
Jian, Le	Supervisor

Approved documents:

Document

Standard conditions of approval

1. Research must be conducted according to the approved proposal
2. Report in a timely manner anything that might warrant review of ethical approval of the project including:
   - proposed changes to the approved proposal or conduct of the study
   - unanticipated problems that might affect continued ethical acceptability of the project
   - major deviations from the approved proposal and/or regulatory guidelines
   - serious adverse events
3. Amendments to the proposal must be approved by the Human Research Ethics Office before they are implemented (except where an amendment is undertaken to eliminate an immediate risk to participants)
4. An annual progress report must be submitted to the Human Research Ethics Office on or before the anniversary of approval and a completion report submitted on completion of the project
5. Personnel working on this project must be adequately qualified by education, training and experience for their role, or supervised
6. Personnel must disclose any actual or potential conflicts of interest, including any financial or other interest or affiliation, that bears on this project
7. Changes to personnel working on this project must be reported to the Human Research Ethics Office
8. Data and primary materials must be retained and stored in accordance with the Western Australian University Sector Disposal Authority (WAUSDA) and the Curtin University Research Data and Primary Materials policy
9. Where practicable, results of the research should be made available to the research participants in a timely and clear manner
10. Unless prohibited by contractual obligations, results of the research should be disseminated in a manner that will allow public scrutiny; the Human Research Ethics Office must be informed of any constraints on publication
11. Approval is dependent upon ongoing compliance of the research with the Australian Code for the Responsible Conduct of Research, the National Statement on Ethical Conduct in Human Research, applicable legal requirements, and with Curtin University policies, procedures and governance requirements
12. The Human Research Ethics Office may conduct audits on a portion of approved projects.

Special Conditions of Approval

Please use the student's Curtin email address in the Participant Information Sheet and Recruitment material.

This letter constitutes low risk/negligible risk approval only. This project may not proceed until you have met all of the Curtin University research governance requirements.

Should you have any queries regarding consideration of your project, please contact the Ethics Support Officer for your faculty or the Ethics Office at hrec@curtin.edu.au or on 9266 2784.

Yours sincerely

[redacted]

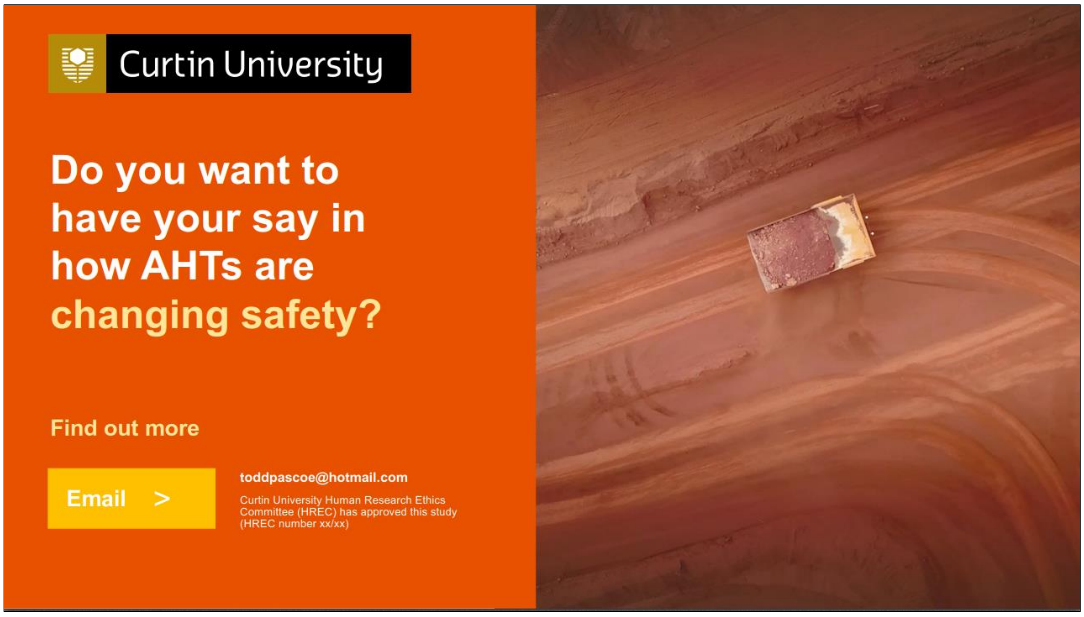
Amy Bowater
Acting Manager, Research Integrity

Appendix II

Recruitment Material

Crib Room Posters

Return to Work Slide



Appendix III

Participant Information Sheet

Curtin University

Research Title: An evaluation of automated haul truck incidents on a mine site: a mixed methodology

Name of Researcher: Todd Pascoe

Aim of Research

This aim of this research is to evaluate the safety incidents involving automated haul trucks on a mine site. This research is a component of the requirements for a Doctor of Philosophy at Curtin University.

Your role

Your perspective related to the research topic will be used to explain safety incidents involving automated haul trucks and your experiences working with the technology. This information will be used to inform the WA mining industry on how safe systems of work can be developed when introducing automated machines on a mine site.

Resources

A set of research questions related to the topic have been developed for this research. One-on-one interviews and group sessions will be recorded to enable the research to engage in conversation and reflect on what had been described.

Consent to Participate

Your participation in the research in voluntary. Participants have the right to withdraw at any time during the course of the interview or group session. A Consent Form will be requested to be signed to indicate the participant's confirmation of consent to partake in the study. Personal information obtained from participants will be restricted to the researcher and can be made available to the participants upon requesting the information. Further enquiries related to the research or information regarding privacy can be directed to Todd.

Confidentiality

Your name will not be recorded during the course of the interview in order for you to remain anonymous. The information obtained from you during the course of the research will be treated as confidential, with only the researcher and research supervisors able to access the information. The data collected in electronic form will be password protected and only able to be accessed by the researcher. Information in hard copy form will be stored in the Curtin University R-Drive and is password secured.

Appendix IV

Consent Form

Curtin University

CONSENT FORM

HREC Project Number:	HREC number HRE2017-0844
Project Title:	An evaluation of automated haul truck incidents on a mine site: a mixed methodology
Principal Investigator:	Todd Pascoe
Version Number:	Version 1
Version Date:	2nd July 2017

- I have read, the information statement version listed above and I understand its contents.
- I believe I understand the purpose, extent and possible risks of my involvement in this project.
- I voluntarily consent to take part in this research project and consent to being audio-recorded.
- I have had an opportunity to ask questions and I am satisfied with the answers I have received.
- I understand that this project has been approved by Curtin University Human Research Ethics Committee and will be carried out in line with the National Statement on Ethical Conduct in Human Research (2007).
- I understand I will receive a copy of this Information Statement and Consent Form.

Participant Name	
Participant Signature	
Date	

Declaration by researcher: I have supplied an Information Letter and Consent Form to the participant who has signed above, and believe that they understand the purpose, extent and possible risks of their involvement in this project.

Name	Todd Pascoe
Signature	
Date	

Appendix V

Participant Interview Questions

Mineworker Interview Questions

General Demographic Information

1. What is your role?
2. How old are you?
3. Male or Female?
4. How long have you been in Mining?
5. What does your working background look like?
6. How long have you worked in autonomy?

Open and Closed-Ended Questions

7. How would you describe your role in autonomy?
8. Has your role changed since moving to autonomy?
9. How would describe the way you interact with the trucks?
10. Have any of your skills changed or diminished since moving to autonomy?
11. How would you describe the specific autonomous training you received?
12. How would you describe your understanding of the autonomous systems' modes and features? (Scale out of 10)
13. Have you ever been involved in an incident that also involved an automated haul truck?
14. Can you recall some of the safety incidents that have occurred in autonomy?
15. What do you think is contributing to those incidents?
16. Do you think new hazards and risks have been introduced through autonomy?
17. Have you ever recovered an AHT or the system from a situation that prevented an incident?
18. Have you observed an AHT perform something that you did not anticipate? (i.e. automation surprise) If so, how long ago did this occur? How often do situations like this arise? What were the consequences of the surprise and how was it dealt with?
19. Has your trust level of towards the AHTs ever change after an experience like that?
20. How would you describe your level of trust out of 10?
21. If the AHTs were 'team players', how would you describe them?

22. How do you determine whether to intervene with or not with the AHTs when something does not seem right?
23. How would you describe the information outputs from the AHT system?
24. Have you ever instructed an autonomous truck to do one thing, yet it performed something different?
25. Do you feel that there are activities you need to complete because the autonomous system is limited in what it can do?
26. Have you ever misinterpreted information that was given to you by the autonomous system?
27. How would you describe the system’s ability to shift with changes in mine site priorities and objectives?
28. Have you ever observed potential safety issues in the way virtual mining areas are built or maintained?
29. Are there situations in the system building or maintenance process that can create risks if builders do not get them right?
30. How do you determine that what you are observing in the virtual system actually exists in the physical mine?
31. Have you ever been faced within a situation that required you to think outside of a structured process or procedure? (i.e. non-designed situation)
32. How would you describe the workload of a pit technician/ system builder in working with the AHTs? (i.e. balance, unbalanced, short intensive moments.)
33. How confident do you feel in redirecting or overriding an AHT? (Scale out of 10)
34. Does the system inform you adequately of what mode or function the AHT is performing? If so or not so, how or why?
35. How would you describe the way you remain ‘in-the-loop’ with what is happening in the system? (i.e. what it is doing now, why is it doing that, and what it will do next?)
36. Does the system inform you on how your actions effect the performance of an AHT or the entire system?
37. Do you feel that you can find the information you need without being inundated with information they don’t need or know how to interpret?

Appendix VI

Publication Information

Authored Publications under Consideration

- Pascoe, T., McGough, S. & Jansz, J. (2020). A multi-industry analysis of human-machine systems: the connection to truck automation. *Cognition, Technology and Work.*
- Pascoe, T., McGough, S. & Jansz, J. (2020). From truck driver awareness to object recognition: A tiger never changes its stripes. *Policy and Practice in Health and Safety*
- Pascoe, T., McGough, S. & Jansz, J. (2020). Haul truck automation: embody the complexity to avoid seeing turtles as rifles. *Cognition, Technology and Work*.
- Pascoe, T., McGough, S. & Jansz, J. (2020). The experiences of mineworkers interacting with driverless trucks: risk, trust and teamwork. *International Journal of Mining Science and Technology*
- Pascoe, T., McGough, S. & Jansz, J. (2020). From truck driver to systems engineer: transforming the miners' contribution. *Mining, Metallurgy & Exploration.*

Publication Statement

(All publications arising from thesis, Chapters 2, 4, 5, 6 & 7)

I, Todd Pascoe, provided the following contributing to the five journal articles currently under consideration:

1. Pascoe, T., McGough, S. & Jansz, J. (2020). A multi-industry analysis of human-machine systems: the connection to truck automation. *Cognition, Technology and Work.*
2. Pascoe, T., McGough, S. & Jansz, J. (2020). From truck driver awareness to object recognition: A tiger never changes its stripes. *Policy and Practice in Health and Safety*
3. Pascoe, T., McGough, S. & Jansz, J. (2020). Haul truck automation: embody the complexity to avoid seeing turtles as rifles. *Cognition, Technology and Work*.
4. Pascoe, T., McGough, S. & Jansz, J. (2020). The experiences of mineworkers interacting with driverless trucks: risk, trust and teamwork. *International Journal of Mining Science and Technology*
5. Pascoe, T., McGough, S. & Jansz, J. (2020). From truck driver to systems engineer: transforming the miners' contribution. *Mining, Metallurgy & Exploration.*

The research contributions included:

- Design and conception of the research
- Data collection and validation
- Data and statistical analysis
- Interpretations and discussion of research findings
- Final approval and submission

Todd Pascoe

I, as a co-author, endorse that this level of contribution by the candidate indicated above is appropriate and consistent with the candidate being named as first author.

My contributions to this work consisted of advising on study design, ethical issues, data analysis approach, content advice, editing, and proofreading the paper prior to submission.

Janis Jansz

Shirley McGough

Paper 1: A multi-industry analysis of engineering human-machine systems: A literature review

CW

Cognition Technology & Work (CTWO) <em@editorialmanager.com>
Wed 8/04/2020 6:49 AM
To: You

Dear Mr Pascoe,

Thank you for submitting your manuscript, A multi-industry analysis of engineering human-machine systems: A literature review of the connection to haul truck automation, to Cognition, Technology & Work.

During the review process, you can keep track of the status of your manuscript by accessing the journal website.

Your username is: toddpascoe@hotmail.com

If you forgot your password, you can click the 'Send Login Details' link on the EM Login page at https://apc01.safelinks.protection.outlook.com/?url=https%3A%2F%2Fwww.editorialmanager.com%2Fctwo%2F&data=02%7C01%7C%7C8ef53302ee8d4ead758608d7db45ecb3%7C84df9e7fe9f640afb435aaaaaaaaaaaa%7C1%7C0%7C637218965674194088&sdata=naD4SglohgrWK5woPGQaUQ8bRlBnheOq9ETSB7K9wVg%3D&reserved=0.

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Paper 2: From driver awareness to obstacle detection: A tiger never changes its stripes

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Paper 3: Haul truck automation: Beyond reductionism to avoid seeing turtles as rifles

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Cognition Technology & Work (CTWO) <em@editorialmanager.com>
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Dear Mr Pascoe,

Thank you for submitting your manuscript, Haul truck automation: beyond reductionism to avoid seeing turtles as rifles, to Cognition, Technology & Work.

During the review process, you can keep track of the status of your manuscript by accessing the journal website.

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Paper 4: The experiences of mineworkers interacting with driverless trucks: risk, trust and teamwork

Successfully received: submission The Experiences of Mineworkers Interacting With Driverless Trucks: Risk, Trust and Teamwork for International Journal of Mining Science and Technology

I

International Journal of Mining Science and Technology <EviseSupport@elsevier.com>
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To: You

This message was sent automatically.

Ref: IJMST_2020_751
Title: The Experiences of Mineworkers Interacting With Driverless Trucks: Risk, Trust and Teamwork
Journal: International Journal of Mining Science and Technology

Dear Mr. Pascoe,

Thank you for submitting your manuscript for consideration for publication in International Journal of Mining Science and Technology. Your submission was received in good order.

To track the status of your manuscript, please log into EVISE® at: http://www.evise.com/evise/faces/pages/navigation/NavController.jspx?JRNL_ACR=IJMST and locate your submission under the header 'My Submissions with Journal' on your 'My Author Tasks' view.

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International Journal of Mining Science and Technology

Paper 5: From truck driver to systems engineer: transforming the miners' contribution

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With kind regards,

Journals Editorial Office MMEX
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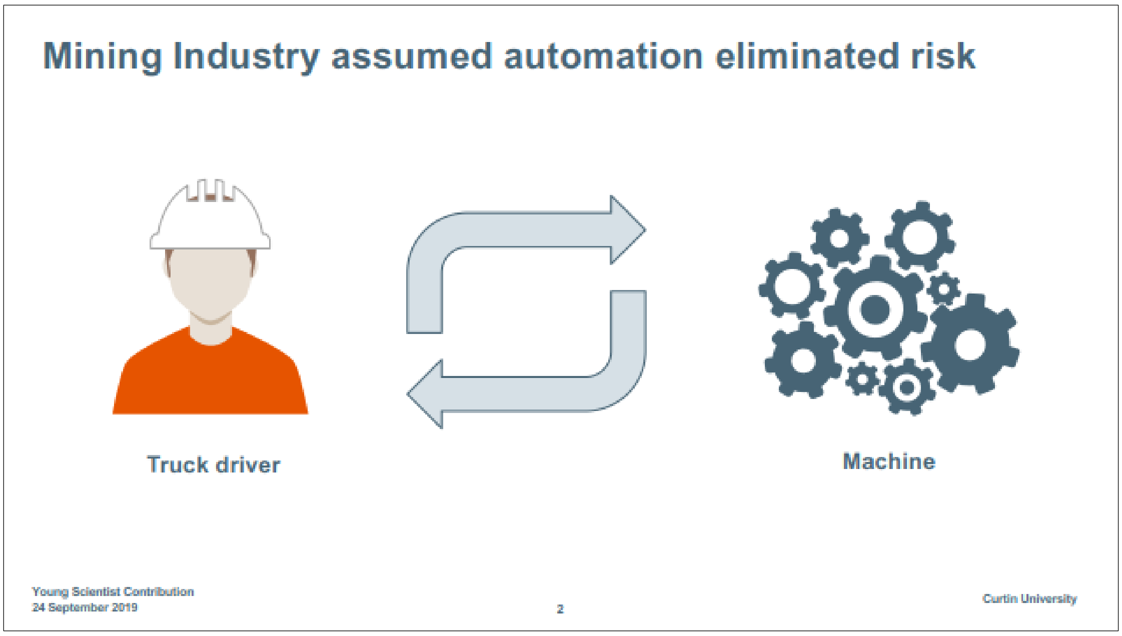
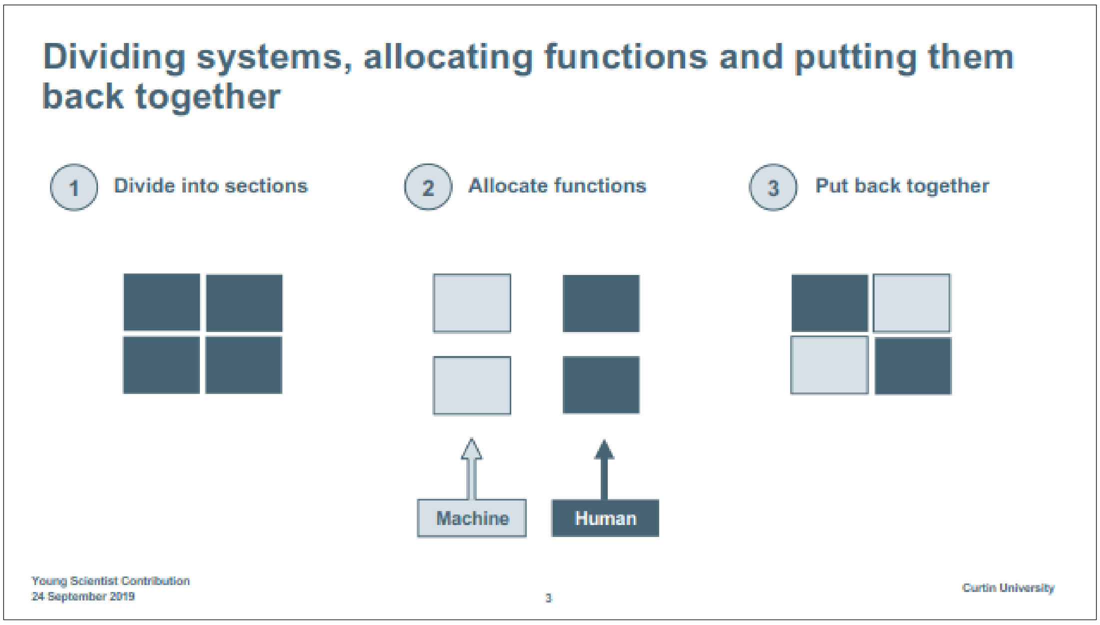
Appendix VII

Power Point Presentation at International Safety Conference in Vienna, Austria

International Conference Presentation

- 10th International Conference on the Prevention of Accidents at Work 2019 Working on Safety (WOS). Paper presentation: From truck driver awareness to object recognition: A tiger never changes its stripes, Vienna, Austria.
  - **3rd Place in the Young Scientist Award at this conference**




Dividing systems, allocating functions and putting them back together
1
Divide into sections
2
Allocate functions
3
Put back together
Machine
Human
Young Scientist Contribution
24 September 2019
3
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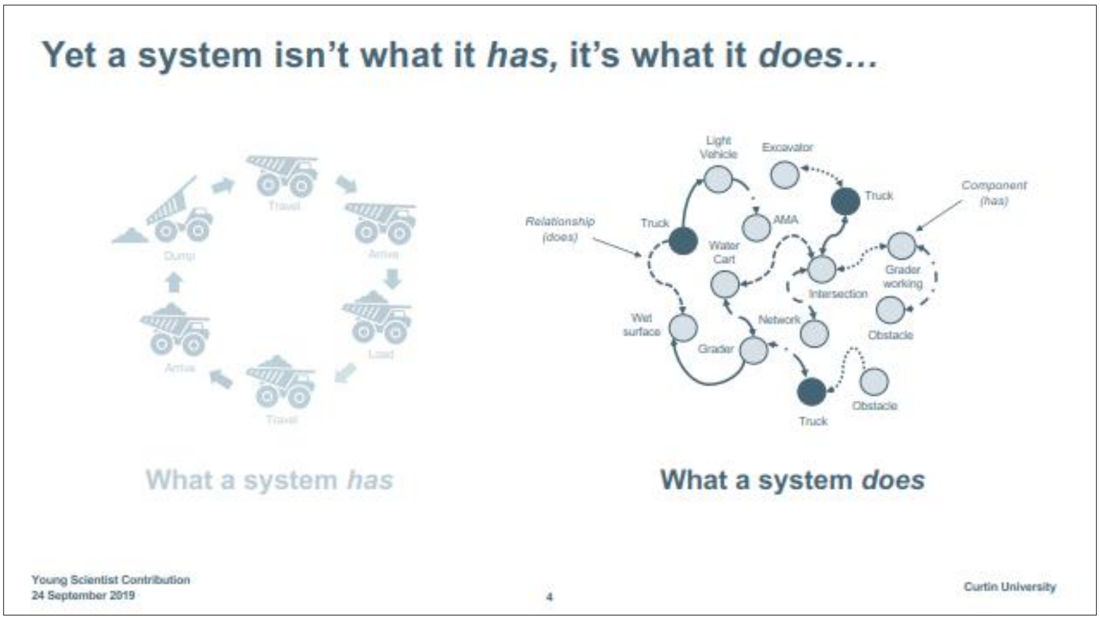
Yet a system isn't what it *has*, it's what it *does*…
Travel
Arrive
Dump
Load
Arrive
Travel
Light Vehicle
Excavator
Truck
Component (has)
Relationship (does)
Truck
AMA
Water Cart
Grader working
Intersection
Wet surface
Network
Obstacle
Grader
Obstacle
Truck
What a system *has*
What a system *does*
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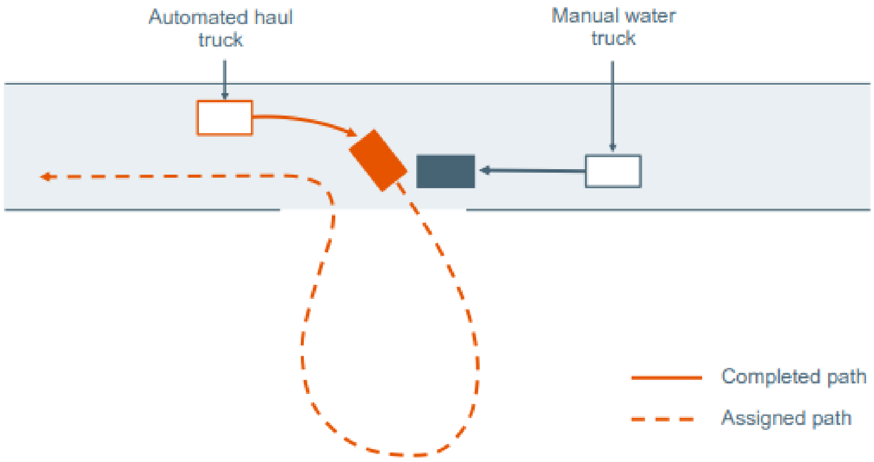
Therefore, the result did not underpin popular notion



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Regulator soon reported emergence of new hazards

"The addition of autonomous mobile equipment can introduce hazardous situations not normally encountered on a conventional manned mining operation. It is important that these safety challenges are addressed early in the planning cycle to maximise opportunities for solutions high in the hierarchy of control…"

In the Regulator's opinion, autonomous technology introduces hazards beyond those found in conventional mining operations.

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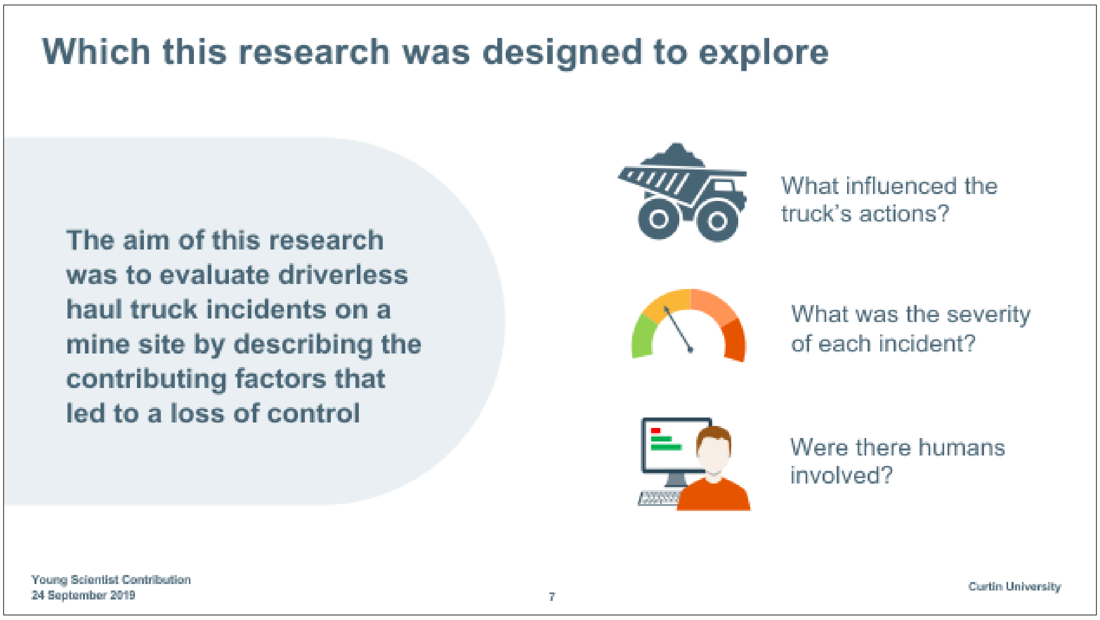
Which this research was designed to explore
The aim of this research was to evaluate driverless haul truck incidents on a mine site by describing the contributing factors that led to a loss of control
What influenced the truck's actions?
What was the severity of each incident?
Were there humans involved?
Young Scientist Contribution
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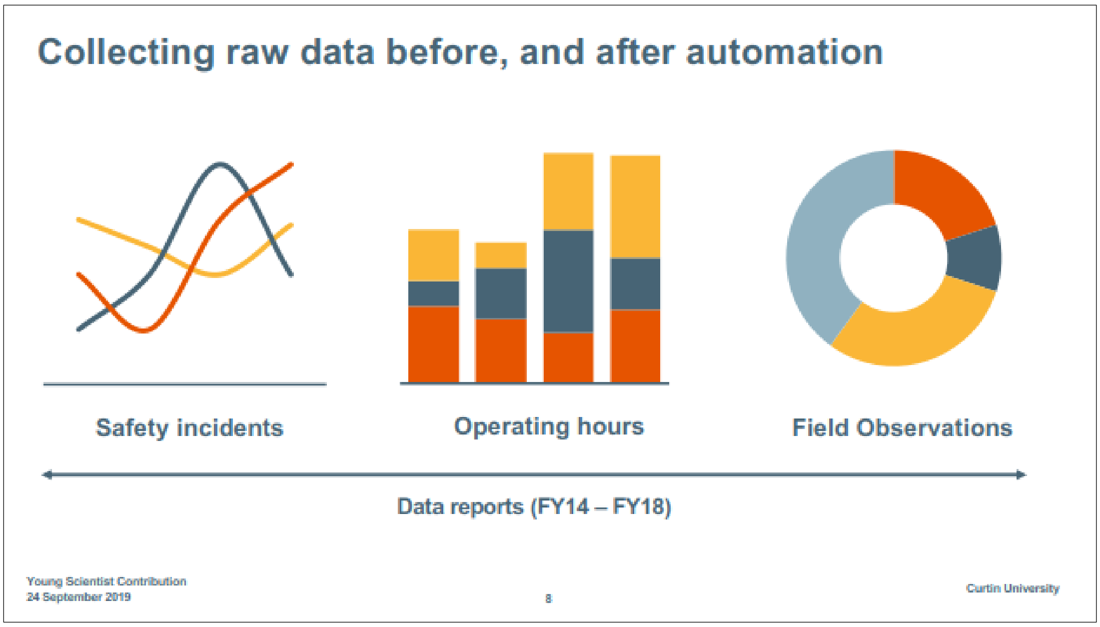
Collecting raw data before, and after automation
Safety incidents
Operating hours
Field Observations
Data reports (FY14 – FY18)
Young Scientist Contribution
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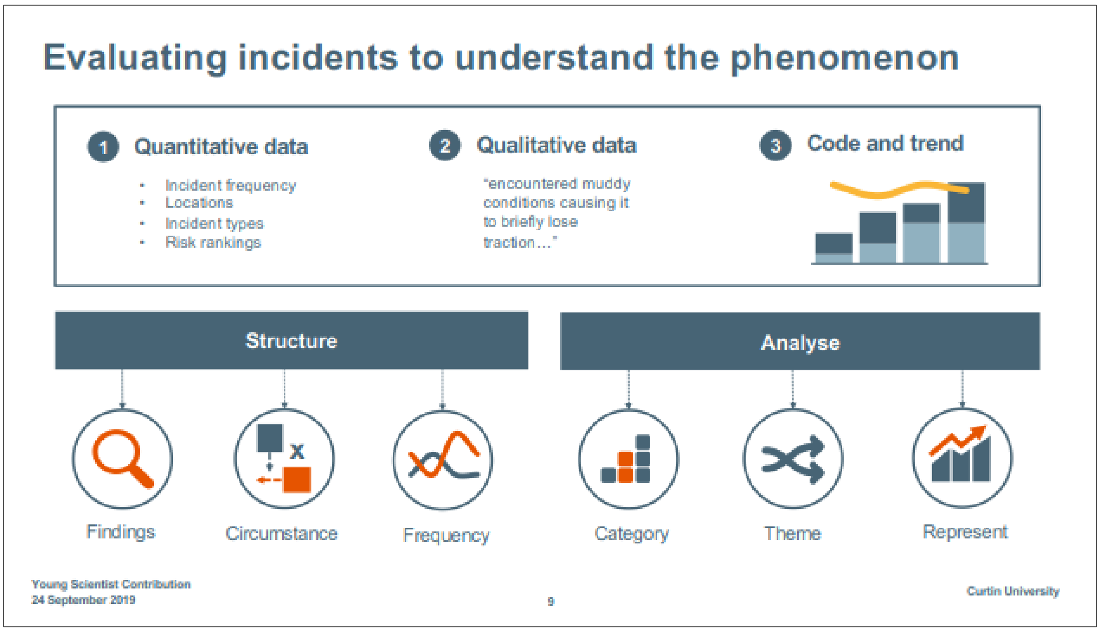
Evaluating incidents to understand the phenomenon
1 Quantitative data
Incident frequency
Locations
Incident types
Risk rankings
2 Qualitative data
"encountered muddy conditions causing it to briefly lose traction…"
3 Code and trend
Structure
Analyse
Findings
Circumstance
Frequency
Category
Theme
Represent
Young Scientist Contribution
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9
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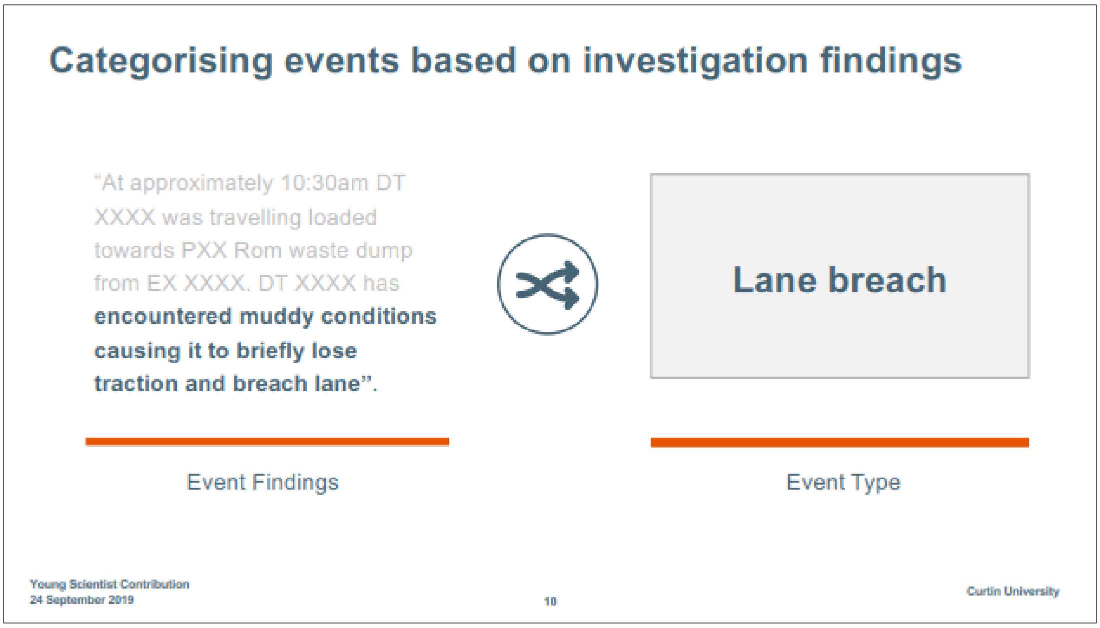
Categorising events based on investigation findings
"At approximately 10:30am DT XXXX was travelling loaded towards PXX Rom waste dump from EX XXXX. DT XXXX has encountered muddy conditions causing it to briefly lose traction and breach lane".
Lane breach
Event Findings
Event Type
Young Scientist Contribution
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10
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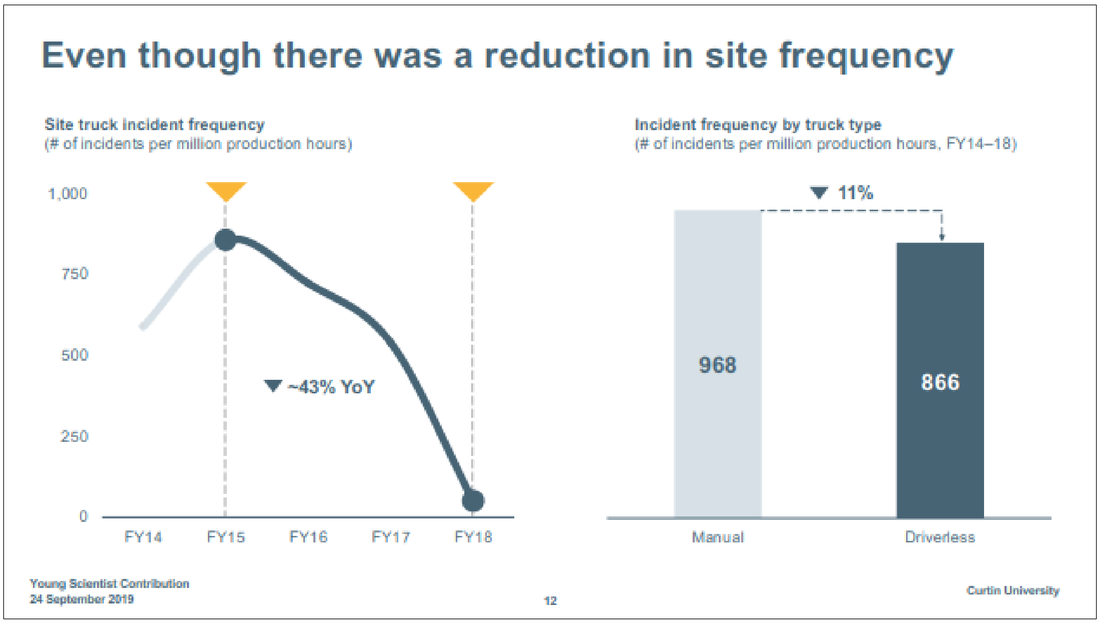
Even though there was a reduction in site frequency
Site truck incident frequency
(# of incidents per million production hours)
1,000
750
500
250
0
~43% YoY
FY14
FY15
FY16
FY17
FY18
Incident frequency by truck type
(# of incidents per million production hours, FY14–18)
11%
968
866
Manual
Driverless
Young Scientist Contribution
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12
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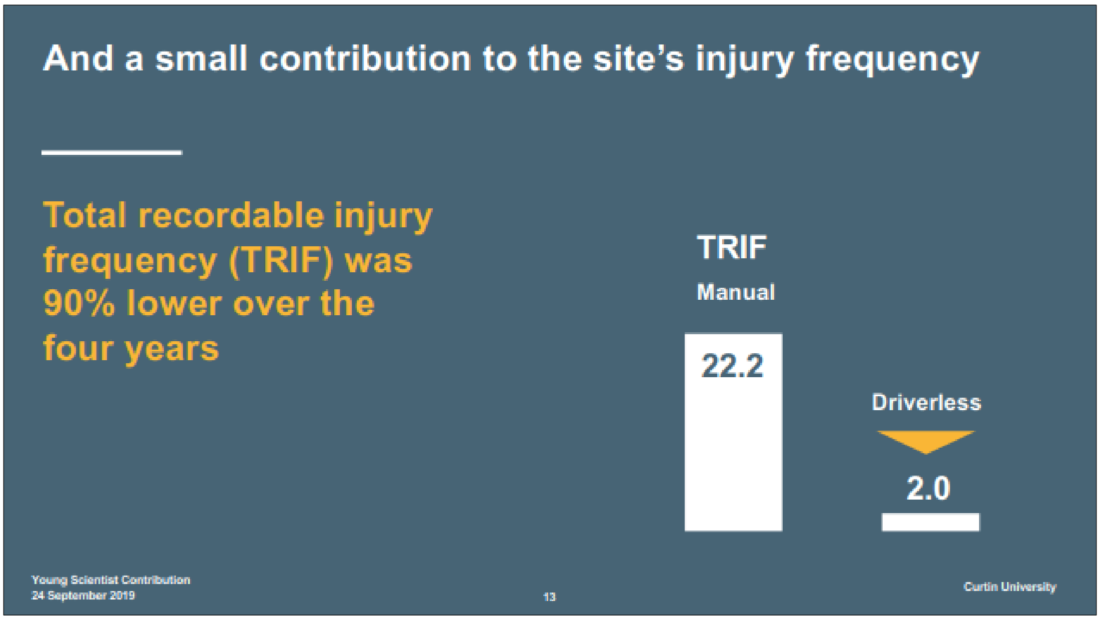
And a small contribution to the site's injury frequency
Total recordable injury frequency (TRIF) was 90% lower over the four years
TRIF
Manual
22.2
Driverless
2.0
Young Scientist Contribution
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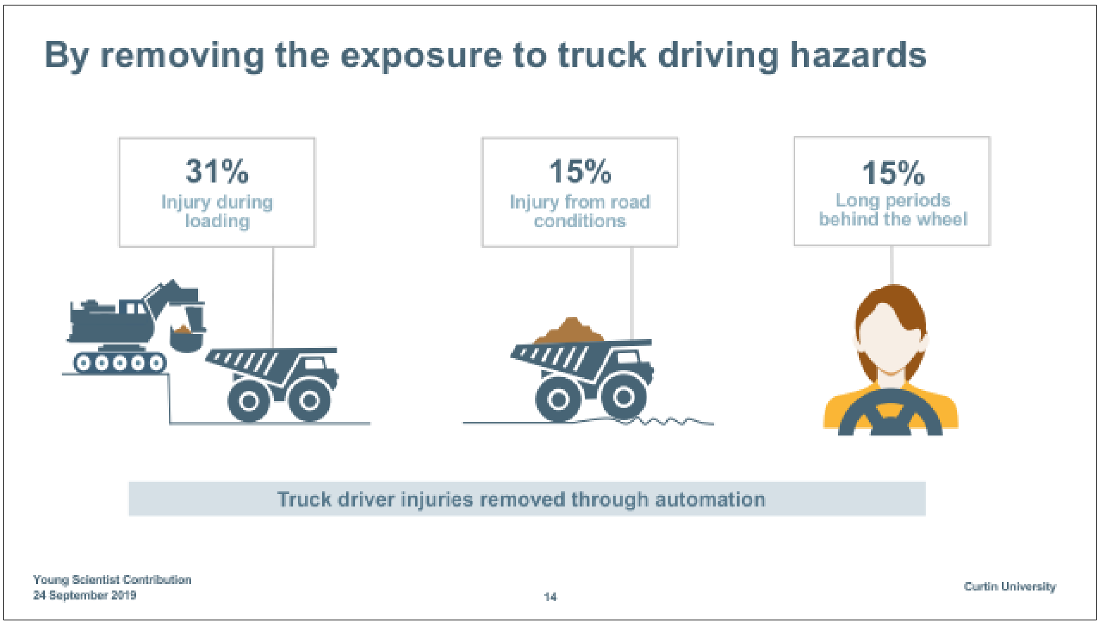
By removing the exposure to truck driving hazards
31%
Injury during loading
15%
Injury from road conditions
15%
Long periods behind the wheel
Truck driver injuries removed through automation
Young Scientist Contribution
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The number of unencountered situations were increasing
Driverless truck incidents
(# of incidents involving a driverless truck)
300
250
200
150
100
50
0
▲ ~35% YoY
FY14
FY15
FY16
FY17
FY18
Young Scientist Contribution
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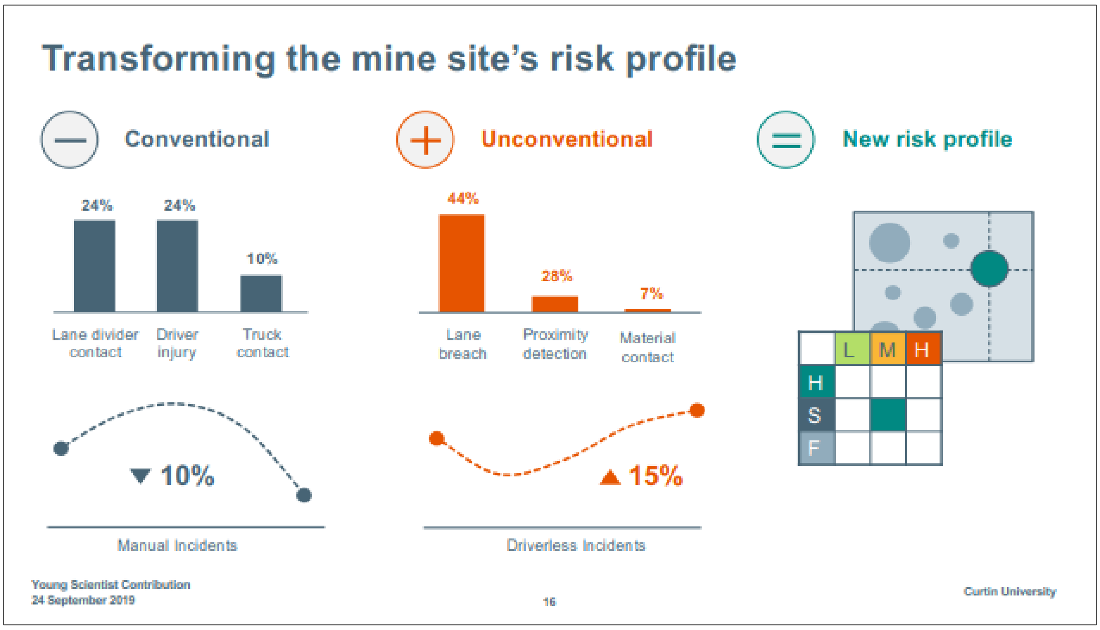

Transforming the mine site's risk profile
Conventional
Unconventional
New risk profile
24%
24%
10%
Lane divider contact
Driver injury
Truck contact
44%
28%
7%
Lane breach
Proximity detection
Material contact
L
M
H
H
S
F
10%
Manual Incidents
15%
Driverless Incidents
Young Scientist Contribution
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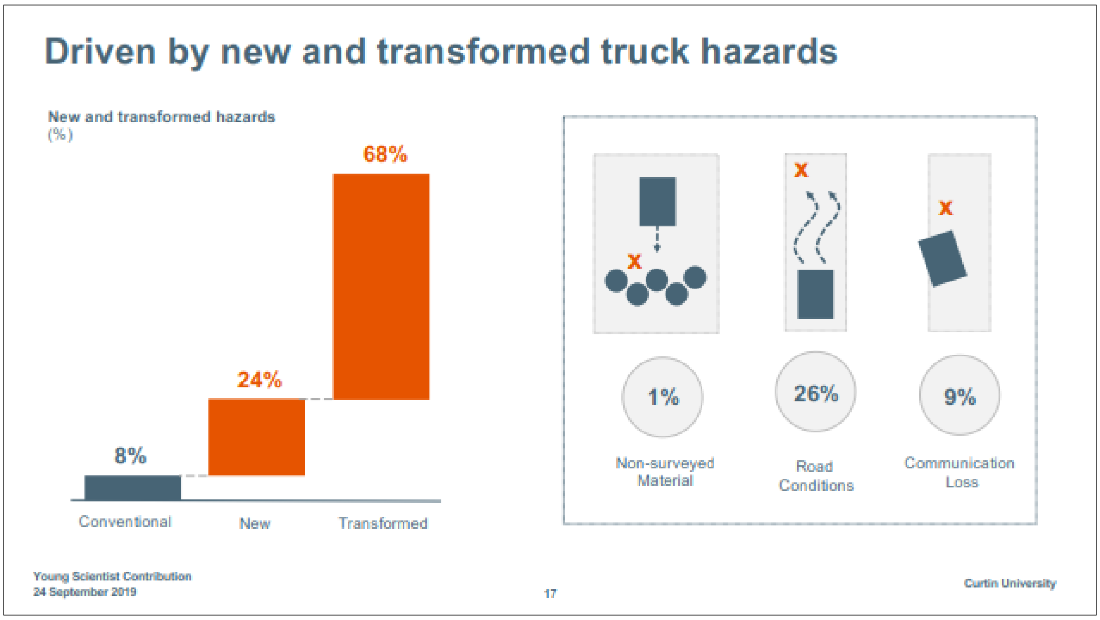

Driven by new and transformed truck hazards
New and transformed hazards
(%)
68%
24%
8%
Conventional
New
Transformed
x
x
x
1%
26%
9%
Non-surveyed Material
Road Conditions
Communication Loss
Young Scientist Contribution
24 September 2019
17
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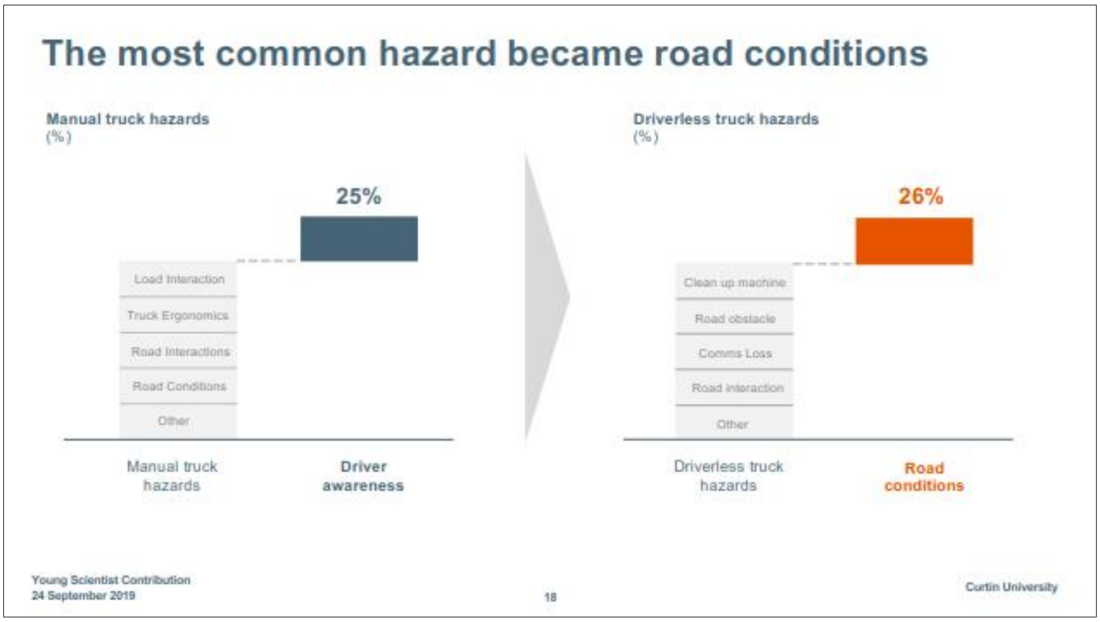
The most common hazard became road conditions
Manual truck hazards
(%)
25%
Load Interaction
Truck Ergonomics
Road Interactions
Road Conditions
Other
Manual truck hazards
Driver awareness
Driverless truck hazards
(%)
26%
Clean up machine
Road obstacle
Comms Loss
Road interaction
Other
Driverless truck hazards
Road conditions
Young Scientist Contribution
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18
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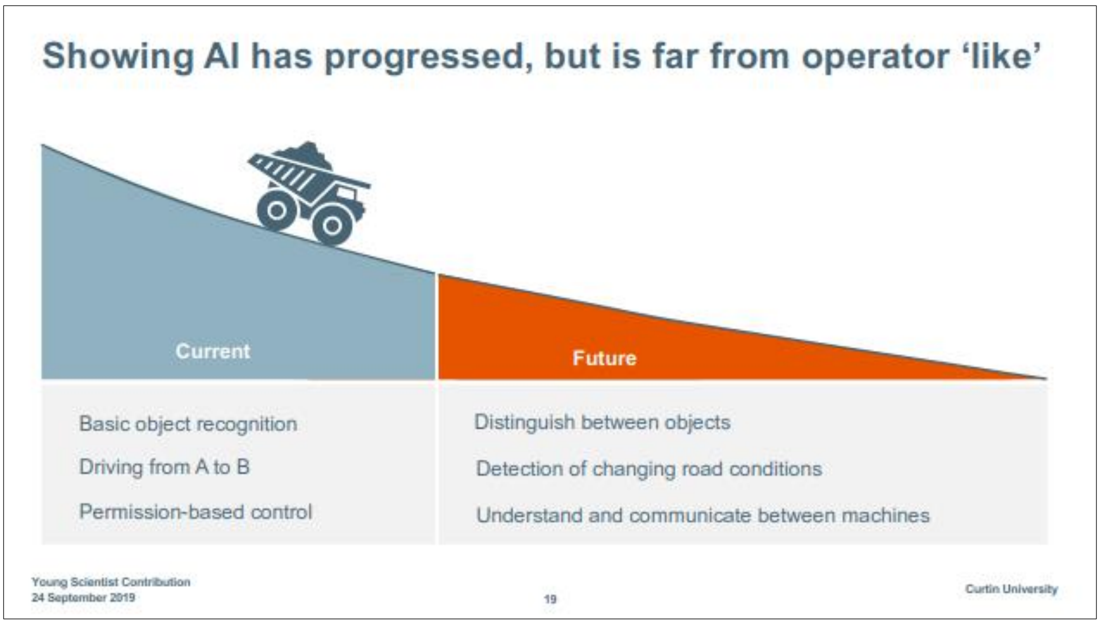
Showing AI has progressed, but is far from operator 'like'
Current
Future
Basic object recognition
Driving from A to B
Permission-based control
Distinguish between objects
Detection of changing road conditions
Understand and communicate between machines
Young Scientist Contribution
24 September 2019
19
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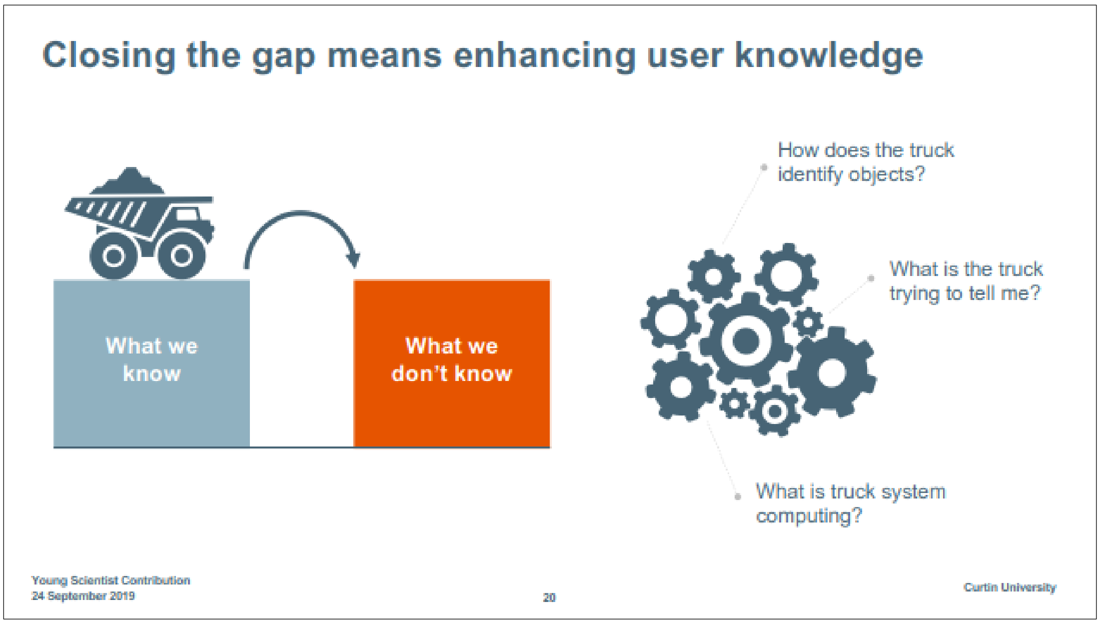

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