DOCTORAL THESIS

Digitalisation and automation perspective of LHD operation

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Mining and Rock Engineering

LULEÅ UNIVERSITY OF TECHNOLOGY

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LHD picture in the front page adapted from LKAB

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PREFACE

The research work presented in this thesis was carried out at the Division of Mining and Rock Engineering, Luleå University of Technology.

I want to thank all the people who contributed to my thesis in one way or another. I would like to thank LKAB for their technical and financial support through the SUM (Sustainable Underground Mining) Academy programme, which extends from 2021 to 2024, and is jointly financed by LKAB and the Swedish Energy Agency, along with Nex Gen SIMS project, which financed part of the thesis work. The valuable input and support of the staff and management at the Kiirunavaara mine are also gratefully acknowledged.

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ABSTRACT

The mining sector has evolved over the years, increasingly adopting automation and digitalisation to improve safety, reduce the carbon footprint, and enhance productivity. The integration of digital technologies and automation is changing traditional mining practices and the nature of work. Load haul dump (LHD) machines remain integral to the automation of underground hauling operations. In mines that utilise the density difference of ore and waste, the bucket weight from these machines is also used to determine the ore grade. The automation of LHDs and their growing use in mines necessitate a comprehensive understanding of their performance and impact on loading control and dilution. The aim of this research was to investigate the impact of digitalisation and automation on future LHD operations. It explored the differences in productivity due to mode of operation, its impact on iron grade calculation, and the need for future training and competence of mining personnel.

Performance data for semi-autonomous and manual LHDs were collected from LKAB's Kiirunavaara mine's central database, GIRON. These data were used to compare payloads of semi-autonomous and manual LHDs for the overall mine and within individual blocks. The data were filtered and sorted further to include only data where both machine types were operating in the same selected areas (crosscut, ring, and ore pass). A ring level comparison in selected areas were done to identify more localised differences in payload and cycle times due to mode of operation. To evaluate the sensitivity of density-based Fe-grade calculation, the data were simulated and analysed using global sensitivity analysis. The data on operator training were collected through baseline mapping and a questionnaire study conducted with the LHD operators at LKAB's Kiirunavaara mine. Whereas the data on end-users' perspective of digitalisation and automation was based on a questionnaire study at LKAB, and workshops conducted with production workers from Aitik and Garpenberg mines at Boliden.

The exploratory research in this thesis identified that automation and digitalisation have transformed the LHD operation. The largest share of LHD operators and production workers anticipated an increased transition towards autonomous operations, and they believed the impacts of digitalisation and automation would be positive, but a small proportion had negative perceptions.

The comparative analysis of manual and semi-autonomous LHDs based on approximately 1.4 million loading cycles showed the mean payload per bucket was 0.34 tonnes higher for manual LHD machines. However, these differences were not consistent across different blocks of the mine. Similarly, when comparing the cycle times, in 57% of the selected areas, manual LHDs had lower cycle times, but the opposite was observed in the remaining 43% of the selected areas. Therefore, the differences in cycle time and payload due to mode of operation are inconclusive. This means one machine type does not consistently outperform the other, highlighting the complexity of mining environments and the importance of understanding the influence of external factors.

The accuracy of density-based Fe-grade calculations was studied using global sensitivity across three operational scenarios. Bucket weight was identified as the most influential parameter, accounting for 49-74% of the total variance, followed by void ratio and fill factor. Therefore, balanced operational control of these parameters is important for improving the reliability of density-based Fe-grade calculation.

Finally, the thesis identified limitations in current LHD operator training programmes and found the need to upgrade training programmes at pace with the current technological advancements, including pedagogical principles and effective simulator-based learning. It was observed that the understanding of mining processes, along with computer skills, will remain crucial future competencies for LHD operators and production workers to facilitate digitalisation and automation.

LIST OF APPENDED PAPERS

Paper A

Title: End-users' perspectives on digitalisation and automation—Insights from the Swedish mining industry.
By: Muhammad Tariq, Annika Pekkari, Anna Gustafson, Håkan Schunnesson and Jan Johansson.
Status: Published.
In: Mining, Metallurgy and exploration
42, 571–582 (2025). DOI: 10.1007/s42461-025-01203-6

Paper B

Title: Comparison of cycle times for manual and semi-autonomous load haul dump (LHD) machines: an operational perspective at LKAB's Kiirunavaara mine.
By: Muhammad Tariq, Anna Gustafson, Håkan Schunnesson, and Sohan Singh Rajpurohit.
Status: Published.
In: International Journal of Mining, Reclamation and Environment
2025. DOI: 1080/17480930.2025.2496911

Paper C

Title: Density-based iron grade estimation: a variance based sensitivity analysis
By: Muhammad Tariq, Anna Gustafson, Håkan Schunnesson.
Status: Submitted.

Paper D

Title: Training of load haul dump (LHD) machine operators: a case study at LKAB's Kiirunavaara mine.
By: Muhammad Tariq, Anna Gustafson, and Håkan Schunnesson.
Status: Published.
In: Mining Technology
2023. Vol. 132, no 4, p. 237-252. DOI: 10.1080/25726668.2023.2217669

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LIST OF KEYWORDS, ABBREVIATIONS, AND SYMBOLS

DEFINITIONS

Drifts: Horizontal openings that are built perpendicular (crosscut) or parallel to the strike of the ore body or mine workings

Ring: It refers to the collection of blastholes drilled in fan shaped from a production crosscut within a single plane

Rock fragmentation: It refers to the fragment size distribution of the post blasting material and is used an index to measure the effect of blasting

Swell factor: The percentage by which the materials original volume increases when it is removed from its bank state to a bulk state due to fragmentation

Fill factor: It is the ratio of the volume of the material actually loaded in the bucket to the rated bucket volume

Void ratio: It is the ratio of the volume of voids to the volume of solid particles in a soil or rock sample

Draw point: It is the limited opening, located at the end of a production cross-cut drift where broken ore is loaded into load haul dump machines

Automation: It refers to utilisation of machinery or process controlled by devices, sensors that can make decisions independently without human intervention

GIRON: It is mines central database, an application tool which creates, stores, and displays mine related data used during unit operations

Blocks: The term used for the different areas in the mine

Loading duration: The loading duration in this thesis refers to the time required at the face to take control of the machine before loading and to complete the bucket filling

Haulage duration: The haulage duration refers to the time for the LHD to haul with a loaded bucket from the loading point (draw point) to the dumping point (ore pass) and to haul back to the loading point with an empty bucket

Dumping duration: The dumping duration refers to the time spent to unload the mucked material at the ore pass, including the waiting time associated with the availability of the ore pass, in particular, the time required to break boulders and secure the rock breaker at the ore pass

ABBREVIATIONS

AD	Anderson–Darling
AI	Artificial Intelligence
AR	Augmented Reality
CM	Cramer–vol Mises
EDF	Empirical Distribution Function
FAST	Fourier Amplitude Sensitivity Test
GLUE	Generalised Likelihood Uncertainty Estimation
IoT	Internet of Things
KS	Kolmogorov–Smirnov
LKAB	Luossavaara Kiirunavaara Aktiebolag
LHD	Load Haul Dump
LiDAR	Light Detection and Ranging
ML	Machine Learning
NSQA	National Skills Qualification Authority
OEMs	Original Equipment Manufacturers
OEE	Overall Equipment Effectiveness
RTIT	Rio Tinto Iron & Titanium
RQ	Research Question
RJ	Ryan-Joiner
SA	Semi-Autonomous
SLC	Sublevel Caving
SW	Shapiro–Wilk
SAQA	South African Qualification Authority

VR	Virtual Reality
WOLIS	Wireless Online Loader Information System
WRST	Wilcoxon Rank-Sum Test

SYMBOLS

X_{50}	The median fragment size, representing sieve openings where 50% of the fragmented material passed
X_i	i^{th} constant input variable
$X_{\sim i}$	All input variables except the i^{th} input variable
V(Y)	Unconditional variance of Y
$E[Y\|X_i]$	Expected value of Y given Xi
S_i	First order Sobol index for the i^{th} input variable
S_{Ti}	Total order Sobol index for the i^{th} input variable
Fe	Iron
G	Grade of magnetite ore
Vb	Volume of bucket
Bw	Bucket weight
OBw	Ore Bucket Weight (Weight of 100% ore in the bucket)
WBw	Waste Bucket Weight (Weight of 100% waste in the bucket)
Ff	Fill factor
Vr	Void ratio
O	Ore density
W	Waste density
Bii	Block ii^{th} number
S1-S6	Scenario number 1 to 6

1 INTRODUCTION

1.1 Background

Driven by automation and digitalisation, the mining industry has evolved over the years, from disconnected manually operated mines to operations valuing sustainability and safety, thus integrating more semi-autonomous and autonomous operations. The digital transformation, accompanied by advancements in Internet of Things (IoT), machine learning (ML), artificial intelligence (AI), augmented reality (AR), virtual reality (VR), robotics [1], and automation technology [2,3], promises to bring improved safety and socio-economic benefits [1–3], paving the way for autonomous operations. Digitalisation and automation can improve the work environment [4] and have positive effects on productivity and safety [2,3]. However, challenges remain in the integration of newer technologies into existing infrastructure, given the complex relationship of mining technology with the work environment [5].

Mining remains a foundation for industrial development [6], and as shallower mineral resources become depleted, mining industries are heading towards deeper mineralisation, with increased engineering [7,8] and health challenges [9]. Unlike operations at shallower depths, operations at greater depths encounter a geological environment characterised by higher temperatures, pressures, and stresses, as well as more disturbances due to mining activities [7]. Thus, the mining industry needs to develop more cost-effective and safer operations, while also addressing other practical challenges and adhering to stricter regulations.

Load haul dump (LHD) machines are a key part of modern underground mining transportation systems [10]. The versatility, reliability, adaptability and power of these machines (see Figure 1) enable them to operate in challenging environments. Mining companies and equipment manufacturers have long recognised innovation in general, and automation of LHDs in particular, as a huge benefit [10]. Since their introduction by the Wagner Company in the 1960s [6], these machines have evolved, revolutionising underground transportation systems in modern mining [11]. The transition from traditionally manually operated machines to line-of-sight remote controlled machines to teleoperated, semi-autonomous, or fully autonomous machines [11] has been enabled by developments in high precision positioning, navigation, and connectivity systems [6].

Figure 1: Sideview of Sandvik Toro^{TM} LH521i [12]

Despite these developments, a fully autonomous LHD that operates without any human intervention on a commercial scale is still under development [6]. This could be attributed to several factors, including the complexity of modelling the bucket-material interaction with the surrounding environment [13,14]. Additional complicating factors include the diversity of mining methods, material properties of the muck pile, and existing mine infrastructure [14,15]. The difficulties involved in testing in a real-world setting for adaptation and validation add to the challenge [14]. Therefore, semi-autonomous LHDs, where operators control only the loading process, are more common in real underground operations.

Digitalisation and automation have also transformed modern mining methods. For example, advancements in technology, adoption of modern designs, and mechanisation have allowed the sublevel caving (SLC) mining method to evolve [16–18]. SLC is an underground mass mining method based on the gravity flow of the blasted ore and the overlying hanging wall, which caves due to mine induced stresses [19]. SLC has gained momentum because of its substantial potential for high production rates and cost-effective operations [20]. However, like any mining method, the efficiency of SLC is influenced by various factors, such as properties of the orebody and the overlying waste rock in the hanging wall [21], as well as the performance of the draw point, defined as the quantity and quality of the excavated material at the draw point [22]. The regulation of loading at the draw point is an ongoing issue in SLC, as the decision to stop a ring and blast the next one is irreversible [22].

Loading in SLC is a complex operation with significant challenges, mostly due to the unpredictable nature of the material flow from the rings. The primary purpose of loading is to maximise ore recovery and simultaneously minimise dilution. However, controlling dilution remains a principal challenge as it generally increases with increasing extraction of the material from the rings [23,24]. This causes costly risks if loading from a ring cannot be stopped at the right time, a decision that normally relies on the operator's judgement [22] and a mine's specific grade values. Mines such as Luossavaara Kiirunavaara Aktiebolag's (LKAB's) Kiirunavaara and Malmberget mines and Rio Tinto Iron and Titanium's (RTIT's) open pit mine near Havre St-Pierre use the density difference between ore and waste to calculate ore grade. Although using density difference is practical for continuous monitoring of grade at the draw point, it poses some challenges.

Fragmentation is a crucial criterion influencing material flow and draw point performance in SLC mines [22,25,26]. Additionally, in mines where the density difference between ore and waste is utilised to calculate grade, fragmentation becomes even more important. A thorough understanding of the impact of fragmentation on the overall mine production system is required [27] for optimal performance, but continuously monitoring fragmentation has remained a challenge [28]. Manzoor et al. [24] investigated the impact of fragmentation and its operational and economic challenges in an SLC operation by observing fragmentation through video recordings from production areas. They found that the occurrence of coarser fragments and boulders increased with increasing extraction ratio (up to 100%), and the occurrence of finer fragments decreased [24]. The impact of fragmentation on various production steps, such as loading at draw points, the availability efficiency of ore passes, and the performance of LHDs [24,25,27,29], has also been highlighted in the literature.

Digitalisation and automation continue to change mining operations and processes at a rapid pace. However, the mining industry is far from achieving "zero-entry mining", mines where there is no human presence [30]. The role of humans remains important as mines move towards more digitalised, automated, mixed fleet automation, and AI-based systems [11,31]. The effect of operators' practices on the efficiency of the loading operation was highlighted by Patnayak et al. [32] and Oskouei et al. [33,34]. The need to improve the operator's skill and understanding through training has also been emphasised in literature [34,35]. Given all these factors, it is important to understand the automation and digitalisation of LHD operations from an operational perspective.

1.2 Problem statement

As mining operations continue to operate in deeper and more susceptible environments, the demand for enhanced safety and operational efficiency becomes increasingly critical. To comply with stricter regulations and rising societal demands, digitalisation and automation are increasingly important. However, limited studies based on real mine data address how production differs for semi-autonomous and manual LHDs, and how this is affected by external factors. One such problem area is the draw control strategy based on density differences between ore and side rock, as it can be significantly affected and disturbed by loading conditions and fragmentation. In addition, how digitalisation and automation will impact future LHD operation and how training and education could contribute towards improving the performance of these machines are rarely studied.

1.3 Aim and objectives

The aim of this research was to understand the differences in productivity for semi-autonomous and manual LHDs and to identify the impact of external factors on the performance of these machines in SLC operations. The research also aimed to evaluate how differences in payload due to mode of operation, machine capacity, and fragmentation could potentially impact the draw control strategy and the decision on when to close a ring and continue with the next. A third aim was to increase knowledge of the operator's influence for both manual and semi-autonomous loading when the operator not only fills the bucket but also performs other tasks in the loading cycle.

1.4 Research questions

The following research questions (RQs) were devised to meet the aim of the thesis:

RQ-1 How will increased digitalisation and automation impact future LHD operations?

RQ-2 How does production differ for semi-autonomous and manual LHDs in an SLC operation?

RQ-3 What are the challenges and limitations of density-based Fe-grade calculations? How does the output of the density-based Fe-grade formula vary in response to changes in its input parameters?

RQ-4 How can operators' training and education be improved to facilitate automation?

The research questions are addressed in the four appended research papers shown in Table 1.

Table 1: List of publications

Research Papers		RQs			
		1	2	3	4
A	End-users' perspectives on digitalisation and automation-Insights from the Swedish mining industry	✓			✓
B	Cycle time comparison for manual and semi-autonomous load haul dump (LHD): an operational perspective at LKAB's Kiruna mine.		✓		
C	Density-based iron grade estimation: a variance based sensitivity analysis			✓	
D	Training of load haul dump (LHD) machine operators: a case study at LKAB's Kiirunavaara mine.				✓

1.5 Scope and limitations

This thesis focuses on the production differences between semi-autonomous and manual LHDs and the sensitivity of a density-based Fe-grade calculation model used in SLC operations. Production data were collected from an actual operation in the Kiirunavaara mine. The thesis also highlights the impact of external factors on the productivity of these machines, as well as the density-based Fe-grade calculation model. It further focuses on how training in general and the inclusion of new technologies in particular could improve operators' influence on the performance of these machines.

This thesis is limited to the loading operation and the density-based Fe-grade calculation used in the SLC mining method, in particular, the loading operation in the Kiirunavaara mine, and the Fe-grade calculation model used in the Kiirunavaara and Malmberget mines. It is also limited to the comparison and analysis of data on manual and semi-autonomous LHDs manufactured by Sandvik.

1.6 Authors' contribution to the appended papers

The details of the contribution of each author to the appended papers are summarised in Table 2. Major activities include:

1. Literature review
2. Problem definition
3. Data collection
4. Data processing
5. Data analysis and results

6. Drafting and editing manuscripts
7. Supervision, reviewing, and editing manuscripts
8. Manuscript submission, revision, and final acceptance

Table 2: Contributions of authors to appended papers

Authors	Paper A	Paper B	Paper C	Paper D
Muhammad Tariq	1-6, 8	1-6, 8	1-6, 8	1-6, 8
Anna Gustafson	2,3,7	2,3,7	6,7	2,3,7
Håkan Schunnesson	2,7	2,7	6,7	2,7
Annika Pekkari	1-6, 8	-	-	-
Jan Johansson	2,7	-	-	-
Sohan Singh Rajpurohit	-	7	-	-

2 LITERATURE REVIEW

SLC is an underground mass mining method that utilises the gravity flow [19] of ore blasted in a ring pattern in cross-cut drifts, together with the overlying waste rock mass in the hanging wall, which caves under the influence of gravity. This method is primarily expected to maintain high production and minimise dilution, but extraction of ore from these blasted rings is not straightforward, as dilution generally increases with extraction [23]. Therefore, the use of LHD machines is central to achieving the desired efficiency and productivity [6,36].

2.1 LHD operation

LHD machines are an important part of modern underground mining transportation systems [10], and together with their surrounding environment, constitute a critical and complex system [15]. These machines are powerful, reliable, and versatile enough to work in hostile environments [37]. Thus, they dominate modern mechanised mines and play a pivotal role in overall mining production [38]. LHDs are central to underground mining haulage operations, performing short cyclic and repetitive tasks, such as loading, hauling, and dumping.

2.1.1 LHD automation

Automation refers to the utilisation of machinery or processes controlled by devices capable of making independent decisions without human involvement [39]. Automation in LHDs has progressed over time [11], with variations in operational modes [40], i.e., manual, line-of-sight, semi-autonomous, and fully autonomous. In semi-autonomous mode, LHDs perform hauling and dumping autonomously, while bucket loading is remotely controlled from a control station [40]. Full automation refers to complete autonomous control of one or multiple machines, thereby eliminating the need for human involvement [39]. In recent years, there has been a shift in mining operations towards the adoption of mixed fleet automation by integrating ML and AI technologies into operations (see Figure 2).

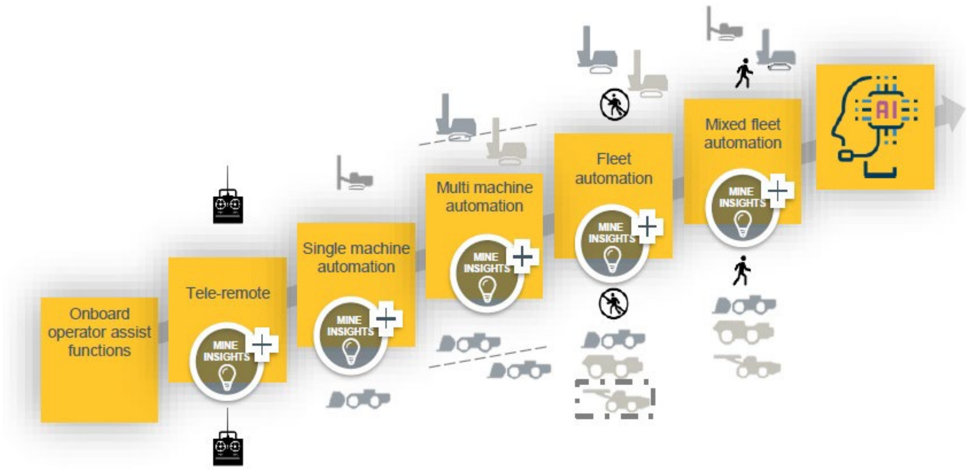

Figure 2: Increasing level of Epiroc's machine automation [41]

Table 3 provides comprehensive information on SLC and block caving mines that have integrated semi-autonomous or autonomous LHDs in their operations, including information about the mine's operator, location, type of mineral extracted, mining method employed, type of fleet, quantity of LHDs used in the mine, software system implemented on the LHDs, and the year automation was introduced.

Table 3: List of mines (sublevel caving and block caving) using semi-autonomous/autonomous LHDs in their operations (updated from [42])

Company	**Location (Mineral)**	**Mining Method**	**Fleet**	**Qty**	**Software System**	**Year**	**Ref**
El Teniente (Codelco)	Chile (Copper)	Block Caving	Sandvik LH517i	1	AutoMine® AutoMine Fleet	2004-To Present	[43]
North Parkes Mine	NSW, Australia (Copper Gold)	Block & Sublevel Caving	Sandvik LH514	5	AutoMine Fleet	2015-To Present	[44]
			Sandvik LH514i	1			
Big Bell (Westgold Resources)	Murchison and Goldfields Western Australia (Gold)	Sublevel Caving	R2900	3	Control Master MMC RCT	2021	[45]
			R2900	4	MineGem® CAT		
			Sandvik LH517	2	Control Master Multiple Machine Control RCT	2021	
			Sandvik LH621	1			
			R1700G	1			
			Sandvik LH151D	1			
Chuquicamata Mine (Codelco)	Chile (Copper)	Block Caving	Sandvik LH621	-	AutoMine® OptiMine®	2004-To Present	[46]
Venetia Mine (Da Beers Group)	South Africa (Diamond)	Sublevel Caving	Sandvik LH517i	1	OptiMine®	2022-Onwards	[47]
			Sandvik LH621i	1			
Kiruna (LKAB)	Sweden (Iron)	Sublevel Caving	Sandvik LH624i	8	Scooptram AutoMine® Multi-Lite	2000-To Present	
			Sandvik LH521& 521i	9			
New Afton (New Gold)	Canada (Gold)	Block Caving	Sandvik LH410	2	AutoMine®	2017-To Present	[48]
Syama Gold Mine (Resolute Mining Limited)	Mali (Gold)	Sublevel Caving	Sandvik*	-	AutoMine® OptiMine®	2018-To Present	[49]
Carrapateena (BHP)	Australia (Copper Gold)	Block Caving	Sandvik LH621i	-	AutoMine®	2019 To Present	[50]

LHDs with different capacities, modes of operation, and power sources are available from Original Equipment Manufacturers (OEMs). LHD power sources include diesel, hybrid, and electric options [51]. These capital-intensive machines are central to achieving the desired efficiency and productivity in underground mines [6,36], when effectively utilised [36]. The efficiency of loading and hauling equipment is a crucial element for determining the correct type, size, and number of units in the fleet [52,53] to ensure profitability [52,54]. The financial and operational performance of mining operations depends on the productivity of this equipment [55,56].

2.1.2 Productivity

Productivity in mining operations is typically defined as the quantity of ore or waste material handled per unit of time measured in tonnes per hour [53], tonnes per month [15], or buckets per hour [57]. For simplicity, the productivity of manufacturing equipment was traditionally assessed in terms of tonnes of material moved [53,58] and equipment utilisation [58]. However, these metrics fail to capture the actual performance of the equipment [58]. Therefore, performance metrics such as overall equipment effectiveness (OEE) proposed by Nakajima [59] are widely used in the industry [60,61] to evaluate the performance and reliability of equipment [62]. OEE is the ratio of actual output to the expected ideal output [58] and is determined by multiplying three efficiency components: availability, performance, and quality [58]. This approach considers six major equipment losses as defined by Nakajima [59]: downtime losses (equipment breakdown losses, set-up/adjustment losses), speed losses (idling and minor stop losses, reduced speed losses), and defect losses (reduced yield, quality defects). By addressing these losses, OEE can play a crucial role in improving equipment performance and increasing productivity [63].

To achieve their planned production targets, mines depend on the effective utilisation of LHDs to their full capacity and on the accurate prediction of machine productivity [64]. The productivity of loading and hauling equipment is typically determined either by computer simulations or cycle time analysis [64]. Both deterministic and stochastic methods are frequently used for predicting productivity. Deterministic approaches rely on average values, do not consider real-world scenarios, and are prone to error [53]. Stochastic approaches provide a more realistic prediction by simulating values from a distribution based on past experiences or historical data rather than using fixed values. To achieve simulation results that resemble reality, it is important to analyse data retrieved from mines or equipment manufacturers prior to formulating a model [65]. The literature on probability distributions used for different input parameters (loading time, dumping time, speed etc.) is highlighted in the appended paper B.

Given the complexity of mining operations, the performance of an LHD cannot be assessed as a single isolated system [66]. Its productivity is affected not only by the mode of operation but also by the surrounding working environment [15], the available infrastructure and technology, and the competence of humans involved in the system [11]. Identifying all factors causing variations leading to productivity losses is crucial [55]. Moreover, in mines such as Kiirunavaara and Malmberget, where production is guided by density-based grade calculation and draw monitoring systems [22], production and grade control depend directly on the performance of these machines and the factors affecting it.

2.1.3 Grade control

The primary objective in SLC is to maintain dilution at an acceptable level. Dilution typically increases as the extraction ratio increases [23]. To ensure the continued profitability of SLC operations, it is crucial to employ grade control to monitor the extent of dilution, but there are limited published accounts of prompt measurement or estimation of ore grade during the initial stages of the mining process, such as during production [67]. On-site methods employed in the mining industry to estimate ore grade include visual inspection performed by an experienced mine geologist at the excavation face, sampling and assaying systems at the draw point [67,68], and periodic geophysical mapping conducted at surface mines to delineate ore and waste [67]. However, visual inspection and geophysical mapping are qualitative in nature and subject to uncertainties [67], while sampling and assaying, although more accurate, are time-consuming and costly. A more quantitative method is to take advantage of the density difference between ore and waste. Mines using density difference to calculate ore grade include LKAB's Kiirunavaara and Malmberget mines, both SLC operations, and RTIT's open pit Havre St-Pierre mine. LKAB's underground operation uses bucket weight to calculate the grade of iron in the bucket, based on the principle that the end weight of the bucket is the sum of ore and waste in the bucket, as derived from equation 1.

$$m_b = m_w + m_o \tag{1}$$

where m_b is the bucket mass, m_w is the mass of waste, and m_o is the mass of ore. Similarly, RTIT's open pit operation bases its calculation on the principle that the end density of the material is constant, and the density of a blend can be derived from equation 2.

$$1/D = G/\rho_{ore} + (1 - G)/\rho_{waste} \quad (2)$$

where D is the density of the blend and G is the haemo-ilmenite grade. Both methods are quantitative. LKAB's system relies on bucket weight and normalises it to the maximum value (bucket with 0% waste) and the minimum value (bucket with 100% waste). These maximum and minimum values for the bucket are calculated using fixed values for volume of the bucket, fill factor, void ratio, density of ore, and waste. At RTIT, an apparent density is used to calculate the grade, with the volume of the material in a truck measured by a laser-based 3D scanner.

Although the quantitative approach of employing density differences for grade calculation is a practical method for continuous ore grade estimation at the draw points, it has certain challenges. Manzoor et al. [69] highlighted that assuming a constant fill factor and swell factor in areas with varying fragmentation is not valid for density-based grade calculation in LKAB's SLC operations. Giroux et al. [67] noted the error (±8%) in grade calculated by apparent density could potentially be reduced by applying an effective grade vs void ratio relationship. Tonvall [70] and Manzoor et al. [69] also argued that the assumption of linearity between Fe-grade and bucket weight in LKAB's Fe-grade model is uncertain (see Figure 3).

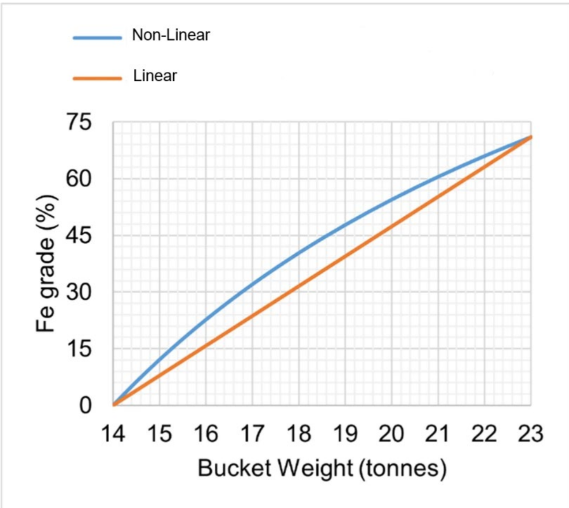

Figure 3: Relationship between bucket weight and Fe grade for 21-tonne LHDs (modified from [69])

It is crucial to understand and evaluate the uncertainty in density-based ore grade calculation and identify which input parameters can significantly impact the output. Global sensitivity analysis is a widely used method across various scientific domains due to its efficiency and ease of interpretation [71]. Methods which are robust and reliable, such as the Sobol index, find broad application across diverse disciplines, including engineering and environmental modelling, underscoring their versatility in addressing uncertainty [72]. However, these methods are limited to input parameters that are independent [71,73,74]. Therefore, methods such as the Kucherenko index, which accounts for dependence, are recommended. The literature offers relatively few examples of global sensitivity analysis applied in the mining sector. In one example, variance-based sensitivity analysis was conducted without accounting for dependence to model the uncertainties associated with geometric parameters affecting the mechanical response of mining dragline joints [75].

2.2 Factors affecting productivity in SLC

The SLC method is a mass mining method that relies on the gravitational flow of blasted ore and the overlying hanging wall, which caves due to stresses induced by mining activities [19]. The high level of mechanisation in an SLC operation facilitates automation, thereby enhancing both productivity and safety [76]. Similar to other mining operations, SLC is influenced by mining, geological, and economic conditions [77]. The operational efficiency of mining equipment in underground mines is crucial for achieving production targets [78] and is affected by various factors [28,56,79,80], including machine performance, machine design, loading operation, condition of the material, machine care, positioning, navigation, continuity and other mining related issues. The details of these factors have already been reported in the licentiate thesis [42] written by the author of the present thesis. It is important to understand that other factors influencing the productivity of LHDs, such as mode of operation, fragmentation, machine capacity, and operator training, could also influence the calculation of density-based ore grade estimation in SLC operations. Density-based methods depend on the weight of the material in the bucket, which is considerably affected by the material's density, void ratio, fill factor, and the operator's experience and expertise in filling the bucket. This thesis focuses on four factors affecting the productivity of LHDs and the calculation of Fe grade using density difference: mode of operation, i.e., semi-autonomous or manual, fragmentation, machine capacity, and operator training. Table 4 highlights the studied factors impacting the payload and thus, the Fe-grade calculation in this thesis research.

Table 4: Studied factors impacting the production and density-based Fe-grade calculation

Parameter	Factors	Production	Grade Control
Payload	Mode of operation	✓	✓
	Fragmentation	✓	✓
	Machine capacity	-	✓
	Operator education and training	✓	✓
Cycle time	Mode of operation	✓	-

2.2.1 Mode of LHD operation

Despite the technological development of LHDs, fully autonomous solutions are yet not widely adopted in the mining industry because of ongoing operational challenges [11]. It is increasingly important to evaluate the performance of these machines in real mining environments, as full scale testing is costly. When it comes to fully autonomous LHDs, progress has been made in autonomous loading, but commercial development remains in the early stages [6]. Consequently, semi-autonomous operations are more common in mines. Factors influencing bucket filling in underground mines include the complex nature of the interaction between the bucket and the material [13,14], the material properties, the mine layout, the constraints of real environments testing for adaptation and validation, and the complexity of different mining methods [14]. Tampier et al. [81] developed with a human-inspired autonomous loading method for sublevel stoping and block/panel caving mines based on the practices of experienced operators. However, as noted by Cardenas et al. [14], implementing this method in a room-and-pillar mine presents challenges because of tunnel dimensions, multiple piles, different pile slopes, and the difficulty of selecting a collision-free trajectory among several potential paths to approach the piles. Unexpected breakdowns have a greater impact on semi-autonomous LHDs than on manual LHDs, as the operator is not present in the machine to fix minor issues [40]. Another issue with autonomous LHDs is the requirement to operate in isolation, without the presence of manual equipment or personnel [8,82]; this could adversely affect the machine's overall performance [83]. For example, Kidds Creek Mine reported increased operational complexity, attributed to automation operation in isolation [84].

The literature on the productivity differences between manual and semi-autonomous LHDs is limited. Gustafson [15] studied tonnes per bucket and cycle times for both semi-autonomous and manual LHDs. The findings indicated that in terms of tonnes per bucket, the mean payload was comparable for the two types.

However, the manual machines moved more tonnes per engine hour than the semi-autonomous ones, a difference that may partly be attributed to the differences in the cycle times [15]. Thus, the mode of operation, in combination with other factors, might influence the overall productivity of the machine.

2.2.2 Fragmentation

Rock fragmentation is defined as the post-blast size distribution of rock [85]. The blasted material varies in fragment size and is influenced by several factors, including the characteristic of the rock mass, blast design, drilling, chargeability, and the blasting operation [27,86]. Blast-induced fragmentation can be classified as fine, medium, coarse, and oversize, with reference sizes varying from mine to mine and depending on the equipment used [86].

Fragmentation is a critical parameter for assessing blast performance [87], as it impacts the downstream processes, such as loading, hauling, crushing, and mill productivity [25,27,88,89]. Fragmentation has a direct impact on the productivity of the loading equipment [57,90,91], and even minor improvements in loading and hauling can result in substantial cost savings for the mine [91]. The impact of fragmentation size on the digability of an LHD [28], a loader [56], and a shovel [90] has been demonstrated in both laboratory and field tests. Doktan [90] reported that finer fragmentation resulted in increased loading efficiency because of a shorter digging time and a higher payload for truck-shovel operations. Similarly, Singh et al. [56] observed a reduction in mean particle size increased the payload and decreased the dig cycle time, and vice versa. According to Danielsson et al. [28], in an SLC operation, the overall loading efficiency of LHDs was the highest for fragmentation with mid-range particle size (X_{50}= 50-400 mm) distribution and a lower percentage of fine particles (X_{50}= 0-50 mm). Both Singh et al. [57] and Danielsson et al. [28] observed that the high percentage of fine particles negatively impacted digability because of increased difficulty penetrating the muckpile. Oversize material and boulders also significantly impact the loading process [24,57,76], sometimes requiring secondary blasting and rehandling and thus negatively impacting production [28,76]. Singh et al. [56] and Ouchterlony [92] defined any fragment above a size of 1.0 m as oversize. The occurrence of oversize fragments reduces the payload per bucket, as the void ratio increases and the bucket fill decreases with an increase in mean fragment size [56,90]. Manzoor [93] highlighted how the dumping of oversize fragments into ore passes reduces the productivity of LHDs, because of the additional time required to remove the oversize fragments.

It is well established in the literature that fragmentation is a major factor that can significantly affect the efficiency of loading operations [94]. Doktan [90] highlighted two key factors affecting the loading and hauling performance of a truck-shovel fleet: digability, which refers to digging time, and bucket payload, which is "a function of fill factor and void ratio" [90]. The void ratio is directly related to fragmentation, whereas the fill factor is more of an operational variable [90]. A higher fill factor does not necessarily mean a higher payload if the material is coarse [90]. A higher void ratio for coarser material results in more empty space in the bucket, thereby reducing overall payload and productivity. Manzoor et al. [69] observed a mean payload difference of 1.8 tonnes between coarse and fine material when analysing the impact of fragmentation on the payload for 21-tonne LHDs.

2.2.3 Operator skill and training

Automation and digitalisation will reshape the nature of mining, but human involvement remains crucial [31]. In loading operations, the operator influences critical parameters, such as the cycle time and the bucket fill factor, both of which have a substantial impact on production rate and energy efficiency [95]. Optimal operator practice is characterised by the ability to achieve more cycles, while minimising the energy consumption and maintaining the loading ratio [95]. The importance of training to achieve the best operator practice has been highlighted in the literature [35,96–98].

Recent technological advancements underscore the challenges the mining industry faces in competence development and training [99,100]. The influence of operator practice on the performance of digging equipment, such as the energy efficiency of shovels [32,34,98] and the productivity of loaders [101], has been highlighted by various researchers. The effective utilisation of these machines is heavily dependent on the skill level of the operators [33,34,76,97,98]. A comprehensive training programme is required to improve operators' skills [97,98]. The significance of operator training, particularly for LHD operators has been emphasised [35,96].

Training is important in the mining industry, and it has evolved over time [96]. The changing nature of work has expanded the goals of training from efficiency and safety to the acquisition of new skills to perform complex and dynamic jobs [96]. This transformation has largely been driven by automation, which has created skill gaps that require upskilling and reskilling [102]. Therefore, training and its continuous improvement have become increasingly important. Conventional training methods such as lectures, videos, written materials etc. may not engage participants, potentially leading to reduced concentration during training sessions [103,104]. Modern tools such as simulators and VR are gaining popularity for their role in skill development and competence enhancement [105,106]. These tools are advantageous as they allow trainees to practice hazardous scenarios in a risk-free environment [103,107]. Moreover, they typically encompass a variety of work scenarios, including control familiarisation, brake testing, hazard avoidance, truck loading, and other related exercises. Zhang et al. [108] highlighted the positive impact of simulators in facilitating knowledge retention and acquisition. Table 5 summarises the features provided by simulator companies to enhance the productivity of LHDs through simulator training, based on the information available on their websites and personal communication with some companies.

Table 5: Simulator training offered by commercial companies and OEMs of LHDs updated from [109]

Focus Areas	Mining Equipment Simulator Providers [reference]					
	Immersive Technologies [110]	5DT Technologies [111]	Thoroughtec (CyberMine) [112]	Sandvik (Digital Trainer) [113]	Epiroc (RCS) [114]	CAT Simulators [115]
Supported OEMs/ models	Caterpillar, Komatsu, Sandvik	NA⋆	Epiroc Caterpillar Joy, MTI Sandvik	LH517i LH621i	ST7, ST14 and ST18	NA⋆
Control familiarisation	✓	✓	✓	✓	✓	✓
Hazard avoidance	✓	✓	✓			✓
Brake testing procedure	✓	✓	✓	✓	✓	✓
Engine management	✓	✓	✓	✓	✓	✓
Operator productivity	✓	✓	✓	✓	✓	✓
Site safety procedures	✓	✓	✓	✓	✓	✓
Minimising unscheduled maintenance	✓		✓	✓	✓	✓
Truck loading	✓	✓	✓			✓
Crusher dumping	✓		✓			✓
Artificially intelligent traffic	✓	✓	✓			
Scenarios (rockslides, water pool and rubble spillages etc.)	✓		✓			
Operator evaluation (feedback)	✓	✓	✓	✓	✓	✓

NA⋆ Information not available

3 METHODOLOGY

Research involves a systematic and well-defined approach to acquiring knowledge or formulating theories, driven by the pursuit of the unknown and aimed at expanding knowledge through original contributions [116]. Regardless of the discipline, the building block of all academic research activities are based on accurately establishing research related to existing knowledge [117]. A critical aspect and initial challenge is to identify all relevant studies related to the research questions [118].

In addition to drawing on journal articles, conference proceedings, research reports etc., this thesis research incorporated internal reports from the studied mines, interviews with relevant personnel, and information available from regulatory authorities and OEMs to gain a comprehensive understanding of the current state of LHD automation, develop a density-based Fe-grade calculation model, review LHD operator training, and determine the operational challenges associated with automation.

Exploratory research, also termed formulative research, is used to devise problem statements and research questions. The primary purpose of exploratory research is to gain familiarity, get new insights, and develop research questions based on the available information [116]. Research can involve the use of a qualitative approach, a quantitative approach, or a combination of both.

This thesis used a qualitative approach to understand the impact of digitalisation and automation on future LHD operations and to determine how training and education can be used to facilitate automation and digitalisation. It used conventional content analysis for qualitative data, an approach considered useful for textural data [119]. Content analysis offers a systematic way to evaluate data gathered through diverse qualitative research methods [119], such as open-ended questions from surveys and workshop discussions, the methods used in this research. It increases the trustworthiness or validity of the study by creating and adhering to a coding scheme, not based on preconceived categories or theoretical perspectives [120].

This thesis used a quantitative approach to obtain and analyse data on the performance of semi-autonomous and manual LHDs. A quantitative approach was also used to quantify the sensitivity of input parameters to the output variance of the density-based Fe-grade calculation model. According to Kothari [116], data analysis involves several interconnected steps, starting with the processing of the raw data to detect errors and ensure data accuracy. This initial step is followed by data coding and classification, where data are systematically put into a defined number of categories or classes [116]. The final step involves summarising data through tabulation to facilitate the extraction of statistical conclusions [116].

This thesis involved data collection, data processing, and data analysis using statistical tools such as parametric and non-parametric tests to compare means/medians and statistical tests such as Anderson-Darling (AD) to check the normality of the data. Global sensitivity tests were performed on different scenarios to check the sensitivity of input parameters on the output variance of the density-based Fe-grade model.

The following topics were covered in the literature review:

- Impact of digitalisation and automation on LHD operations
- Automation of LHD machines
- Density-based Fe-grade calculation models
- Impact of external factors on loading operation and grade control
- Sensitivity of density-based Fe-grade calculation model
- Current status of LHD operator training and inclusion of new technologies
- Regulations of LHD operator training

A comprehensive baseline mapping of the studied mine's current loading procedure was performed for manual and semi-autonomous LHDs, LHD operator training, and the method currently used at the mine for density-based Fe-grade calculation. Technical reports, internal documents, and the mine's training curriculum were studied. Supervisors from the mine and managers from equipment manufacturers and simulator companies were contacted. Mine visits, workshops and individual discussions and communications with mine personnel were used to get more insights and gain a thorough understanding of the overall loading procedure, issues with Fe-grade calculation, grade control, and operator training.

3.1 Data collection

To understand the various aspects of LHD operation and their impact on the productivity and Fe-grade calculation, various types of data (see Figure 4) were collected from the studied mines.

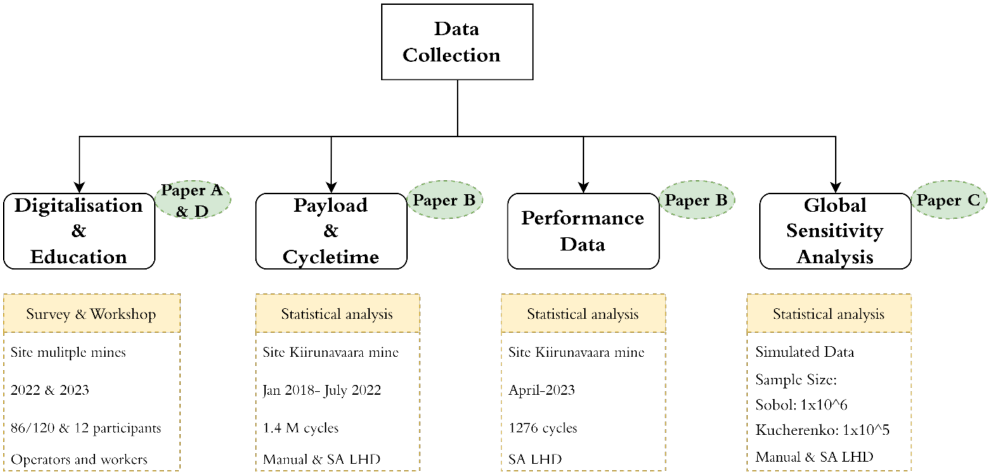

Figure 4: Summary of data collected

The following types of data were collected:

End-users' perspectives on the impact of digitalisation and automation: The data on the end-users' perspectives on digitalisation and automation were based on two separate studies conducted independently at two organisations, LKAB and Boliden Mineral AB. The study at LKAB's Kiirunavaara mine involved a qualitative survey carried out as part of an operator training survey from June 2022 to October 2022. A questionnaire was sent to all 120 LHD operators through the online platform Survey Monkey®; 79 (66%) LHD operators completed questionnaires. The second study collected qualitative data at two workshops conducted with production personnel at Boliden's Aitik and Garpenberg mines. A total of 12 persons participated in workshops organised and led by two persons from Boliden's Human resource (HR) department and two from the Division of Human Work Science at Luleå University of Technology.

Payload and cycle time comparison: The data on the payloads and cycle times of manual and semi-autonomous LHDs were retrieved from the Kiirunavaara mine's central database, GIRON, between 1 January 2018 and 5 July 2022. The data came from 6 semi-autonomous and 6 manual LHDs. The machines included 4 Sandvik LH621i (2 semi-autonomous, 2 manual) and 8 Sandvik LH621 (4 semi-autonomous, 4 manual) diesel LHDs. The data from the Wireless Online Loader Information System (WOLIS) contained 1.4 million cycles for manual and semi-autonomous LHDs.

Performance data for semi-autonomous LHDs: The data on the performance of semi-autonomous LHDs were retrieved from Sandvik's AutoMine® system for April

2023. A total of 1276 cycles were retrieved, with information on load duration, haulage speed, haulage distance, and total duration. The dumping duration was calculated by subtracting the haulage duration and the load duration from the total duration.

Sensitivity analysis of Fe-grade calculation model: The simulation data for the sensitivity analysis were generated by the Latin Hypercube Sampling (LHS) method for both the Sobol and the Kucherenko method. Using UQLAB, 1000000 samples were simulated for the Sobol method, and 100000 samples were simulated for the Kucherenko method.

LHD operator training: The data on the training of LHD operators were based on a survey carried out at Kiirunavaara mine from June 2022 to October 2022. A questionnaire was sent to all 120 LHD operators through the online platform Survey Monkey®; 86 (70%) LHD operators participated. The mine currently has 34 autonomous loading operators and 86 manual loading operators.

3.2 Data processing and analysis

The data processing was mainly done using MATLAB®. The statistical analysis used both MATLAB® and MINITAB® software.

3.2.1 Impact of digitalisation and automation

The impact of digitalisation and automation was examined in two separate studies. The survey included three open-ended questions focusing on the impact of digitalisation, levels of automation, and future skills. The responses were initially analysed inductively to develop the codes, categories, and themes from the data using conventional content analysis [119,120]. The coding was largely kept consistent with the technical terms, such as maintenance, loading, mining knowledge, and job change. This method provides direct participant insights [119] and new perspectives without imposing preconceived theoretical perspectives or categories [120]. The workshops' results were coded and analysed using the same method as the surveys. However, the questions were broad and were not asked sequentially, as in the survey. Overall, a holistic approach was used to compare the studies across mines using different methods and audiences to capture the perspectives of end-users' on technology, as well as the associated challenges and opportunities in the future.

3.2.2 Payload and cycle time

The data used to compare the cycle times and payloads of manual and semi-autonomous LHDs included block number, loading point (crosscut), ring number, date and time stamps, machine number, dumping point (ore pass), and payload (tonnes) obtained from 16 different blocks in the mine. However, only 12 blocks were considered in the analysis, as the remaining four blocks contained few or no cycles of the semi-autonomous LHDs. The differences in the payload due to the mode of operation were analysed using multilevel comparative analysis. First, the overall difference was analysed for all blocks. Second, a block level comparison examined how the payload differed within individual blocks. Finally, a more localised ring-level analysis compared the payloads and cycle times for both machine types operating within selected rings.

A part of the raw data from Block 10 is shown in Table 6.

Table 6: Sample data used for payload and cycle time comparison of LHDs

Block	Crosscut	Ring nr.	Date & Time	Machine nr.	Ore pass nr.	Payload (tonne)
10	o1080	26	2022-05-21 04:10	588	121	21.6
10	o1080	26	2022-05-21 04:13	588	121	21.6
10	o1080	26	2022-05-21 04:19	588	121	21.5
10	o1080	26	2022-05-21 04:28	588	121	23.6
10	o1080	26	2022-05-21 04:33	588	121	21.7
10	o1080	26	2022-05-21 04:37	588	121	21.1
10	o1080	26	2022-05-21 04:41	588	121	23.2
10	o1080	26	2022-05-21 04:45	588	121	23.8
10	o1080	26	2022-05-21 04:49	588	121	24.5

The semi-autonomous LHDs were sometimes operated manually, but during the night shifts and post-blasting periods, they were exclusively utilised in semi-autonomous mode. Therefore, to ensure the data did not contain information on manual operations, only the data from the night shifts were used. The data were further sorted based on crosscut, ring, and ore pass combinations. The aim was to minimise the impact of external factors and to make the data comparable. When comparing the cycle times, similar mining conditions could be ensured for both machine types by considering the same crosscut, ring, ore pass, and haulage distance. In this study, the combination of crosscut, ring, and ore pass where payload and cycle times data were filtered for both semi-autonomous and manual LHDs are referred as selected areas.

Figure 5 depicts the layout of one of the production levels in Block 10. In this case, the LHD loads material from the loading point of ring 26 (Figure 5, point 1) located in crosscut 1080 (Figure 5, point 3) and dumps it into ore pass 121 (Figure 5, point 2). From now on, this selected area is referred to as B10. However, if the data come from multiple crosscuts in the same block, for example, Block 16, they are referred to as $B16_1$, $B16_2$, $B16_3$, $B16_4$, and so on.

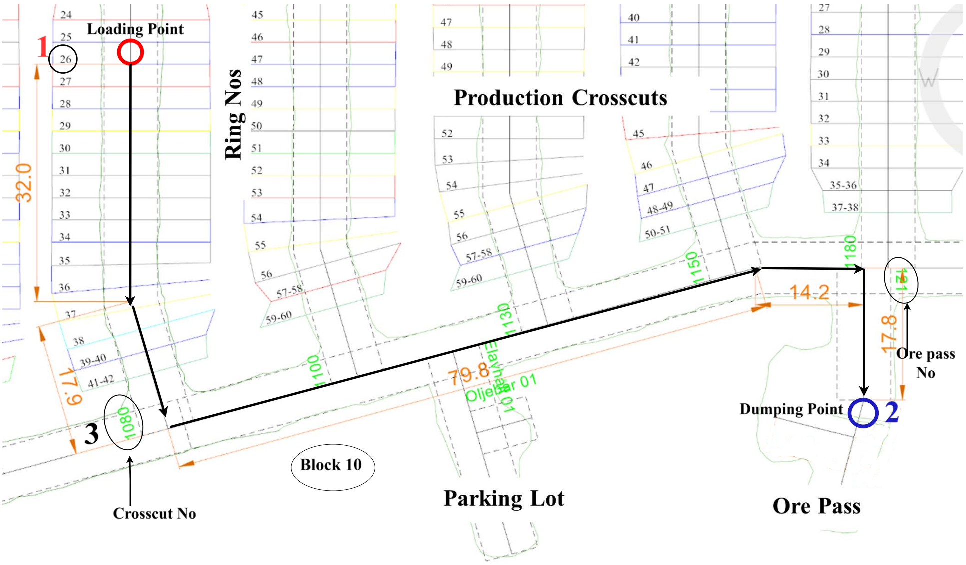

Figure 5: Production layout from Block 10 (B10)

In total, 23 selected areas were studied for cycle time comparison whose data were obtained from six different blocks (B10, B12, B16, B26, B30, and B34) where both manual and semi-autonomous LHDs were operating (see Table 7).

Table 7: Summary of cycle times and payloads comparison of both machine types in selected areas

Area no.	Selected area	Block	Distance (m) [ring-ore pass]	Level	Crosscut	Ring nr.	Ore pass nr.
1	B10	10	166.9	1022	o1080	26	121
2	B12	12	115.2	878	o1240	52	124
3	$B16_1$	16	121.8	964	o1520	30	151
4	$B16_2$		118.4	964	o1550	35	151
5	$B16_3$		162.1	964	o1570	15	151
6	$B16_4$		199.9	993	o1630	10	153
7	$B26_1$	26	140.6	1051	o2550	27	264
8	$B26_2$		109.9	1051	o2720	20	264
9	$B26_3$		429.2	1079	o2710	2	303
10	$B26_4$		80.6	1051	o2700	19	264
11	$B26_5$		402.3	1079	o2730	5	303
12	$B30_1$	30	234.7	1079	o2830	50	303
13	$B30_2$		223.4	1079	o2860	37	303
14	$B30_3$		220.4	1079	o2860	38	303
15	$B30_4$		209.7	1079	o2880	37	303
16	$B30_5$		82.8	1079	o3030	32	303
17	$B34_1$	34	176.2	1022	o3230	55	342
18	$B34_2$		151.4	1022	o3250	62	342
19	$B34_3$		105.4	1022	o3300	57	342
20	$B34_4$		61.1	1051	o3340	17	342
21	$B34_5$		245.1	1051	f3451	13	342
22	$B34_6$		218.1	1051	f3451	22	342
23	$B34_7$		113.1	1051	f3451	57	342

During the data pre-processing, cycle time was limited to values between 1 min and 10 min. As the minimum haulage distance was 61 m, it was not practically feasible to achieve a cycle time of less than 1 min even with the assumption of ideal loading duration, dumping duration, and haulage speed. Similarly, a cycle time of 10 min and above was considered influenced by other activities, such as machine breakdown, unavailability of loading areas, occurrence of boulders, or other mine related issues. Overall, 8745 cycles (7182 manual and 1563 semi-autonomous) were used to compare the payloads and cycle times of the two machine types.

3.2.3 Performance data for semi-autonomous LHDs

The data on the performance of semi-autonomous LHDs contained information on the machine number, block location, start and end point with time stamps, distance, load duration, and speed. The data came from three machines operating in six crosscuts in two blocks. In addition to the cycle time data for both semi-autonomous and manual LHDs, loading duration, dumping duration, and haulage speed of the semi-autonomous LHDs were analysed. An example of the raw data is shown in Table 8.

Table 8: Sample data for loading and dumping durations, and haulage speed of semi-autonomous LHDs

Machine nr.	Block-level	Start Point (crosscut)	Start time (hh:mm:ss)	End Point (ore pass)	End time (hh:mm:ss)	Distance (m)	Load duration (s)	Speed (km/h)
595	38-1108	381	01:49:07	396	01:53:08	341	98	5.1
595	38-1108	381	01:55:38	396	01:59:22	381	81	6.1
595	38-1108	381	02:03:14	396	02:06:44	350	53	6.0
595	38-1108	381	02:09:11	396	02:12:20	361	45	6.8
595	38-1108	381	02:14:46	396	02:19:05	365	57	5.1
595	38-1108	381	02:21:27	396	02:25:57	377	50	5.0
595	38-1108	381	02:28:23	396	02:32:56	357	52	4.7
595	38-1108	381	02:35:25	396	02:39:19	359	58	5.5

The original data records had missing information on the start point, end point, and time entries for some of the cycles. All cycles with missing entries were removed before the final analysis. Furthermore, loading and dumping durations were capped at a minimum of 20 s and 10 s, respectively, and at a maximum of 600 s. The minimum values were chosen as it was practically impossible to have values lower than that, whereas the maximum value was chosen assuming any value above the maximum was due to other disturbances, such as machine breakdown, hang ups, boulder handling etc., and would be accounted for in machine availability.

3.2.4 Sensitivity analysis data for density-based Fe-grade model

This study used global sensitivity analysis using UQLAB's [73] variance-based sensitivity module in MATLAB to assess and quantify the uncertainty and relative importance of each individual input parameter on the output variance of the density-based Fe-grade model. The current density-based Fe-grade model used at the mine has seven input parameters. The mine calculates the grade of iron using fixed values for void ratio (Vr), fill factor (Ff), grade of magnetite (G), volume of bucket (Vb), bank density of ore (O), and bank density of waste (W), excluding bucket weight (Bw). Fixed values for these input parameters were chosen based on the assumption that these values depicted the majority of the areas, since involving operators to select values for individual buckets would over-complicate the model. Consequently, the measured bucket weight was independent of the average fill and swell factors used in the mine.

In this thesis, scenario 1 and scenario 2 assumed the input values were independent and thus used the Sobol method for sensitivity analysis. However, to address a more realistic scenario considering the dependencies among the input parameters, scenario 3 used the Kucherenko method for sensitivity analysis. A Gaussian copula-based approach was employed to capture the dependency among the input parameters: bucket weight, fill factor, and void ratio. This approach was used as it is robust for simulating and analysing multivariate dependencies [71]. In addition, the copula function enables modelling joint distributions while preserving the marginal distribution of each variable [73].

The range of each input parameter for each scenario was selected based on the actual values used at the mine, references in the literature, data analysed in this study, and the mine's internal reports. Table 9 summarises the seven input parameters and the range of input values used for 21-tonne and 25-tonne LHDs in all three scenarios. The description and references used for selecting the range for each input parameter can be found in detail in Paper C.

Table 9: Range of input values used in density-based Fe-grade calculation model used in all the three scenarios (μ-mean, σ-standard deviation)*

Parameters (Symbol)	Distribution [Range]	Scenario 1 Method: Sobol		Scenario 2 Method: Sobol		Scenario 3 Method: Kucherenko	
		21-t	25-t	21-t	25-t	21-t	25-t
Bucket weight (Bw)	Gaussian [μ σ]*	[20 3]	[24 3]	[17.5 3]	[22 3]	[20 3]	[24 3]
Fill factor (Ff)	Uniform [min max]	[0.9 1.2]		[0.9 1.2]		[0.9 1.2]	
Void ratio (Vr)		[0.25 0.45]		[0.25 0.45]		[0.25 0.45]	
Bucket Volume (Vb)		[7.22 8]	[8.49 10]	[7.22 8]	[8.49 10]	[7.9 8]	[9.9 10]
Waste density (W)		[2.6 2.8]		[2.6 2.8]		[2.6 2.8]	
Ore density (O)		[4.6 5]		[4.6 5]		[4.6 4.8]	
Grade (G)		[0.60 0.72]		[0.60 0.72]		[0.60 0.72]	

3.2.5 Operator training and competencies

In addition to the baseline mapping, a survey consisting of both qualitative and quantitative methodologies was used to gain a deeper understanding of the organisation, effectiveness, and satisfaction associated with the operator training. To ensure maximum participation, the original survey was carried out in Swedish, the respondents' personal information was kept confidential, and the survey was made available on multiple platforms, including computers, tablets, and mobile phones.

The survey also obtained demographic information from 22 out of 34 (65%) operators of semi-autonomous LHDs, and 64 out of 86 (74%) operators of manual LHDs. The information included operators' LHD experience (Figure 6a) and the type of LHD they operated (manual or semi-autonomous) (Figure 6b). The length of time working as an operator was added as a variable for both semi-autonomous (Figure 6c) and manual (Figure 6d) LHD operators to see if the training differed based on experience. Other information included their training year and the inclusion of simulator training. The purpose of including this information was to identify factors that might have a significant effect on the operators' education.

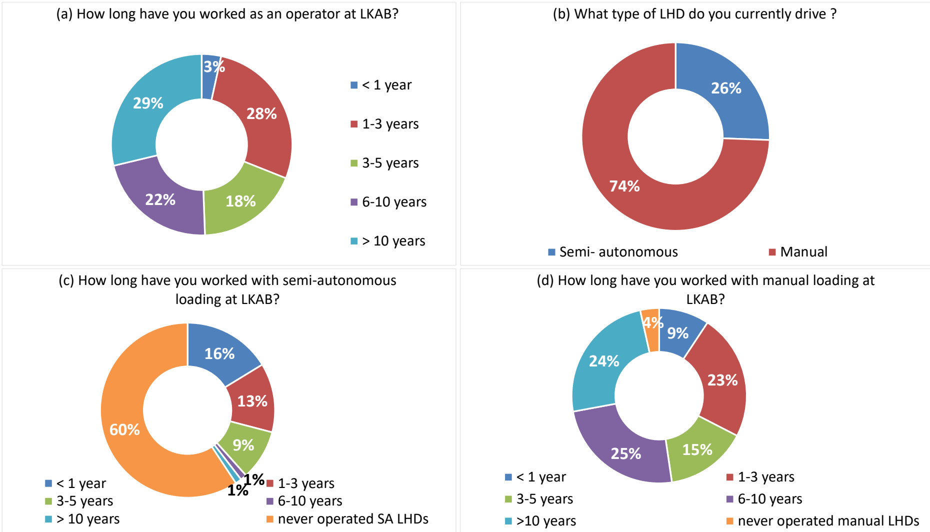

Figure 6: (a) Operators' experience with loading at LKAB; (b) Machine types; (c) Semi-autonomous loading (SA); (d) Manual loading

The effectiveness of training can be assessed by tools such as surveys, questionnaires, ratings, checklists, and performance measurements of the operator [121]. This study used the first two levels of the Kirkpatrick model, "reaction" and "learning", to devise several questions in the survey. "Reaction" measures the relevancy of the training to the operator's work, and "learning" assesses whether the operator has acquired knowledge matching the training objectives. The demographic information obtained during data collection was also utilised to analyse the responses based on variables such as the type of machine operated, years of experience, and training year etc.

3.2.6 Statistical analysis

A non-parametric test was conducted to compare the cycle times of semi-autonomous and manual LHDs. Both non-parametric and parametric tests were used to compare their payloads. To avoid misapplication of the test and choose a method that better suited the data, a preliminary data analysis was performed to check the normality and assumption of equal variance before using any statistical method. Additionally, a global sensitivity analysis was used to quantify the uncertainty and determine the total and joint effect of multiple parameters on the output of the density-based Fe-grade model.

3.2.6.1 **Normality test**

A statistical test has to meet specific pre-assumptions, and failure to adhere to these assumptions can result in misapplication of the test [122,123]. It is important to consider these limitations, as failing to do so may result in incorrect conclusions and poor decisions [33]. Oskouei et al. [33] highlighted many examples from the literature where the basic assumption of normality or equal variance was not verified before significance tests were performed. Failure to verify these basic assumptions can cause Type I error, i.e., when a true null hypothesis is rejected [33], thus incorrectly concluding significant difference.

The normality of a dataset can be tested using several different methods. Commonly used methods include Shapiro–Wilk (SW), Kolmogorov–Smirnov (KS), AD, and Cramer–vol Mises (CM) [33]. Just like other statistical methods, they have individual limitations in terms of sample size and power. For example, the SW test is considered the most powerful but is limited to a sample size between 7 and 2000 [124,125]. KS, AD, and CM are recommended for even larger (>2000) datasets. They have, however, their limitation of being rejected at the sample mean and variance, because they evaluate not only the mean and variance but also the entire distribution and its alignment with a theoretical normal distribution [124,126]. KS is arguably the most widely used test in statistical software packages [127,128]. KS and AD are based on the empirical distribution function (EDF) [127,128], while the Ryan Joiner (RJ) test is based on regression and correlation [127].

This study performed the AD test to check the normality assumption. This test was preferred because of its sensitivity to variations in the tails of the distribution and its wide applicability in checking the goodness of fit for distributions other than the normal distribution.

The procedure of the statistical analysis is summarised in Figure 7.

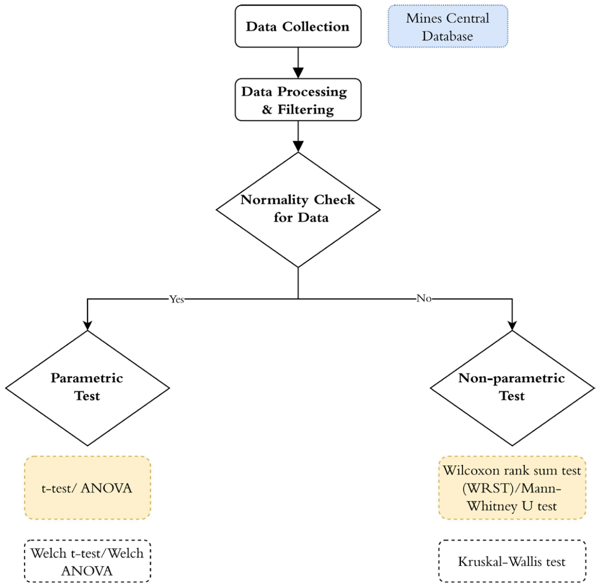

Figure 7: Summary of the statistical analysis performed for data comparison

3.2.6.2 **Significance test**

The choice of which statistical tests to perform depends on the results of the preliminary analysis for normality. Commonly used tests to compare the means of two groups include both parametric (t-test/ANOVA) and non-parametric tests (Wilcoxon Rank-Sum Test (WRST), also called Mann-Whitney U test and Kruskal-Wallis test). Parametric tests are commonly used in the literature [33,129] because of the widespread assumption of normality for data with larger sample sizes [33,129]. For sample sizes greater than 30, the central limit theorem is applied, assuming the sampling distribution approximately follows a normal distribution [33,129]. However, the literature mentions the improper use of parametric tests in non-parametric studies in medical [130] and engineering [33] fields. Therefore, it is important not to assume normality but to verify it with an established statistical method, such as AD, KS, SW, or RJ.

Since the data needs to be normally distributed to conduct parametric tests, the non-parametric WRST was chosen for this study. Moreover, WRST is more intuitive [129,131,132] and can be used for datasets of two different groups with small sample sizes [129,132] or different sample sizes [133]. It is also more resistant to outliers when they are small compared to the sample size [132]. Therefore, despite being less efficient computationally [129], WRST was chosen to compare the payloads and cycle times of semi-autonomous and manual LHDs. WRST was used to test the following hypotheses:

H_0 = There is no difference between the median cycles' time/payloads of 21-tonne semi-autonomous and manual LHDs.

H_1 = There is a significant difference between the median cycles' time/payloads of 21-tonne semi-autonomous and manual LHDs.

A t-test was used for the payload comparison when the data met the pre-assumption of normality. The t-test was performed to test the following hypotheses:

H_0 = There is no difference between the mean payloads of 21-tonne semi-autonomous and manual LHDs.

H_1 = There is a significant difference between the mean payloads of 21-tonne semi-autonomous and manual LHDs.

3.2.7 Global sensitivity analysis

Global sensitivity analysis is a quantitative framework used to evaluate how the uncertainty of each input parameter of a model contributes to the variability of the model output. It aims to identify the relative importance of each input parameter. Sensitivity analysis includes local and global methods. Whereas the local method only analyses the impact of individual parameter on the model output, the global method can analyse the total and joint effect of multiple parameters on the model output. Various Monte Carlo based global sensitivity analyses have been developed, such as Morris, Fourier amplitude sensitivity test (FAST), generalised likelihood uncertainty estimation (GLUE), Sobol, and extended FAST methods. The Sobol method is widely used [134,135] because of its suitability for non-linear and non-monotonic mathematical models with robust [135] and reliable results [134,135]. Despite its strength, the method cannot be applied when the inputs are not correlated [73,136]. Therefore, methods such as Kucherenko, which define the dependence among the input variables are used [136]. The workflow for the global sensitivity analysis of the three scenarios used in this study is summarised in Figure 8.

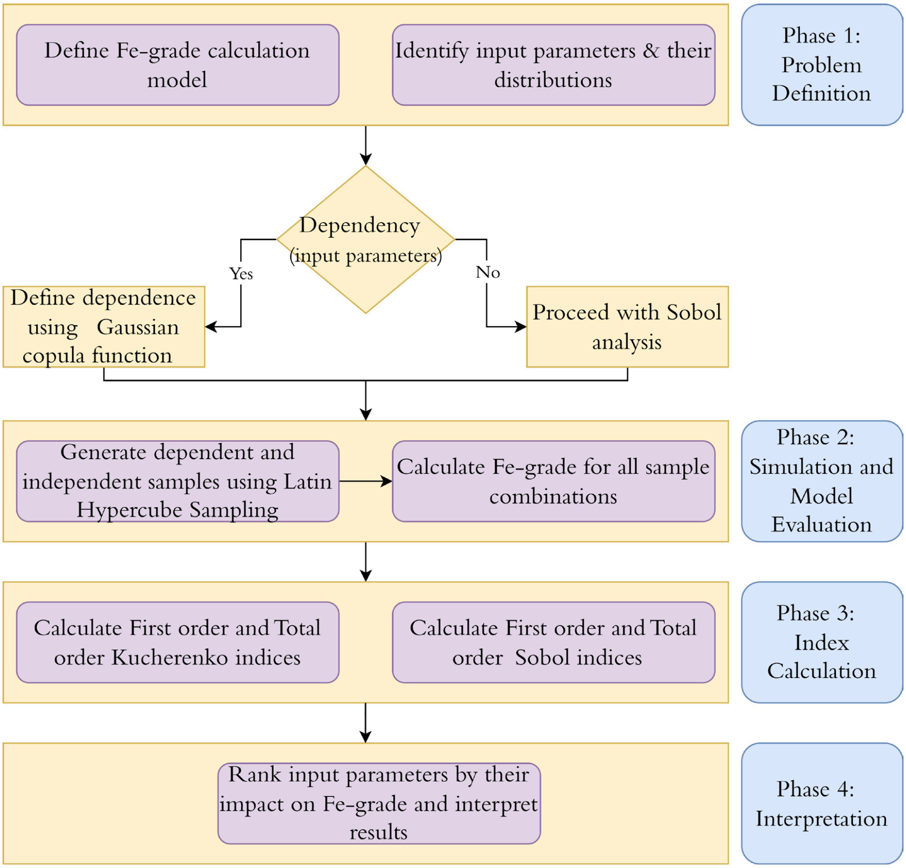

Figure 8: Workflow for sensitivity analysis of density-based Fe-grade calculation model

3.2.7.1 **Sobol sensitivity analysis**

Sobol, a variance-based approach, quantitatively evaluates the significance of each input variable by decomposing the output variance into the contributions of each input variable [137]. This method is considered a model-free approach, which means it is suitable for complex nonlinear and non-additive models [137]. Sobol indices are based on the idea of defining the expansion of the computational model into summands of increasing dimension. Similarly, the model's total variance is represented as the sum of the variances of these summands [73]. This approach generates indices that highlight the importance of each input variable and consider their interactions [137]. Sensitivity is measured in terms of first order and total order effects. The first order considers the main effect caused by the corresponding input, while the total order accounts for the total contribution to the output variance due to the primary and high order effects resulting from interactions among the inputs [137].

The Sobol method is primarily used to compute the first order and total effect indices. The first order (Si) in equation 3 quantifies the primary influence of a single input variable on the variance of the model output by varying a specific variable while keeping all others constant:

$$S_i = \frac{V(E[Y|X_i])}{V(Y)} \quad (3)$$

where $V(Y)$ is the unconditional variance of Y, X_i is the i^{th} constant input variable, and $E[Y|X_i]$ is the expected value of Y given Xi.

Similarly, the total effect index (S_T) in equation 4 quantifies the total contribution of specific input variables by taking into account both the variable itself and all related interaction effects [138,139]:

$$S_{T_i} = \frac{V(E[Y|X_{\sim i}])}{V(Y)} \quad (4)$$

where $X_{\sim i}$ is all input variables except the i^{th} input variable Xi, and $E[Y|X_{\sim i}]$ is the expected value of Y given all inputs except Xi.

3.2.7.2 **Kucherenko sensitivity analysis**

Kucherenko analysis is a novel approach for estimating variance-based sensitivity indices in models with dependent variables [71]. It distinguishes between the correlated and uncorrelated contribution of each input parameter, something traditional variance-based methods such as Sobol fail to do [136]. It defines sensitivity indices using a direct composition of the output variance with the law of total variance. The law of total variance states that the variance of a random variable can be decomposed into two parts: the variability within groups and the variability between groups [71]. This approach generalises the Sobol indices to scenarios where input variables are dependent, and it derives formulas and Monte Carlo numerical estimates similar to Sobol formulas [71]. Kucherenko indices use the same mathematical expressions for the first order (S_i, equation 1) and the total order (S_{Ti}, equation 2) as Sobol indices, but they are generalised to correlated input variables by computing expectations and variances without assuming independence [73]. This method utilises a copula-based sampling technique to generate samples from arbitrary multivariate probability distributions with specified dependence structures [136].

4 BASELINE MAPPING

4.1 Site description

This study included three Swedish mines as test sites. Kiirunavaara mine, owned and operated by LKAB, is an underground iron ore mine using SLC as a mining method and operating a mixed fleet of semi-autonomous and manual LHD machines. Data on the impact of digitalisation and automation, performance of LHDs due to mode of operation, and operator training were collected from the Kiirunavaara mine. Aitik, an open pit copper mine, and Garpenberg, an underground zinc mine using sublevel stoping as a mining method, both owned and operated by Boliden Mineral AB, were included to obtain data on digitalisation and automation.

4.2 SLC operation at Kiirunavaara mine

The orebody at the Kiirunavaara mine has an average thickness of 80-100 m with a dip of 60-70° towards east, which enables a cross-cutting SLC layout [140]. An overall layout of the SLC operation in the Kiirunavaara mine is shown in Figure 9. The orebody has a strike length of around 4 km and for production and planning reasons is sub-divided into individual blocks of about 400 m and sublevel heights of 28.5 m [140] to approximately 30 m [141,142]. The orebody is accessed through horizontal mine workings called crosscuts/drifts placed 25 m apart, which typically are 5 m in height and 7 m in width and can extend up to 138 m towards the hanging wall contact [141,142].

In each crosscut, blast holes are drilled in a ring pattern in a vertical or near-vertical orientation to reach the sublevel above. A ring typically has 8 blast holes with 115 mm diameter, and there is a burden of approximately 3 m between the rings. The process is initiated by an opening blast that establishes a new draw point closest to the hanging wall. Upon establishing a contact with the upper level, the rings are blasted in a sequence against the material in front, comprising of caved waste and minor amounts of remaining ore. The extraction of ore from these blasted rings proceeds until the dilution level or another critical parameter reaches a specified threshold. At this point, the subsequent ring is blasted, and the retreating process continues [140] until the end of the crosscut. Where the ore width is relatively wide, the mine mostly uses transverse layouts, i.e., crosscuts perpendicular to the strike of the orebody, but longitudinal layouts, i.e., crosscuts parallel to the strike of the orebody, are used in some areas where the ore width is narrower [140,141].

LHD machines are used to load material from the draw point and transport it to the ore pass or to trucks at the same haulage level.

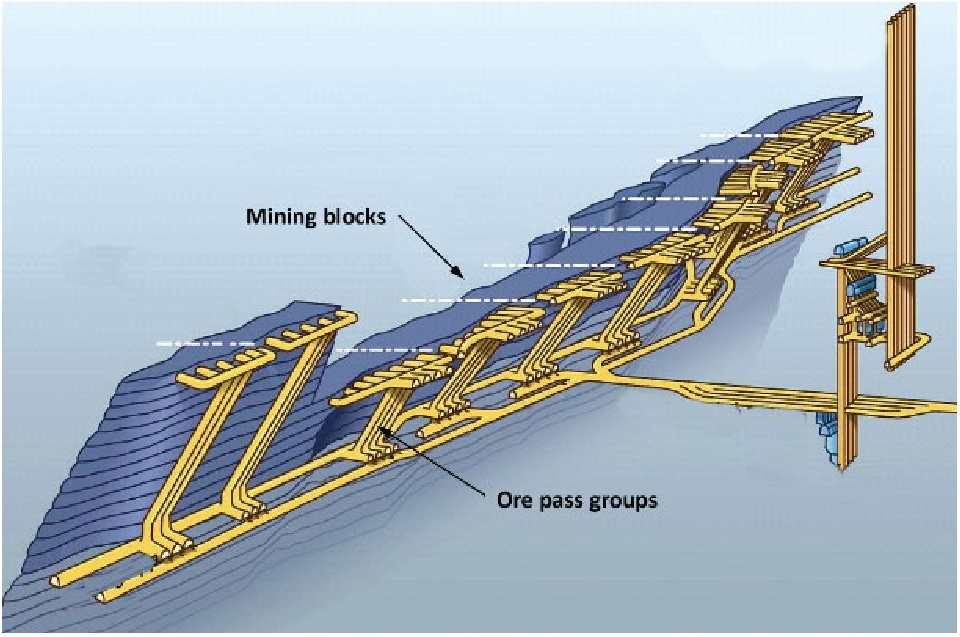

Figure 9: Layout of Kiirunavaara mine (not to scale) [141]

4.3 LHD operation

The loading operation in the Kiirunavaara mine is performed by a mixed fleet consisting of both autonomous and manually operated machines. In this study, autonomous loading refers to semi-autonomous LHDs with autonomous hauling and dumping, but manual bucket loading. The operators operate the semi-autonomous LHDs from an underground control station using a joystick and a control panel to load the bucket (see Figure 10). These autonomous machines can also be operated manually, if required.

Figure 10: Underground control station of semi-autonomous LHDs at Kiruna mine [143]

In a typical haulage operation for manual LHDs, the operator loads ore from the loading point (Figure 11, point 2), dumps it into the ore pass (Figure 11, point 3), and then hauls the empty LHD back to the loading point (Figure 11, point 2). In contrast, for a semi-autonomous operation, the LHD stops at a pre-determined point before the loading point (Figure 11, point 1), allowing the operator to manually take control of the LHD to perform bucket filling from the control room. The operators of the semi-autonomous LHDs also switch to handle remote-controlled rock breakers when the LHDs are automatically hauling or dumping the material without human intervention. The complete haulage cycle is shown in the schematic diagram in Figure 11.

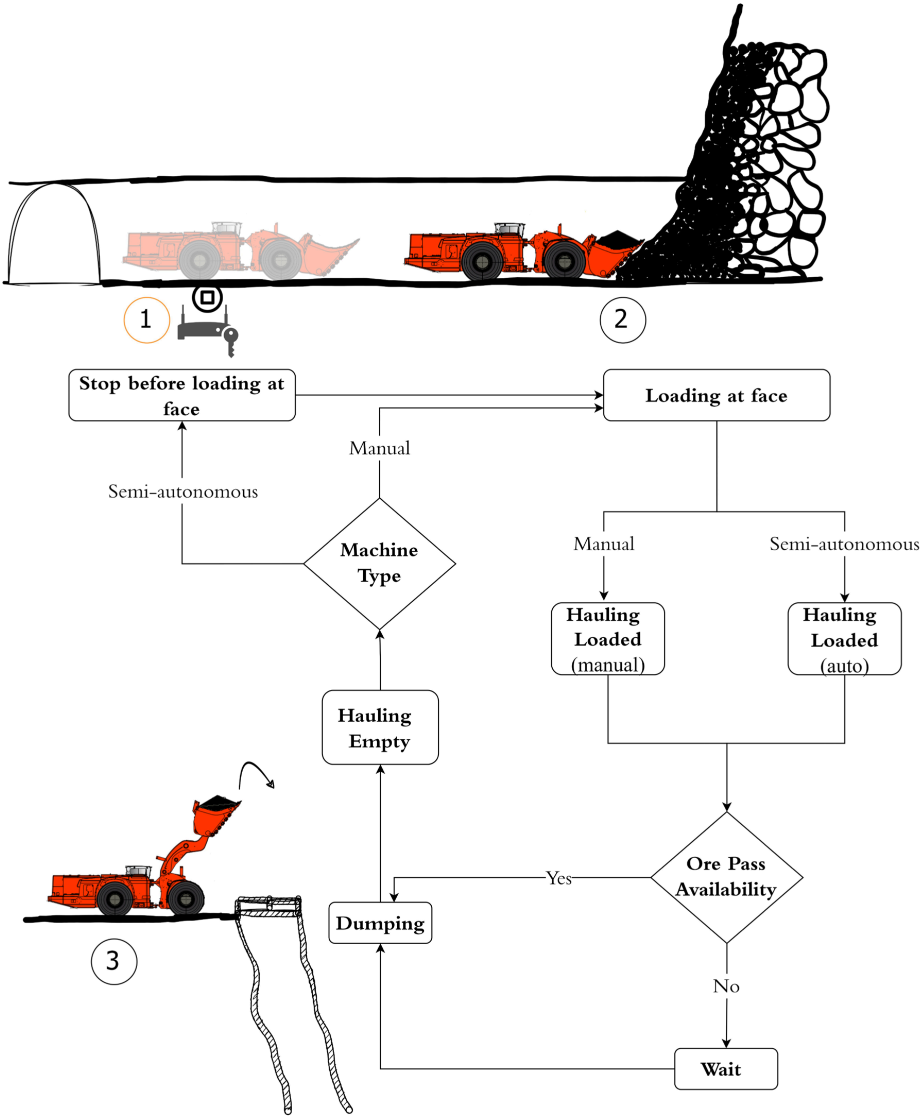

Figure 11: Schematic diagram of haulage cycle for semi-autonomous and manual LHDs loading operations (LHD model from Sandvik [12])

4.4 Density-based Fe-grade calculation: Current practice

The density difference of ore and waste is used to calculate the grade of iron in the Kiirunavaara mine. The basic formula for the density-based Fe-grade calculation used in WOLIS is shown in equation 5:

$$\text{Fe-grade} = \frac{\text{Bucket Weight - Waste Bucket Weight}}{\text{Ore Bucket Weight - Waste Bucket Weight}} \times 0.71 \quad (5)$$

Bucket Weight (Bw) is the weight of the bucket from the Loadarite system. It is measured by monitoring the hydraulic pressure in the cylinders using load cells, and converting it into the weight of the material in tonnes [141,144]. The other two variables, Ore Bucket Weight (OBw) and Waste Bucket Weight (WBw), are predetermined constants, where OBw is the maximum weight of the bucket containing only ore and no waste, and WBw is the maximum weight of the bucket containing only waste. The OBw and WBw values differ for different machine capacities and are calculated as shown in equation 6 and 7:

$$\text{OBw} = (\text{Fill factor} \times (1\text{-Void ratio}) \times \text{Vol. of bucket} \times \text{Ore density}) \quad (6)$$

$$\text{WBw} = (\text{Fill factor} \times (1\text{-Void ratio}) \times \text{Vol. of bucket} \times \text{Waste density}) \quad (7)$$

$$\text{Swell factor} = 1/\,(1\text{- Void ratio}) \quad (8)$$

In the current system, OBw and WBw are calculated assuming a theoretical fill factor of 1, a swell factor of 1.6, calculated using equation 8, ore density of 4.6 t/m^3, and a waste density of 2.7 t/m^3, with 71% set as the theoretical Fe content for magnetite. The bucket volume is assumed to be 8 m^3 for 21-tonne LHDs and 10 m^3 for 25-tonne LHDs.

5 RESULTS AND DISCUSSION

5.1 Digitalisation and automation

In the mining sector, digital transformation is at the heart of advancement and development and together with automation, it is changing conventional mining practices in many mines [145,146]. The Swedish mining industry has been one of the early adopters of automation and digitalisation. This thesis evaluates the perspective of LHD operators and production workers at LKAB and Boliden's mines on how digitalisation will impact their present and future jobs.

In terms of the impact of digitalisation, 34% of the LHD operators surveyed anticipated the operation would transition more towards semi-autonomous loading. Twenty-five percent highlighted the positive impact digitalisation will have on their jobs, mentioning enhanced safety, efficient production, improved working conditions, better machines, reduced damage on machines, and expanded Wi-Fi coverage. However, despite the generally positive perception, 16% of the LHD operators also highlighted some negative effects. For example, they thought over-reliance on technology can lead to management's lack of trust in their competencies as skilled employees. Moreover, it eliminates personal responsibility and thus can reduce the knowledge and understanding of the overall operation, which could lead to missing some of the major risks associated with the operation. The production workers mostly anticipated a major impact on their jobs, whereby the nature of work would change from physical to more office-like environments, predominantly consisting of monitoring production systems and problem solving related to issues with automation and digitalisation. They highlighted that they would lose experience and the "feeling for the rock", a kind of fingertip feeling that requires practical experience. They also raised concerns about cybersecurity threats that may have a negative impact on security and production.

The survey results were further analysed based on the mode of LHD operation (manual versus semi-autonomous). Findings showed the differences between operators of manual and semi-autonomous LHDs were significant. A higher percentage of semi-autonomous LHD operators (50%) perceived digitalisation positively than manual LHD operators (17%). The majority of these manual LHD operators had 6-10 years of experience. However, despite the more negative perception among the manual LHD operators, approximately 40% still expected an increasing shift towards semi-autonomous loading (see Figure 12).

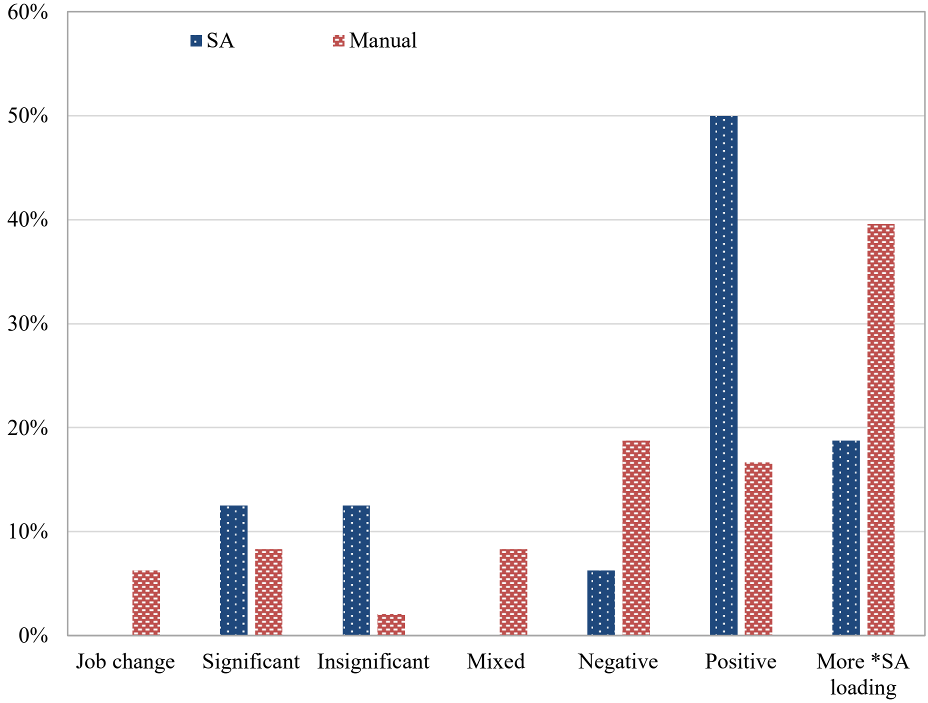

*Figure 12: How will digitalisation impact your job as an operator? (results by machine type) (*SA semi-autonomous)*

In response to an open-ended question asking which operational activities cannot be automated, the largest share (29%) of the LHD operators thought that machine maintenance cannot be automated. This was followed by road maintenance (22%), bucket filling (20%), scaling (15%), charging (9%), daily supervision (6%), priming (5%), drilling (3%), and relocating machines (3%). Other activities, such as bolting, preparing areas for loading, area monitoring (port/gate control), cleaning, oil refilling, boulder handling, system installation, and administrative jobs, were mentioned by 19% of the LHD operators. It is worth mentioning that 6% answered that all tasks in the mine could be automated. It was evident from the responses of the LHD operators that the majority thought there would be more semi-autonomous loading in the future, and the top three activities (machine maintenance, road maintenance, and bucket filling) that they thought cannot be automated were directly related to LHD operation.

5.2 Comparison of manual and semi-autonomous LHD payloads

The payload is an important parameter for measuring the production efficiency as well as calculating the Fe-grade utilising density-based models. Therefore, to understand the differences in payload due to mode of operation (manual vs. semi-autonomous), a multilevel comparative analysis was performed on three levels. First, an overall comparison was performed across the whole mine. Second, a block level assessment was performed to see how the payload differed in individual blocks. Finally, a ring level comparison was done to identify more localised differences due to the mode of operation in selected areas.

5.2.1 Comparison of LHD payloads: Overall mine

A comprehensive payload comparison of manual and semi-autonomous LHDs was conducted. To improve the accuracy of the comparison, the analysis focused on 21-tonne machines operating in blocks where data were available for both machine types. Figure 13 illustrates the overall payload comparison using a box plot. The difference between manual and semi-autonomous LHDs was minimal: 0.34 tonnes per bucket when comparing the means and 0.3 tonnes per bucket when comparing the medians.

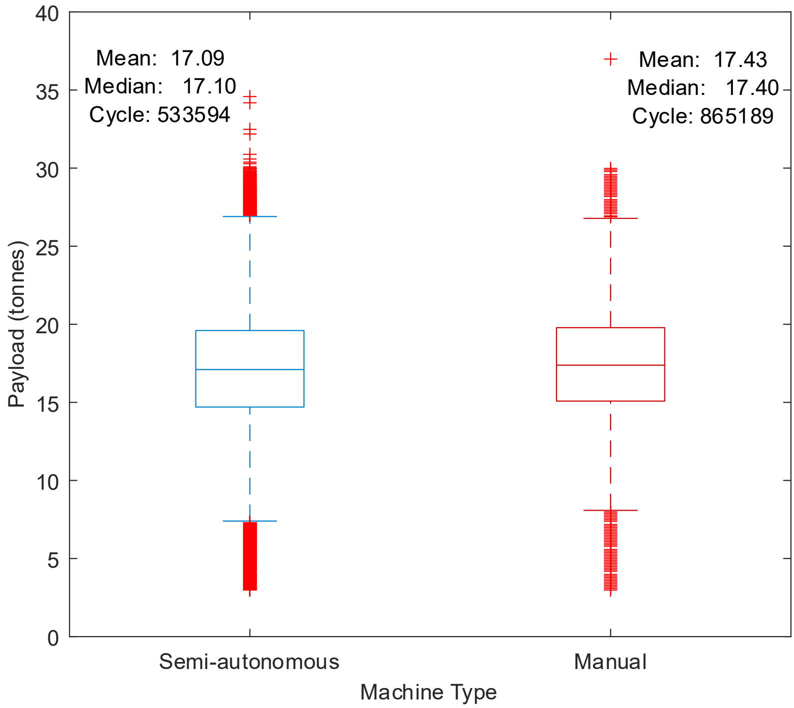

Figure 13: Box plot showing 21-tonne semi-autonomous and manual LHD payload

5.2.2 Comparison of LHD payloads: Individual blocks

The Kiirunavaara orebody is approximately 4 km long, and for production and planning reasons, the mine is divided into separate blocks from north to south. To compare the payloads across the mine, the data were sorted and analysed per block to examine if and how the payload values differed in individual blocks. This analysis showed the median payload capacity for semi-autonomous and manual LHDs had an inconsistent variation (see Figure 14). Overall, the semi-autonomous LHDs had higher payloads than the manual LHDs in seven blocks, but the opposite was observed in the remaining five blocks. The reduced payload for both machine types in Block 22 could be attributed to present operational difficulties in the block. Similarly, the payloads were significantly lower in Blocks 38 and 41, possibly due to the complex shape and geology of the orebody in the south.

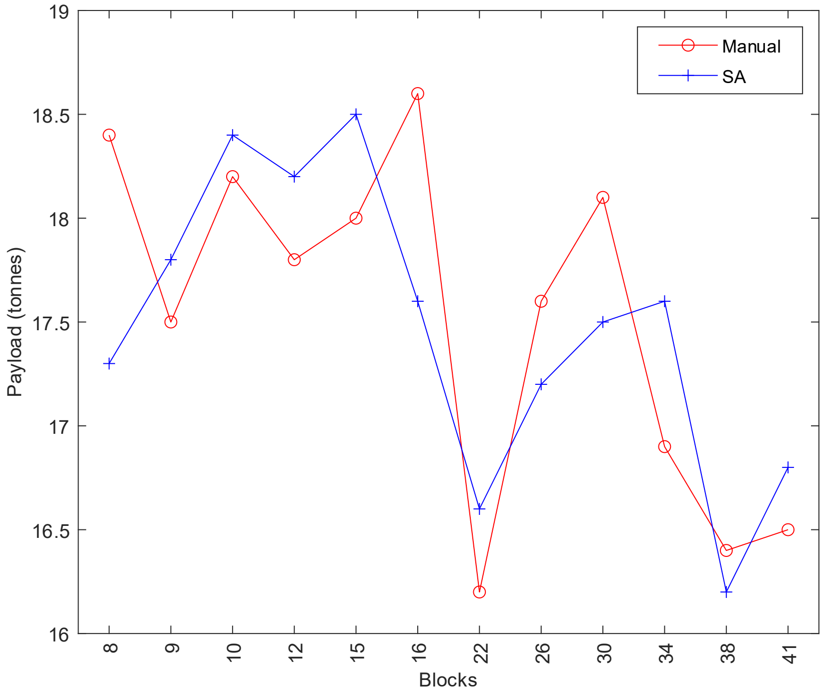

Figure 14: Payload comparison across blocks for semi-autonomous (SA) and manual LHDs

5.2.3 Comparison of LHD payloads: Same ring

When comparing the payloads of semi-autonomous and manual LHDs on the ring level, the data for the semi-autonomous LHDs were filtered to include only night shift data, as only semi-autonomous LHDs are allowed to operate post-blasting during the night shifts. This ensured the semi-autonomous LHDs did not include manual operation, as it is possible to operate the semi-autonomous machines manually if required. Moreover, to increase the accuracy of the analysis, only machines operating in the same ring were considered for both manual and semi-autonomous LHDs. The median payload values for both machine types are illustrated in Figure 15. Overall, the median payload of semi-autonomous LHDs was higher than that of manual LHDs in 14 of the 23 selected areas, and the opposite was observed in the remaining nine selected areas. A statistical analysis was conducted to determine if this difference was significant.

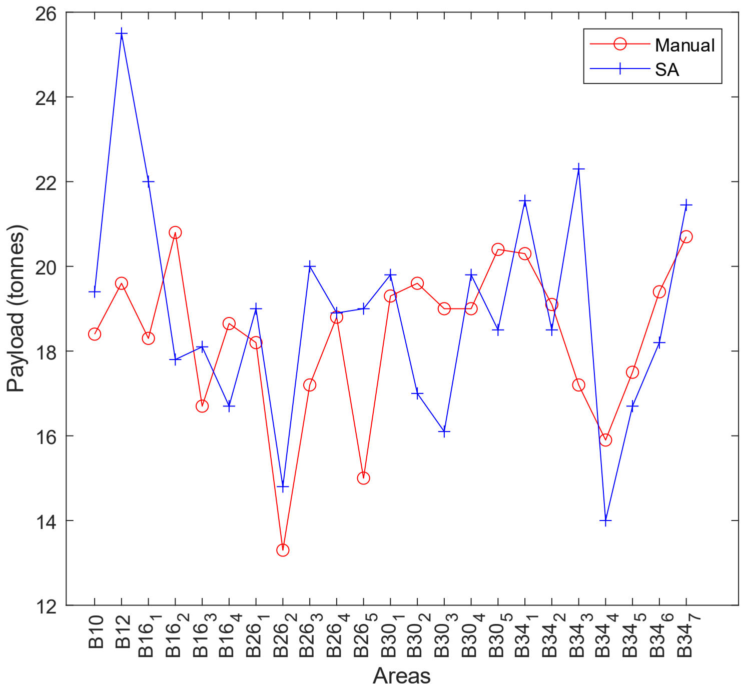

Figure 15: Comparison of median payload for manual and semi-autonomous (SA) LHDs in all selected areas

A normality test was conducted prior to the significance test. As the data did not follow a normal distribution in the majority (20 out of 23) of the selected areas, a WRST was performed in these selected areas. In the remaining three selected areas, $B26_1$, $B26_3$, and $B30_2$, where the data followed a normal distribution, a t-test was performed. The t-test (comparing means) and WRST (comparing medians) were performed with the following hypotheses:

- H_0 = There is no difference between the mean/median payload of 21-tonne semi-autonomous and manual LHDs.

- H_1 = There is a significant difference between the mean/median payload of 21-tonne semi-autonomous and manual LHDs.

In 17 out of 23 selected areas, the p-value was less than the 5% significance level, thus rejecting the null hypothesis (H_0) and indicating there was a significant difference between the payload of semi-autonomous and manual LHDs. In the remaining six areas, B10 (p-value 0.22), $B26_4$ (p-value 0.80), $B30_1$ (p-value 0.25), $B30_4$ (p-value 0.56), $B34_2$ (p-value 0.19), and $B34_7$ (p-value 0.26), the p-value was greater than 0.05, thus failing to reject the null hypothesis (H_0) at the 5% significance level. Overall, for the 17 selected areas where the difference in payload was statistically significant, in 10 selected areas, the semi-autonomous LHDs had higher payloads, and in 7 selected areas, manual LHDs had higher payloads. Thus, neither type of machine consistently outperformed the other.

The difference in median payloads ranged from 0.1 to 3 tonnes, except for outliers observed in B12 (5.97 tonnes), $B16_1$ (3.7 tonnes), $B26_5$ (4 tonnes), and $B34_3$ (5.1 tonnes), where the median payload for manual LHDs was significantly lower. This could partially be explained by the fact that the data for the manual LHDs came from multiple days and might have included different loading conditions or been affected by operator efficiency. Having said that, this significant difference would have a large impact on the productivity of these machines and the density-based Fe-grade calculation. Therefore, it is recommended to further study the reasons for the differences in payload.

5.3 Comparison of cycle times of manual and semi-autonomous LHDs

To determine if there was a difference between the cycle times of semi-autonomous and manual LHDs, data for modes of operation were compared and statistically analysed for all the studied selected areas using a significance test. Prior to the significance test, an AD test was performed to check the normality of the data. A p-value of less than 0.05 was observed for all selected areas, suggesting the data did not follow a normal distribution in any of the 23 selected areas. Therefore, a non-parametric WRST test was carried out in all selected areas to test the following null and alternate hypotheses:

H_0 = There is no difference between the median cycle times of 21-tonne semi-autonomous and manual LHDs.

H_1 = There is a significant difference between the median cycle times of 21-tonne semi-autonomous and manual LHDs.

The results showed that in 19 out of 23 selected areas, the p-value was less than 0.05, thus rejecting the null hypothesis (H_0) at a 5% significance level and indicating a significant difference in the cycle times for the two modes of operation. However, in the remaining four selected areas, $B16_1$ (p-value 0.35), $B26_2$ (p-value 0.42), $B30_4$ (p-value 0.27), and $B34_4$ (p-value 0.13), the p-value was greater than 0.05; thus, the null hypothesis could not be rejected at a 5% significance level.

The median cycle times of both machine types are plotted in Figure 16. In 13 out of the 23 selected areas, the cycle times of the semi-autonomous LHDs were longer than those of the manual LHDs. However, in the remaining 10, the semi-autonomous LHDs had shorter cycle times. The differences in median cycle times ranged from 0.01 to 1.83 min, except for two outliers: in $B26_1$ the median cycle time was 3.6 min longer for manual LHDs than for semi-autonomous LHDs, and in $B30_2$, the cycle time was 2.6 min shorter for manual LHDs than for semi-autonomous LHDs. However, $B26_1$ had considerably more data for manual LHDs. Moreover, the data came from eight days, thus involving multiple shifts, different operators, and different loading, dumping, and road conditions. In contrast, the data for the semi-autonomous LHDs came from a single day's operation. Similarly, in $B30_2$, the data for semi-autonomous operation came from a single day.

Nonetheless, the conditions in an SLC operation could vary within a single day's operation. For example, in $B16_4$, a semi-autonomous LHD was operating during the night shift and was replaced by a manual LHD in the following day shift. Both machine types loaded from the same loading point (ring) from crosscut o1630 and dumped to ore pass 153, ensuring similar loading conditions. Even so, the semi-autonomous LHD showed a much more consistent operation, with a variance of 0.3 min, while the manual LHD showed a much higher variance of 2 min.

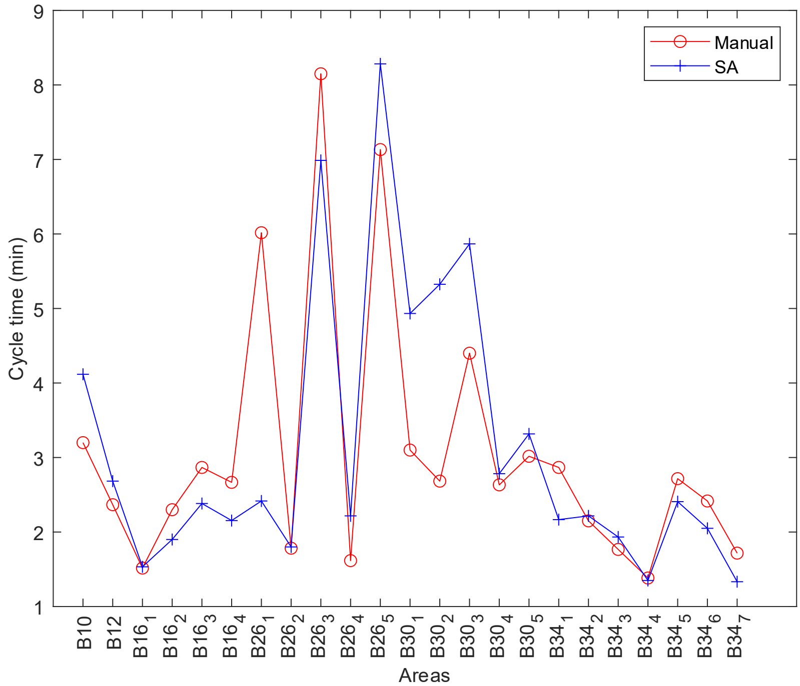

Figure 16: Median line plot for cycle times of semi-autonomous (SA) and manual LHDs

The observed median cycle time differences between semi-autonomous and manual LHDs could be up to 4 minutes. Besides modes of operation, these differences could reflect difficult loading conditions, boulder occurrences, harsh road conditions, haulage distance, influence of operators, traffic congestion, etc. or a combination of these factors. For example, the occurrence of boulders would impact the loading and dumping duration of both manual and semi-autonomous LHDs. The occurrence of boulders at the ore pass could cause the unavailability of the ore pass, higher waiting times before dumping, traffic congestion, etc., thus adding to the total cycle time. It is also important to note that the semi-autonomous LHD operators controlled the remote rock breakers stationed at each ore pass. Therefore, the occurrence of boulders would increase the time required to shift from controlling one machine to another. Thus, it is important to identify the external factors increasing the waiting time for these machines.

5.4 Complete load-haul-dump duration for semi-autonomous LHDs

To deepen the understanding of the impact of external factors on the overall cycle time, the total load-haul-dump duration for semi-autonomous LHDs was analysed. The total duration included:

- Loading duration: The loading duration in this thesis refers to the time required at the face to take control of the machine before loading and to complete the bucket filling.
- Haulage duration: The haulage duration refers to the time for the LHD to haul with a loaded bucket from the loading point (draw point) to the dumping point (ore pass) and to haul back to the loading point with an empty bucket.
- Dumping duration: The dumping duration refers to the time spent to unload the mucked material at the ore pass, including the waiting time associated with the availability of the ore pass, in particular, the time required to break boulders and secure the rock breaker at the ore pass.

To better understand the longer cycle times observed for semi-autonomous LHDs, and the occurrences of rare larger differences between the cycle times of manual and semi-autonomous machines, as in selected areas $B26_1$, $B30_1$, $B30_2$, and $B30_3$ (see Figure 16), the individual components of the cycle time were investigated, i.e., the median loading duration, dumping duration, haulage distance, and speed of semi-autonomous LHDs. Six combinations of crosscuts and ore passes were studied from blocks B15 and B38. These are referred to here as six scenarios (S1-S6). The details are summarised in Table 10.

Table 10: Summary statistics for all scenarios

Scenarios	Block	No. of Cycles	Distance (m)	Loading Duration (s)			Speed (km/h)			Dumping Duration (s)		
			Mean	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
S1	15	115	233	56	45	17	4.8	5.0	0.8	80	70	47
S2		135	261	61	42	32	4.6	4.7	0.9	98	101	51
S3		72	288	46	68	26	4.8	4.9	0.6	75	77	43
S4	38	238	289	53	47	32	5.2	5.4	1.2	97	103	37
S5		331	253	73	56	21	5.2	5.2	1.1	71	72	30
S6		385	359	51	44	25	6.0	6.3	1.2	108	106	46
Total		1276										

Figure 17 depicts the layout of block B15, illustrating three scenarios, S1, S2, and S3, where the semi-autonomous LHD loaded material from loading points 1, 2, and 3 and dumped it into the nearest available ore pass (dumping point). Similarly, S4, S5, and S6 represent three scenarios in block B38.

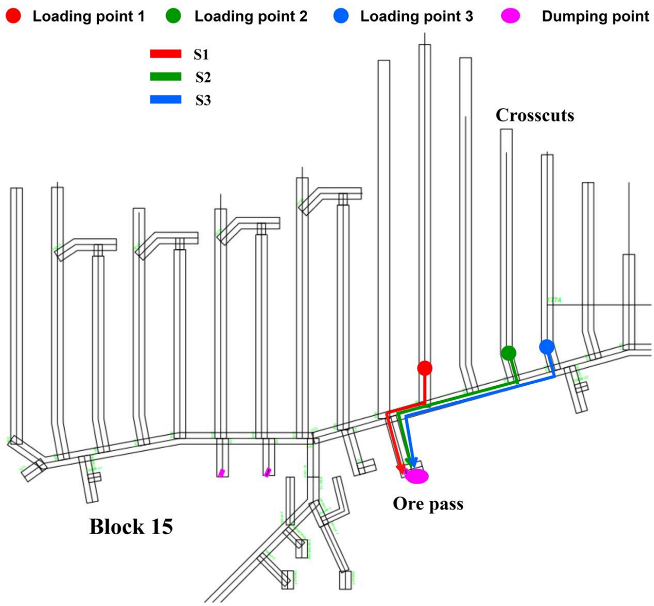

Figure 17: Schematic layout of three scenarios in Block 15 (not to scale)

5.4.1 Loading duration and dumping duration

Table 10 summarises the loading and dumping durations for the six scenarios. The median loading duration ranged from 42 s to 68 s (see Table 10) for the scenarios, relatively close to the value for the Kiirunavaara mine (40 s) and the Malmberget mine (59.8 s) previously used by Skawina et al. [142,147]. Overall, the median loading duration was lower than 46 s in four scenarios. Higher values observed in scenarios S3 (median 68 s) and S5 (median 56 s) may have been the result of difficult loading conditions or operator efficiency.

The median dumping duration for all six scenarios ranged from 70 s to 106 s (see Table 10). The observed median dumping duration was distinctly different from the average values of 5 s for the Kiirunavaara mine and 10.4 s for the Malmberget mine reported by Skawina et al. [142,147], or 1.8 s [12] specified by the manufacturer. However, the previous values were based on data from a 21-tonne manual LHD, where only the actual dumping time was considered. In this research, the additional waiting time associated with the semi-autonomous operation, where the operator must secure the rock breaker before the machine can perform the autonomous dumping, was also considered.

When comparing the loading and dumping durations, it is important to note that the dumping duration could reach values up to 480 s, whereas the maximum values observed for loading duration was 243 s, significantly lower than the maximum value for dumping duration. Moreover, S4, S5, and S6 in block B38 had more rare high values (outliers) for the loading and dumping durations (Figure 18) than S1, S2, and S3 in block B15. This highlights the impact of external factors and could be explained by the fact that the mine had coarser fragmentation in B38 than B15. This might have caused increased occurrences of boulders, creating difficult loading conditions and adding extra waiting time at the ore pass as longer time is required to break boulders.

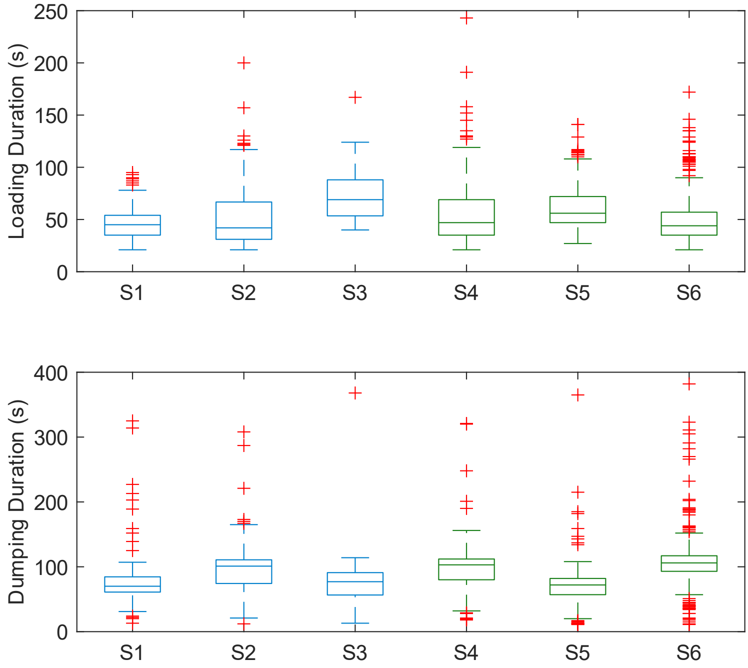

Figure 18: Box plot of loading and dumping duration for Block 15 (S1, S2, S3) and Block 38 (S4, S5, S6)

5.4.2 Haulage duration

Haulage duration is primarily determined by the haulage distance and speed of the LHD. Table 10 summarises the mean and median haulage speeds for the six scenarios. The mean speed for all scenarios ranged from 4.6 to 6.0 km/h. The haulage speed of individual trips varied from as low as 1 km/h to as high as 8 km/h (Figure 19). The haulage speed observed in this study was significantly lower than the speed reported in the literature or recommended by Sandvik [12]. The mean (6 km/h) and the maximum (8 km/h) haulage speeds of S6 were the highest. A possible explanation is that S6 had the longest haulage distance (359 m), thus allowing LHDs to haul in a higher gear than in the other scenarios.

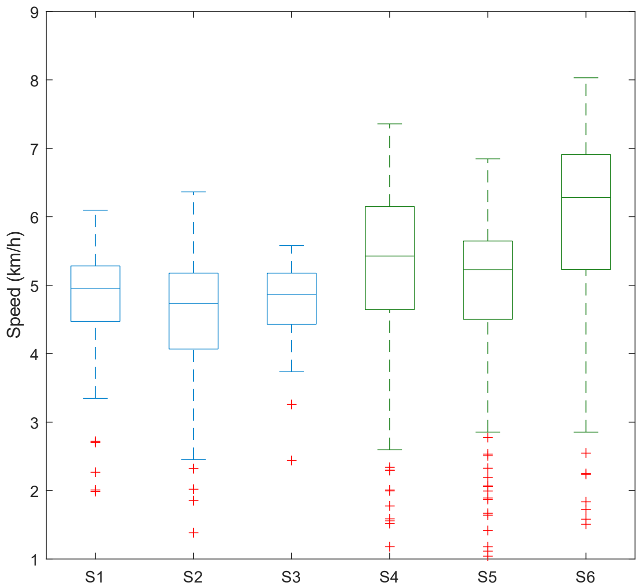

Figure 19: Box plot for speed data from Block 15 (S1, S2, S3) and Block 38 (S4, S5, S6)

The haulage speed depends upon variety of influencing factors, including the quality of the road, the condition of the machinery, the efficiency of the operator, the design of the mine, the mode of operation, and the traffic control measures in place. Since the machines in all six scenarios were running in autonomous mode, the operators' influence on the haulage duration was removed. However, the differences in speed observed in blocks B15 and B38 (see Figure 19) highlight the impact of external factors such as road maintenance, distance, and road condition on the haulage speed. This was confirmed by the LHD operators' responses to the survey when they were asked what thing was the most difficult to learn about semi-autonomous loading. Almost half (49%) identified road maintenance as the most challenging to learn, followed by bucket filling (43%), keeping track of traffic and people (28%), and handling boulders (21%).

5.5 Fe-grade calculation

5.5.1 Limitations and challenges

The density-based Fe-grade estimation methods irrespective of whether they use a scanning-based method such as in RTIT's open pit operation or a bucket weight as in LKAB's underground operation, utilise the density difference between ore and waste. However, constant average values are used for some input parameters in the Fe-grade equation. Both methods use constant average values for the bank densities of ore and waste as well as for the void ratio. While the used bank densities normally should not vary significantly from the average values, the void ratio can vary depending on the particle size distribution of the blasted material, increasing with increasing fragment size. Thus, depending on the fragmentation size, the bucket weight can vary significantly for fine and coarsely fragmented material. For material with the same iron grade, fine material will have a higher loading productivity and higher predicted grade than coarser fragmented material. To understand the difference in payload due to fragmentation, this study looked at regions of the test mine with different fragmentation.

5.5.1.1 **Impact of fragmentation on Fe-grade calculation**

Previously, Tonvall [70] and Manzoor et al. [69] highlighted the impact of different fragmentation categories (fine, medium, coarse, and oversize) on the mean payload. Tonvall [70] confirmed that the bulk densities for both ore and waste are negatively correlated with fragmentation size i.e. lower bulk densities for coarser fragmented material. In Manzoor et al.'s [69] study of 9736 loaded buckets, the mean payload decreased from 20.49 tonnes (fine fragmentation) to 19.28 tonnes (medium fragmentation) and 18.68 tonnes (coarse fragmentation). The mean payload difference between the fine (20.49 tonnes) and the medium (19.28 tonnes) fragmentation was 1.21 tonnes, corresponding to an Fe-grade difference of 9 percentage units. Similarly, the mean payload difference between the medium (19.28 tonnes) and the coarse (18.68 tonnes) fragmentation was 0.60 tonnes, corresponding to an Fe-grade difference of 4.5 percentage units. The highest payload difference between the fine and the coarse fragmentation (1.81 tonnes) resulted in an Fe-grade difference of 13.5 percentage units. For the dynamic loading control model, i.e., an economic model for optimising loading control at the draw points, the differences observed between the fragmentation categories would have a significant impact on loading control, for example, the fixed shut-off grade for closing a ring.

These previous studies from Tonvall [70] and Manzoor et al. [69] used data from 2013-2014 and were based on fewer buckets. In addition, the mean payload values observed for the different fragmentation categories of 21-tonne LHDs were considerably higher than the mean values of 17.09 tonnes observed for 21-tonne semi-autonomous LHDs and 17.43 tonnes observed for 21-tonne manual LHDs in the current study.

In the Kiirunavaara mine, the fragmentation, despite an identical blast design, varies in the northern and southern parts of the mine. According to the underground production personnel, the fragmentation in the northern blocks (B8-B16) is mostly fine, and the fragmentation in the southern blocks (B30-B41) is comparatively coarser. Therefore, to understand the differences in payload due to fragmentation, the payload was compared for both machine types across the northern and southern regions. Block B22 was excluded from analysis because it had various operational challenges, and these might have affected the comparison.

Figure 20 is a box plot showing the overall payloads of manual and semi-autonomous LHDs in both regions. The difference between the machine types in both regions was as small as 0.2 tonnes per bucket when comparing the medians. The regional differences, however, were significantly higher. The median payload was approximately 0.6 tonnes higher for the manual LHDs in the northern blocks than in the southern blocks and about 1 tonne higher for the semi-autonomous LHDs. This corresponds to an Fe-grade difference of 4.5 percentage units for the manual LHDs and an Fe-grade difference of 7.5 percentage units for the semi-autonomous LHDs.

The payload differences in the different regions for semi-autonomous and manual LHDs due to different assumed fragmentation were consistent with the values reported by Manzoor et al. [69].

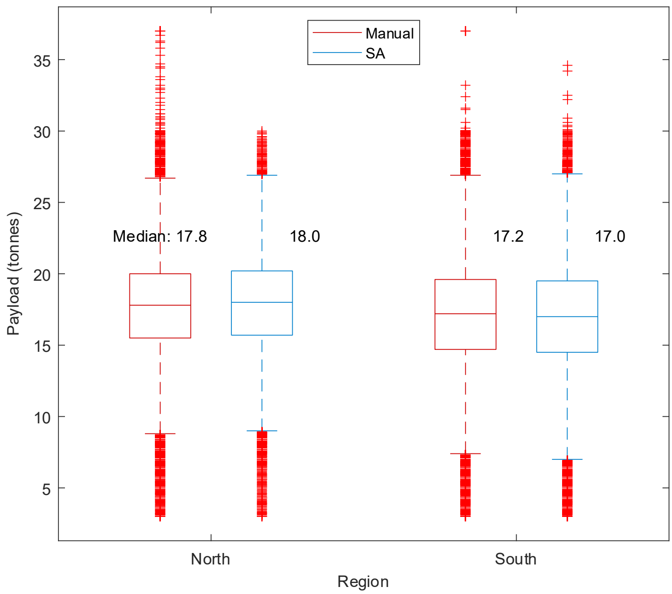

Figure 20: Payload comparison across northern and southern regions

5.5.1.2 **Impact of other factors**

Tonvall [70] and Manzoor et al. [69] highlighted the payload differences for the different fragmentation classes and the non-linear relationship in the grade equation given in Section 2.1. The Fe-grade values calculated by the non-linear relationship were higher than those calculated by the linear equation. However, it also varied depending on the bucket weight and the machine type. Depending on the bucket weight, the Fe-grade varied from 2-10 percentage units for 21-tonne LHDs and 1-6 percentage units for 25-tonne LHDs. For example, for 21-tonne LHDs, if the bucket weight was 14 tonnes, the difference in Fe-grade was 2 percentage units, and when the bucket weight was 18 tonnes, the difference was 10 percentage units. Manzoor et al. [69] also highlighted the issues of moisture content and the use of a constant magnetite grade for individual rings. However, the sensitivity of these parameters on the Fe-grade calculation were not studied by Manzoor et al. [69]. The system also used fixed values when calculating the WBw (bucket with 100% waste) and OBw (bucket with 100% ore) for both 21-tonne and 25-tonne LHDs.

5.5.2 Sensitivity analysis

To understand the impact of various input parameters on the density-based Fe-grade calculation used in the mine for both 21-tonne and 25-tonne LHDs, this study used a range of input values and calculated the sensitivity coefficient of each parameter to the variance in the model output. A global sensitivity analysis using Latin hypercube sampling was conducted in three scenarios, with the generated samples used as inputs to subsequent Sobol and Kucherenko sensitivity analyses.

5.5.2.1 **Sobol sensitivity analysis**

Scenarios 1 and 2 did not consider the dependency of parameters, and the Sobol analysis was performed with the assumption that all input parameters were independent. The first order index showed the individual effect of an input parameter on the output variance. Scenario 1 showed the highest first order index of the bucket weight, accounting for 56% of the output variance for 21-tonne LHDs and 46% of the output variance for 25-tonne LHDs. The bucket weight was followed by the void ratio, which accounted for 19.6% of the output variance for 21-tonne LHDs and 23% of the output variance for 25-tonne LHDs. This was followed by the fill factor, which contributed to 16.8% of the output variance for 21-tonne LHDs and 19.7% of the output variance for 25-tonne LHDs. Similarly, bucket volume explained 6.4% of the output variance for 25-tonne LHDs and 2.1% of the output variance for 21-tonne LHDs. The remaining parameters were waste density, ore density, and ore grade; these had negligible impacts on the output variance, accounting for less than 1% of the total variance. The results for all the input parameters for scenario 1 are summarised in Table 11, and the first order and total order indices for 21-tonne and 25-tonne LHDs are graphically shown in Figure 21a and Figure 21b.

Table 11: First order and total order Sobol indices for 21-tonne (mean 20t, std 3) and 25-tonne (mean 24, std 3) LHDs in scenario 1

Input Parameter	First Order (S_1)		Total Order (S_T)	
	21-tonne	25-tonne	21-tonne	25-tonne
Bucket weight (Bw)	0.563	0.455	0.601	0.485
Fill factor (Ff)	0.168	0.200	0.192	0.221
Void ratio (Vr)	0.196	0.233	0.223	0.256
Volume of bucket (Vb)	0.021	0.064	0.026	0.073
Waste density (W)	0.002	0.002	0.002	0.002
Ore density (O)	0.006	0.007	0.008	0.009
Ore grade (G)	0.006	0.007	0.008	0.009

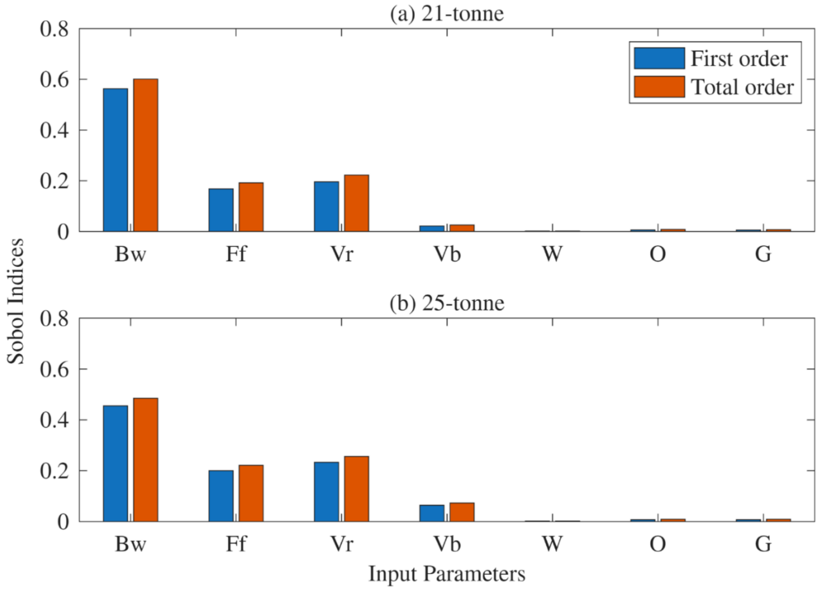

Figure 21: First order and total Sobol indices for 21 tonne LHDs in scenario 1

The total order indices account for the combined effect of all the input parameters. This encompasses the first order effect of an input parameter and its interaction with all the other input parameters. Therefore, theoretically, it has higher values for the same set of input variables. In this case, the total indices were slightly higher for all the input parameters than for the first order indices (see Table 11). Moreover, the ranking of the parameters for the total order indices was the same as the one observed for the first order indices for both LHD types (see Figure 21a, 21b).

To investigate whether the actual payload observed in the mine for both machine types had any impact on the sensitivity of the model, this study used Sobol analysis for both machine types in scenario 2, assuming the actual payloads were 3 tonnes and 3.5 tonnes less than the rated capacity for 21-tonne and 25-tonne LHDs, respectively. The ranking of the input parameter was not changed when assuming lower payloads for both machine types. In addition, in scenario 1, the total Sobol indices for the bucket weight increased by 4.7 percentage units for 21-tonne LHDs and 3.5 percentage units for 25-tonne LHDs. The first order and the total order indices increased for bucket weight in scenario 2. However, the opposite was observed for void ratio and fill factor. Table 12 gives the summary of the first order and the total order Sobol indices for each of the input parameters in scenario 2.

Table 12: First order and total order Sobol indices for 21-tonne (mean 17.5t, std 3) and 25-tonne (mean 22, std 3) LHD in scenario 2

Input Parameter	First Order (S_1)		Total Order (S_T)	
	21-tonne	25-tonne	21-tonne	25-tonne
Bucket weight (Bw)	0.596	0.484	0.648	0.520
Fill factor (Ff)	0.149	0.187	0.177	0.208
Void ratio (Vr)	0.173	0.218	0.206	0.242
Volume of bucket (Vb)	0.019	0.060	0.024	0.069
Waste density (W)	0.002	0.003	0.003	0.003
Ore density (O)	0.007	0.005	0.006	0.007
Ore grade (G)	0.007	0.005	0.006	0.007

5.5.2.2 **Kucherenko sensitivity analysis**

The Sobol sensitivity analysis performed for scenario 1 and scenario 2 did not consider the dependence of one parameter on another. However, these input parameters are not independent. For example, coarser material has a lower bucket weight because it has a higher void ratio and a lower fill factor. Therefore, in scenario 3, the dependence among different variables was defined using a Gaussian copula model. The copula parameter between bucket weight and void ratio was -0.8, while the dependence between bucket weight and fill factor was defined using a copula parameter of 0.8. Similarly, the dependence between fill factor and void ratio was defined using a copula parameter of -0.8.

After considering the marginal distributions for all the input parameters and defining their dependencies, sensitivity analysis was performed using Kucherenko indices. The first and the total order Kucherenko indices for 21-tonne and 25-

tonne LHDs are summarised in Table 13 and graphically shown in Figure 22a and Figure 22b.

Table 13: First order and total order Kucherenko indices for 21-tonne (mean 20t, std 3) and 25-tonne (mean 24t, std 3) LHDs in scenario 3

Input Parameter	First Order (K_1)		Total Order (K_T)	
	21-tonne	25-tonne	21-tonne	25-tonne
Bucket weight (Bw)	0.092	0.060	0.742	0.533
Fill factor (Ff)	0.177	0.361	0.229	0.238
Void ratio (Vr)	0.190	0.380	0.266	0.277
Volume of bucket (Vb)	0.001	0.001	0.001	0.001
Waste density (W)	0.007	0.007	0.008	0.001
Ore density (O)	0.006	0.006	0.007	0.006
Ore grade (G)	0.021	0.021	0.023	0.020

As observed in Table 13, after defining dependencies among the input parameters, the highest first order Kucherenko index was for the void ratio; it accounted for 19% of the output variance for 21-tonne LHDs and 38% of the output variance for 25-tonne LHDs. The void ratio was followed by fill factor, which accounted for 17.7% of the output variance for 21-tonne LHDs and 36% of the output variance for 25-tonne LHDs. Unlike scenarios 1 and 2, bucket weight had significantly lower first order values and accounted for less than 10% of the output variance for both LHD types. The remaining parameters, volume of bucket, waste density, ore density, and ore grade, similarly had negligible impact and accounted for less than 5% of the total output variance for both LHD types.

For the total Kucherenko indices, the input parameters (bucket weight, void ratio, and fill factor) followed the same sequence observed in scenarios 1 and 2 for 21-tonne and 25-tonne LHDs. The total order Kucherenko index for 21-tonne and 25-tonne LHDs showed the highest Kucherenko index values, despite a significantly lower first order index for bucket weight. The total output variance by bucket weight for 21-tonne LHDs was 74%, and 53% for 25-tonne LHDs (see Figure 22). This was followed by the void ratio, accounting for 27% of the total output variance for 21-tonne LHDs and 28% of the variance for 25-tonne LHDs. Similarly, the fill factor contributed to 23% of the total output variance for 21-tonne LHDs and 24% of the variance for 25-tonne LHDs. The remaining input parameters shared less than 5% of the total output variance.

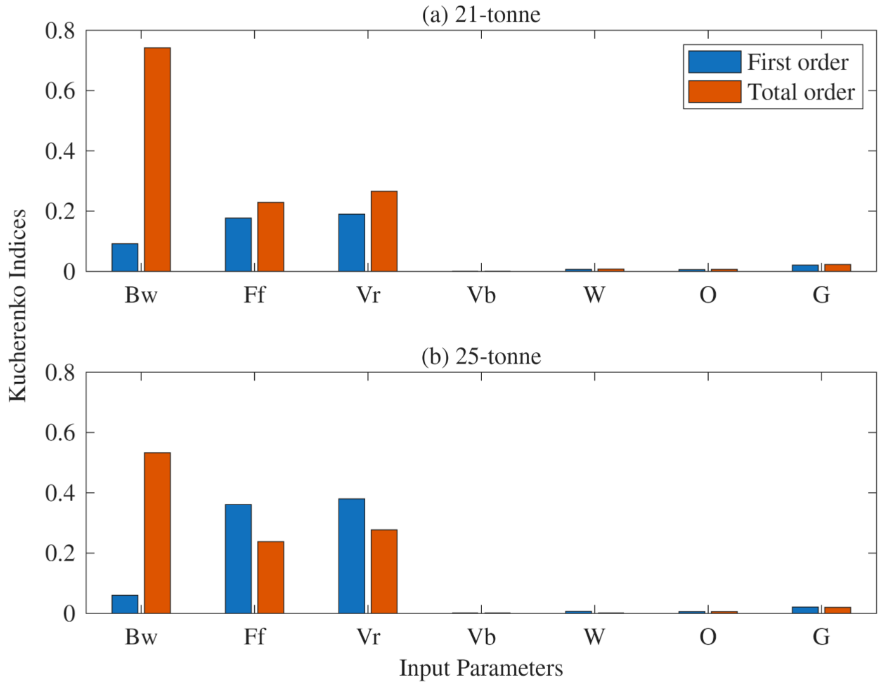

Figure 22: First order and total Kucherenko indices for 21-tonne and 25-tonne LHDs in scenario 3

Overall, for all scenarios, two using Sobol analysis and one using Kucherenko analysis, irrespective of the method and the input values, the bucket weight had the highest total order sensitivity index. This was followed by the void ratio and the fill factor with comparable sensitivity indices. Other input parameters had negligible impact on the output variance. However, the index values differed slightly based on the machine type. For example, the sensitivity indices for the void ratio and the fill factor were slightly higher for 25-tonne LHDs than for 21-tonne LHDs, while the bucket weight was slightly lower. Therefore, arguably, the void ratio and the fill factor would have an even greater impact on the output variance of 25-tonne LHDs than 21-tonne LHDs. All in all, the density-based Fe-grade control would be significantly influenced by the fragmentation classes if the values of the void ratio and the fill factor were significantly different. However, if the differences were not significant, using average values would still give values very comparable to reality. Bucket filling is an operational issue [90] and could be influenced by the skills of the operators and other factors, making it difficult to quantify merely on the basis of the fragmentation classes.

The utilisation of the density-based Fe-grade estimation and its application as an operational tool, together with the dynamic loading control to achieve the maximum recovery and the minimum dilution, is an important tool for the mine. Therefore, the sensitivity of the input parameters highlights the need for updating these models based on different fragmentation categories. However, involving operators to decide the fragmentation of the bucket at the operational level is very subjective and could be prone to significant errors. Similarly, the chaotic nature of the material flow in SLC operation does not allow oversimplification using finer to coarser fragmentation with increasing extraction ratios. Therefore, automated fragmentation classification and the use of bucket scanning are recommended to increase the accuracy of density-based Fe-grade calculation. However, even when using automated processes to increase accuracy, operators are an integral part of the process and are the end users of these tools. Therefore, the education and training of LHD operators is very important in understanding and improving these models.

5.6 Operator education and competencies

LHD operators are central to the current loading operation at LKAB. Over the years, LHD operators have been part of the transformation of the loading operation through digitalisation and automation. Their role has changed from visual inspection of ore and the experiential judgement of bucket filling, based on the interaction between the bucket and muckpile, to data-driven decision making using onboard measurement systems. These systems provide operators with feedback to monitor dilution and make objective decisions regarding the closure of a ring. While the subjectivity of operators has been reduced with automation and digitalisation, challenges remain in operational efficiency based on the skills and knowledge of the operators.

5.6.1 Regulatory framework

Operator skill and knowledge remain important for the performance of the machines [33,34] and the efficiency of the loading operation [77]. LHDs have been in underground operations since the early 1960s, and regulatory frameworks have been put in place in various countries to ensure safety, standardise basic skill levels, and increase the efficiency of operators and machines. This study assessed the regulatory framework in different countries and found that many countries including South Africa, Australia, India, and New Zealand (among others), have regulations specific to manual LHDs, but only South Africa, Australia, and Canada have specific regulations for remote (semi-autonomous) LHDs. Although the regulations are quite general and specific to some countries, they are useful for devising an effective training programme or validating the content of existing training initiatives. Therefore, they were compared with the training programme at LKAB.

5.6.2 Operator training at LKAB

Using a baseline mapping approach, the details and structure of the training programme were determined from the training materials and from interviews with instructors and personnel involved in the training. The normal training programme for LHD operators at LKAB lasts 10-11 weeks and does not differ considerably for manual and semi-autonomous LHD operators. The training starts with a theoretical part, followed by a visit to the subprocesses, practical training, and finally an evaluation. These details of the training programme were affirmed by LHD operators' responses to the survey. Operators were asked about the parts included in their training, and their responses were categorised based on how long ago the training occurred (see Figure 23).

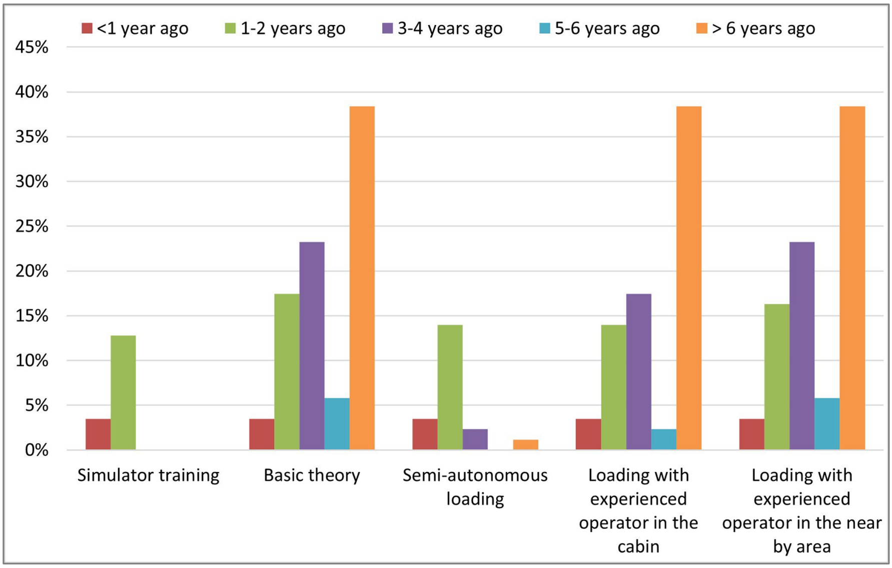

Figure 23: Parts included in the LHD operator training based on how long ago the training occurred

5.6.2.1 **Theoretical part**

Over the years, the training was consistent in including both a theoretical part and a practical part. The theoretical part of the training comprised 11 modules and covered a wide range of topics related to different mining operations, SLC method, organisational structure, loading operation, maintenance, and driving style. The duration of the theoretical training, however, was approximately 4-8 h, considerably different from some of the regulations. For example, the South African Qualification Authority (SAQA) [148] specifies a mandatory 12 h classroom-based teaching for diesel, electric, and remote LHDs. Similarly, in India, a compulsory 110h classroom-based programme is regulated by India's National Skills Qualification Authority (NSQA) [149]. The duration of the theoretical part seemed short to cover the content of the 11 modules. Moreover, the responses from the survey showed duration was inconsistent (2-5 days for the majority) compared to what was observed during the baseline mapping (4-8 h), when the people responsible for training were interviewed. Since the theoretical part was followed by visits to the sub-processes, the operators may have added that part to the theory.

5.6.2.2 **Practical part**

Overall, the mine focused more on the practical part and learning from experienced operators. The practical part of the training consisted of loading under the guidance of a senior operator either in the same cabin or in a nearby area. The operators drove in a special training area for 1-2 weeks followed by training in production areas with mentors for 7-8 weeks. Simulators, which were the initial part of the practical training, were a recent addition in 2019, something affirmed by the operators (see Figure 23). All the operators who used simulators in their training had taken the training less than two years previously.

5.6.2.3 **Simulator training**

Simulators were used for control familiarisation and practice of scenarios of mining operations which were difficult or dangerous to perform, such as hazard avoidance, brake testing, manoeuvring in sharp turns, truck loading etc. The mining industry is not as mature as other industries in utilising simulators in training. Even the simulator companies lack scenarios such as road maintenance, boulder handling etc., which some operators considered difficult tasks to learn. The curriculum for the simulator training varies from mine to mine. Although some companies have successfully integrated the system into their training, others have not. This study reviewed the training simulators for LHDs offered by various commercial simulator companies. It was observed that the simulator training programme at the studied mine had some shortcomings compared to commercial companies.

Simulator training was not very efficiently utilised at the Kiirunavaara mine and has not been upgraded at a pace consistent with the improvement of technology. It only focused on driving and control familiarisation. This was also evident from the responses of the 16% of the operators who took the simulator training. All operators were asked what parts of the training they found difficult. They could choose multiple options. The difficulty associated with simulator training was mentioned by 36% of the respondents (as shown in Figure 24). This could be attributed to the poorly developed instructional design and cognitive overload. Additionally, the simulator graphics mainly represented surface operations and did not effectively simulate realistic underground loading scenarios. The level of difficulty also varied depending on the type of machine the operator was assigned to; 80% of the operators who found the simulator training difficult were the operators of manual LHDs, and 20% were the operators of semi-autonomous LHDs.

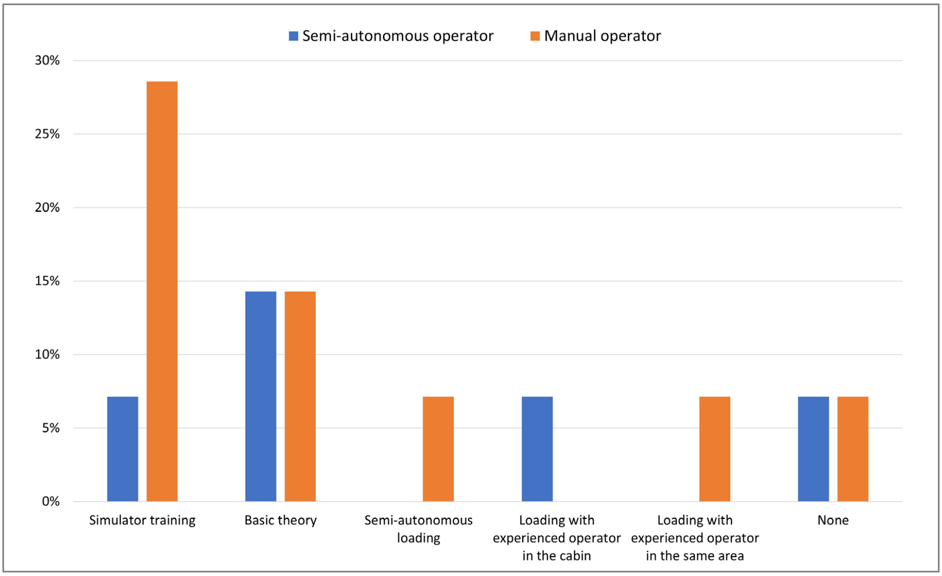

Figure 24: What part of operator training was difficult?

5.6.2.4 **Evaluation**

Evaluation is an important tool in training and is considered a good measure of training effectiveness. Using valid instruments to assess the competencies of trainees upon completion of training increases the effectiveness of a training programme [150]. It is important to note that at LKAB, tonnage is used as the sole criterion for measuring the performance of LHD operators. The tonnage difference between an experienced operator and a new operator could be in the range of 2000-2500 tonnes per shift. Therefore, training is an integral part of the operators' skill development.

5.6.2.5 **Refresher training**

The regulations in USA and Canada recommend refresher training to keep operators up to date and refresh their knowledge. This was also highlighted by the operators in this study. Refresher training is not currently part of the training for the studied mine. However, operators receive some form of additional training upon the introduction of a new technique or whenever a new machine is added to the fleet. According to the survey results, approximately one-third of the operators had received some form of retraining, while 91% desired such training.

5.6.2.6 **Operator feedback**

An effective training programme should constantly seek constructive feedback to enhance its methodologies and processes to achieve its objectives, including different ways of using the same resources [151]. Overall, the majority of the operators expressed general satisfaction with the training duration, training structure, class size, and practical application of the training. They agreed that they had enough opportunities to learn from experienced operators. However, there were some disagreements about the organisation of the training and its coverage of the knowledge needed for loading underground. Despite the overall satisfaction with the training, the LHD operators wanted some improvements, such as additional practical loading, visits to external departments, and training in areas like rock mechanics, truck loading, road maintenance, boulder handling, etc.

5.6.3 Future skills and competencies

LHD operators and production workers were asked about the skill sets they thought would be needed by future miners. Production workers pointed out basic computer skills, along with the need for some cutting-edge competencies such as automation, networks, IT, and electrification due to the increasing complexity of the machines and processes. LHD operators were given an open-ended question; 66% of the operators responded, but approximately 30% remained neutral in their answer, responding either "no idea" or "no comment" (Figure 25). Data or digital literacy (28%) was most frequently mentioned by LHD operators as a future skill. This was followed by manual loading (9%). Many believed that despite driving semi-autonomous LHDs, future operators would need to have manual loading skills; this would enable them to have the real feel of the rock and thus increase their understanding of the loading process and mining operation. Production workers also said "knowledge of the rock" would remain important in the future. Manual loading was followed by semi-autonomous loading (8%), knowledge of the mine (5%), understanding of how the rock behaves at different depths, that is, rock mechanics (4%), and building interest in their job and social skills (3% each). The production workers placed greater emphasis on social skills than the LHD operators. They highlighted the increased need for communication, cooperation and collaboration among groups. The LHD operators also mentioned some other issues, categorised as Others (11%); these included safety at deeper levels, learning for the future, trusting technology, and sharing knowledge. Some operators thought future operators would need the same skill set as current operators needed. Production workers suggested the necessity for future workers to possess effective listening skills, strong analytical and problem-solving skills, adaptability to change, and a willingness to learn and share knowledge.

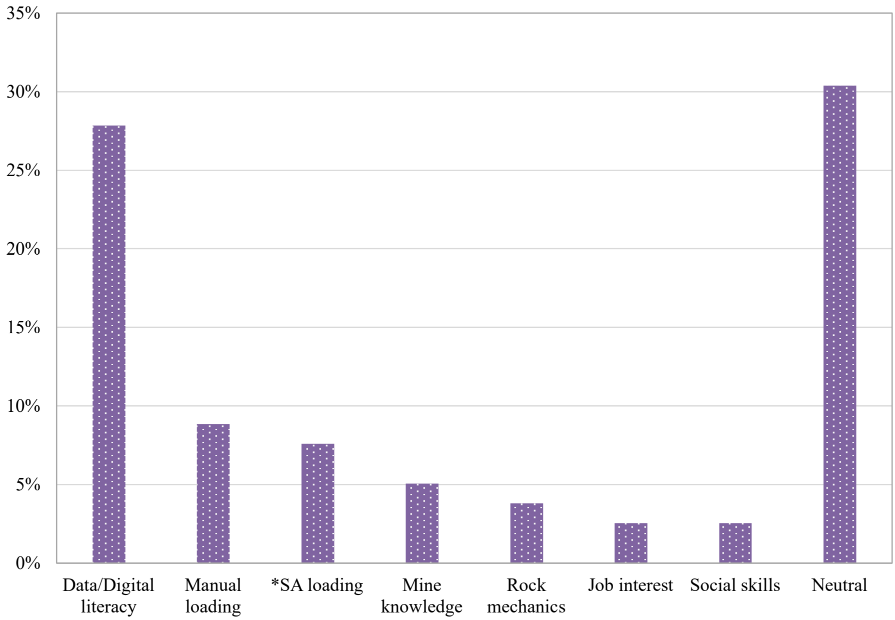

*Figure 25: What new skills will the future operators require? (*SA-semi-autonomous)*

6 CONCLUSIONS

LHDs are an integral part of underground mine production and grade control. Automation and digitalisation are at the centre of recent technological advancements, changing conventional mining practices in general and LHD operations in particular. Therefore, it is increasingly important to understand how these developments impact the overall performance of these machines and the current density-based Fe-grade calculation models.

Research Question 1: How will increased digitalisation and automation impact future LHD operations?

The exploratory research in this thesis identified that automation and digitalisation have transformed and will continue to shape LHD operations. The largest share of LHD operators (34%) anticipated increased transition towards semi-autonomous LHD operations. The majority of production workers foresaw a transition in their roles from predominantly physical jobs to tasks requiring supervision, diagnostics, maintenance of production systems, and problem-solving related to automation and digitalisation. However, despite the anticipated transition towards automation by the largest share of LHD operators and production workers, both expected machine maintenance would remain the most challenging task to automate in future. It is important to mention that the top three activities considered difficult to automate by LHD operators – machine maintenance (29%), road maintenance (22%), and bucket filling (20%) – are all an integral part of today's manual LHD operation, thus highlighting the continuing role of operators in future LHD operations. However, even though LHD operators and production workers had a generally positive perception about automation and digitalisation, they expressed concerns that future operators and production workers may have less practical experience due to automation and digitalisation, potentially leading to reduced knowledge and understanding of the overall mining operation.

Research Question 2: How does the production differ for semi-autonomous and manual LHDs in an SLC operation?

The results of the analysis of the payload difference of semi-autonomous and manual LHDs, based on approximately 1.4 million loading cycles from Kiirunavaara mine for both types of machines, showed the average payload difference was as low as 0.34 tonnes per bucket, and the median payload difference was 0.30 tonnes per bucket in favour of manual 21-tonne LHDs. However, despite the overall average difference favouring manual LHDs, the payloads for semi-autonomous and manual machines were not consistent; they varied within and between different mining blocks. Similarly, the comparison of the cycle times of manual and semi-autonomous LHDs was inconclusive. In 13 (57%) out of the 23 selected areas, the median cycle time of manual LHDs was lower than that of semi-autonomous LHDs. In the remaining 10 (43%) selected areas, the opposite was observed. The differences in cycle times due to mode of operation were therefore inconsistent, indicating neither machine type consistently outperformed the other. The inconclusiveness highlights the complexity of mining operations and the impact of external factors. For example, the longer dumping duration for semi-autonomous LHDs could potentially be explained by the occurrence of boulders, which increases the waiting time at the ore pass and the time required for semi-autonomous operators to switch from controlling LHDs to rock breakers or vice versa.

Research Question 3: What are the challenges and limitations of density-based Fe-grade calculations? How does the output of the density-based Fe-grade formula vary in response to changes in its input parameters?

The density-based Fe-grade calculation methods that utilise the significant difference between the densities of ore and waste are constrained by the use of constant values for some of the input parameters. For example, the void ratio depends on the fragmentation of the material. Similarly, fill factor depends on both fragmentation size and operational conditions. Finally, calculating the Fe-grade using a non-linear equation under-calculates the Fe-grade, whereas increasing the moisture content can lead to over-estimation.

The global sensitivity analysis conducted across three scenarios showed that the bucket weight was the most significant parameter, accounting for the largest share (49-74%) of the total variance. This was followed by void ratio and fill factor, which together accounted for up to 52% of the total variance. The total variance was slightly higher for 25-tonne LHDs than for 21-tonne ones. Other parameters such as bucket volume, waste density, ore density, and ore grade, explained a negligible (<10%) share of the total variance. Therefore, in operation, balanced attention to all three parameters – bucket weight, void ratio, and fill factor – is recommended to improve the accuracy of the model and reduce uncertainty.

Additionally, while the sensitivity profiles were similar in terms of sequence of responses to the input parameters for both 21-tonne and 25-tonne LHDs. However, due to the slightly greater impact of void ratio and fill factor on 25-

tonne LHDs, the sensitivity profiles were not directly transferable between the two machine types. The input values should therefore be calculated separately for each LHD type.

Research Question 4: How can operators' training and education be improved to facilitate automation?

LHD operators have played an important part in transforming the loading operation through automation and digitalisation, but given the complexity and diversity of mining operations, the development of standardised education and training programmes across the mining industry is difficult and uncommon. The current LHD operator training studied in this research included theoretical instructions, practical training, and simulator-based learning. However, the efficient utilisation of simulators for training in the mining industry is not as advanced as in other industries. Simulator companies do not include scenarios such as road maintenance, boulder handling, etc. which are considered difficult by LHD operators. Present training programmes do not incorporate the pedagogical principles necessary for effective training curriculum development. Additionally, the duration of the theoretical part is not consistent across countries.

To facilitate automation, operator training needs to be updated in line with technological development. The current training programmes need to include pedagogical principles when developing their curriculum. The effectiveness of simulator-based learning could be improved further by tailoring it to the needs of individual mines and including scenarios that operators consider difficult to master. Finally, to ensure the training remains updated and consistent, mines should establish standards and guidelines for instructors and trainees, supported by ongoing feedback from all stakeholders.

7 FUTURE RESEARCH

The research identified some key factors related to LHD productivity, loading efficiency, and density-based Fe-grade calculation that need to be addressed in future research.

- **Impact of fragmentation size on payload and density-based Fe-grade calculation model**

Fragmentation is an important parameter when measuring the performance of SLC operations. The current literature on the impact of different fragment sizes on the payload and on density-based Fe-grade calculation is limited. Future research should focus on quantifying the values of void ratio and fill factor for different fragment sizes. Field tests using bucket scanning and image classification would help measure the void ratio and fill factor for different fragmentations to determine the payload differences due to fragmentation. The Fe-grade calculation could also be improved by using accurate void ratio and fill factor values for different fragmentation sizes.

Moreover, the global sensitivity analysis of the density-based Fe-grade model showed that the void ratio and the fill factor share higher variance for 25-tonne LHDs than for 21-tonne LHDs. Therefore, future research should focus on the differences between machine capacities, which may be influenced by fragmentation, breakout forces, and power sources.

- **Comparison of density-based Fe-grade calculation methods**

Scanning-based methods such as light detection and ranging (LiDAR), photogrammetry, etc. have rapidly advanced and are being integrated more into mining operations because of improvements in sensors, automation, real-time data processing, and declining hardware costs. The calculation of Fe-grade using scanning-based methods and its challenges have been highlighted. Future research should compare the density-based Fe-grade calculation methods used at LKAB and RTIT to evaluate the deviation of the estimated Fe-grade from the actual Fe-grade measured in the bucket.

- **Impact of boulder occurrence, road maintenance, and multiple machine control**

This research identified some rare outlier values for speed and dumping duration. The impact of external factors on the productivity of LHDs has been highlighted in the literature. However, the impact of switching from one machine to another (multiple machine control) on the idling time of semi-autonomous LHDs has not been studied. Future research should analyse the impact of these factors on the utilisation and reliability of manual and semi-autonomous LHDs.

- **Future competencies**

There is a consensus in the literature on the impact of operators' skills on the efficiency of loading equipment. However, the literature says little about the new skill sets future LHD operators will need and how training can contribute to improve these skills. Research should try to capture the perspective of all stakeholders to improve existing training programmes for LHD operators.

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