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Evaluation of Homogeneous Exposure Grouping to Estimate Individual Workers' Exposure in South African Gold Mines, 2019–2022

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EVALUATION OF HOMOGENEOUS EXPOSURE GROUPING TO ESTIMATE INDIVIDUAL WORKERS' EXPOSURE IN SOUTH AFRICAN GOLD MINES, 2019-2022

A Research report submitted to the Faculty of Health Science, University of The Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science in Medicine: Exposure Science

Supervisor: Professor Brouwer

Johannesburg, 15 August 2025

DECLARATION

I, **Constance Titi Kekana**, student number 512654, hereby declare that the **Evaluation of Homogeneous exposure grouping to estimate individual workers' exposure in South African gold mines, 2019-2022,** is entirely my own and has not received any outside assistance. I am submitting it for consideration for the degree of Master of Science in Medicine: Exposure Science with a focus on occupational hygiene at the University of the Witwatersrand in Johannesburg. This particular piece of work has not been presented for assessment or certification at any other academic institution before. Any sources from external authors that have been incorporated into this research have been appropriately acknowledged and referenced.



15 August 2025 in Johannesburg

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ABSTRACT

Background: The South African Mining Industry (SAMI) operates under the guidance of the Mine Health and Safety Act, which obligates employers to ensure the health and safety of mine workers. This legislation outlines the need for mining operations to develop and implement a mandatory code of practice (MCoP) to monitor airborne contaminant exposure, assess occupational health risks, and apply suitable control measures. Due to practical and resource constraints, conducting personal exposure monitoring for every worker is not feasible. Therefore, employees are organized into Homogeneous Exposure Groups (HEGs), where it is assumed that individuals performing similar duties in comparable environments are exposed to similar levels of airborne hazards. Exposure estimates for individuals are then based on the average exposure level of the group. However, this grouping method may not account for variations in specific job functions, task-related hazards, behavioral differences, or inconsistent use of protective equipment. Such factors can result in inaccurate exposure estimations, which may compromise the effectiveness of control strategies designed to reduce the risk of overexposure.

Objectives: This study aimed to explore existing literature to identify standard methodologies used in defining HEGs. It also sought to assess how exposure metrics assigned to HEGs align with those of the individual occupations nested in them. Additionally, the research compared individual exposure characteristics with both their respective occupations and associated HEGs over five years, or a shorter duration where data availability was limited.

Methods: This cross-sectional study analysed secondary data from two underground gold mines, focusing on respirable crystalline silica measurements recorded in an electronic database. Exposure data were collected through gravimetric sampling over four years (2019–2022). The study population consisted of individuals whose airborne pollutant exposure measurements were sampled while working in the Stope and Development End areas at different levels in underground mines. Ten HEGs were selected based on consistent exposure measurements and with at least more than two occupations recorded per year throughout the study period.

To evaluate occupational exposure levels, a combination of statistical methods, including Independent t-tests, ANOVA, Welch's ANOVA, Kruskal-Wallis tests, and Linear Mixed Models, was applied to assess variations in exposure within HEGs and across individual workers. Additionally, measures of central tendency (AM, SD, GM, GSD, and 90th percentile) were used to identify exposure trends over time.

Results: Statistical analyses indicate that exposure levels within HEGs were generally comparable across occupational groups, with no statistically significant differences ($p > 0.05$) in most cases. However, some occupational roles, particularly in Stoping activities, exhibited higher exposure variability. Though, some occupational roles, particularly in Stoping activities, exhibited higher exposure variability. However, some HEGs were accurately defined, with exposures generally comparable across occupational groups, whilst others showed clear deviations from expected homogeneity. Stoping activities, in particular, displayed high variability, with certain workers experiencing significantly higher or lower exposures than their HEG classification suggested. Development areas also remained a concern, with exposures in some years approaching or exceeding the RCS occupational exposure limit (OEL). Individual-level analysis revealed notable outliers, reinforcing that group-level estimates can mask extreme exposures. Over the four-year period, exposure patterns fluctuated, with spikes in 2021 and 2022 likely linked to operational or environmental changes. The GM values confirmed right-skewed exposure distributions, indicating that a small proportion of workers bore disproportionately high exposure risks. The 90th percentile metric proved effective in identifying these upper-bound risks. Overall, while HEG classification remains a useful tool, these results show that relying on it alone may lead to under- or overestimation of risks, highlighting the need for targeted individual monitoring, enhanced dust control, and periodic HEG reassessment. Despite overall declining exposure trends, some occupations in the Stoping and Development Ends under the study recorded RCS concentrations which, in certain years, remained close to or exceeded the RCS occupational exposure limit (OEL) of 0.1 mg/m³.

Conclusion: The literature review and statistical findings underscore the significance of accurate HEG classification in occupational exposure assessment, particularly in mining environments. This study confirms that while HEG-based exposure monitoring offers a practical framework for occupational exposure assessment, it is not without limitations. HEGs generally grouped workers with similar exposure profiles; however, individual deviations and temporal fluctuations exposed critical gaps in accurately capturing personal exposure risk. The results advocate for a hybrid approach that combines traditional HEG methodologies with individualized or task-based monitoring to improve exposure classification. Additionally, reliance on AM alone for risk categorization may obscure peak exposures, reinforcing the need to incorporate complementary metrics such as GM, GSD, and the 90th percentile. To ensure worker protection and regulatory compliance, periodic reassessment of HEGs and the integration of real-time monitoring technologies are recommended. These refinements are essential for enhancing exposure estimation accuracy and improving health outcomes in dynamic mining environments.

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ABBREVIATIONS

ANOVA – Analysis of Variance

AQI – Air Quality Index

CIoM – Chief Inspector of Mines

DMRE – Department of Mineral Resources and Energy

HEG – Homogeneous Exposure Group

NaN - Not a Number

JEM – Job Exposure Matrices

MCoP – Mandatory Code of Practice

MHSA – Mine Health and Safety Act No. 29 of 1996

MHSI – Mine Health and Safety Inspectorate

NIOSH – U.S. National Institute of Occupational Safety and Health

OEL – Occupational Exposure Limit

PPM – Parts per million

SA – South African

SAMI – South African Mining Industry

SAMOHP – South African Mines Occupational Hygiene Program

SEG – Similar Exposure Group

TWA – Time Weighted Average

DEFINITIONS

Airborne pollutant – any substance in the air that is harmful to health, including dust, fumes, aerosols, gases, fibres, vapours or mists[1]

Air quality index - an index for reporting daily air quality[2]

Dose: The amount of a substance available for interaction with metabolic processes or biologically significant receptors after crossing the outer boundary of an organism. The potential dose is the amount ingested, inhaled, or applied to the skin[3].

Exposure - a substance or a factor affecting human health, either adversely or beneficially; upon intake into the body, it becomes a dose and is defined as a quantitative estimate of the amount of substance that reaches the subject(s) of interest for a given exposure event[1]

HEG - A group of employees who experience agent exposures similar enough that monitoring the agent exposures of any worker in the group provides data useful for predicting exposures to the remaining workers[4] .

Respirable crystalline silica. Particles smaller than 10 μm in aerodynamic diameter that, when airborne, can be inhaled deep into the lungs and cause serious health issues[5].

Sampling area – an area derived from the breakdown of a mine into a ventilation district or combination of ventilation districts with a common air intake and return, where the return is not used as an intake for another area[6]

SEG - a group of workers having the same general exposure profile for an agent because of the similarity of the materials and processes they use, as well as the way in which they perform tasks[7].

SCOPE OF THE RESEARCH AND STUDY REPORT LAYOUT

This was a cross-sectional study, comprising an analysis of secondary data from the gold mining companies. Electronic personal airborne pollutant exposure concentrations from 2019 to 2022, from companies' reports. Both Mine 1 and 2 provided the records on the airborne pollutant exposure measurements from 2019 to 2022 in an Excel format. The data were analysed using Microsoft Excel, JASP (Jeffreys's Amazing Statistics Program, version 0.19.2), and Tool 2 of EXPOSTATS.

Chapter 1 describes the requirement for the South African Mining Industry (SAMI) to conduct personal exposure assessments and report in accordance with the Mandatory Guideline on airborne pollutants legislated by the Department of Mineral Resources and Energy (DMRE). It provides the study's background, problem statement, and significance and states the research question, aim, and objectives.

Chapter 2 comprises the literature review, synthesising and comparing SEG/HEG methodologies.

Chapter 3 describes the materials and methods used in the study: the study design, study setting, study population, data sources, study variables, and data management and analysis.

Chapter 4 presents the results of the analysis of personal airborne pollutants to silica dust concentrations from 2019 to 2022, as well as the results of the measure of central tendency comparison of silica between the HEG, job title, and individual assessment for the period between 2019 to 2022 on silica dust concentrations.

Chapter 5 covers the interpretation of the findings and discusses the limitations of the study.

Chapter 6 provides recommendations to improve the assessment and reporting of exposure to airborne pollutants, as well as the conclusions.

CHAPTER 1: INTRODUCTION

This chapter provides the context for the research, highlighting the importance of gold mining in South Africa and the associated health risks from airborne pollutants like respirable dust and respirable crystalline silica (RCS). Emphasizing the need for more accurate exposure assessments to better protect workers' health and safety in South Africa's gold mines. It introduces the legislative framework, including the Mine Health and Safety Act (MHSA) and the Mandatory Code of Practice (MCoP), which guides exposure assessments in the mining industry. It discusses the traditional occupational exposure assessments which involve individual sampling, are logistically challenging, leading to the adoption of Homogeneous Exposure Groups (HEGs) as a practical alternative. The effectiveness of the HEG methods and its impact on occupational exposure monitoring outlines the problem statement and significance of the study. It concludes with the research question, aim, and objectives.

1.1 Background

Mining is one of South Africa's most significant economic contributors, with gold mining playing a crucial role. However, it comes with substantial health risks for workers, particularly due to exposure to airborne pollutants like respirable dust (particles less than 10 μm that can access the gas-exchange region of the lungs)[8,9]. Prolonged exposure to these pollutants can lead to occupational diseases, including silicosis and tuberculosis, which are highly prevalent in the mining industry. Ensuring the health and safety of workers in these environments depends heavily on accurate assessments of their exposure to harmful agents through occupational exposure assessments.

Occupational exposure assessments typically involve sampling individual workers to determine the composition and concentration of hazardous substances they are exposed to during their shifts. However, individual sampling presents logistical challenges—it is time-consuming and resource-intensive, requiring significant equipment and skilled personnel. These limitations make it impractical to sample every worker in a mine regularly. As a result, the concept of HEGs was introduced. HEGs categorise employees into groups based on similar exposure risks, allowing a small sample of individuals within the group to represent the exposure levels of the entire group [10].

However, the assumption that all workers within a HEG are exposed to similar levels of hazardous agents does not always hold true. Variations in job roles, work habits, task frequency, and the use of personal protective equipment (PPE) can result in significant

differences in individual exposure levels [7,11]. Consequently, using group averages to estimate individual exposure can either overestimate or underestimate the actual exposure experienced by workers, potentially leading to inadequate protective measures. This misrepresentation challenges occupational health programs aiming to reduce risks and prevent occupational diseases effectively.

1.2 Introduction

The Mine Health and Safety Act (MHSA), Act 29 of 1996 governs the South African Mining Industry (SAMI), focusing on preventing health and safety hazards as its core philosophy and intent. Mining employers bear the responsibility for the health and safety of their employees and are obligated to establish a set of practices that encompass work risk assessments and medical surveillance [12] to achieve zero harm. One of the key tools for ensuring compliance with this act is the Mandatory Code of Practice (MCoP), developed in line with the Chief Inspector of Mines (CIoM) mandatory guideline for an "occupational health programme on personal exposure to airborne pollutants", first issued in 2002 with a supplementary code book "South African Mines Occupational Hygiene Programme" (SAMHOP)[6], and revised and gazetted in 2018[12].

The purpose of the MCoP is to assist employers to assess and document individual exposure, determine the extent of employee risk, to develop interventions to manage and reduce exposure to airborne pollutants (means any substance in the air that is harmful to health, including dust, fumes, aerosols, gases, fibres, vapours or mists)[12]. The MCoP requires that employers implement a system that adheres to the standards outlined in the guideline, ensuring that exposure assessments are carried out consistently across the industry. This systematic approach not only facilitates regulatory compliance but also supports proactive occupational health management through early identification and control of hazards. This structured approach aligns with broader principles of exposure assessment, which emphasise the use of comprehensive methods such as personal monitoring, biological markers, modelling[13] and not only to facilitate regulatory compliance but also to support proactive occupational health management through the early identification and control of hazards. Moreover, empirical evidence shows that workplace interventions, ranging from control measures such as ventilation to behavioural and policy interventions, can meaningfully reduce airborne exposure and related health risks[14], underscoring the practical value of implementing a guideline-driven system like the MCoP

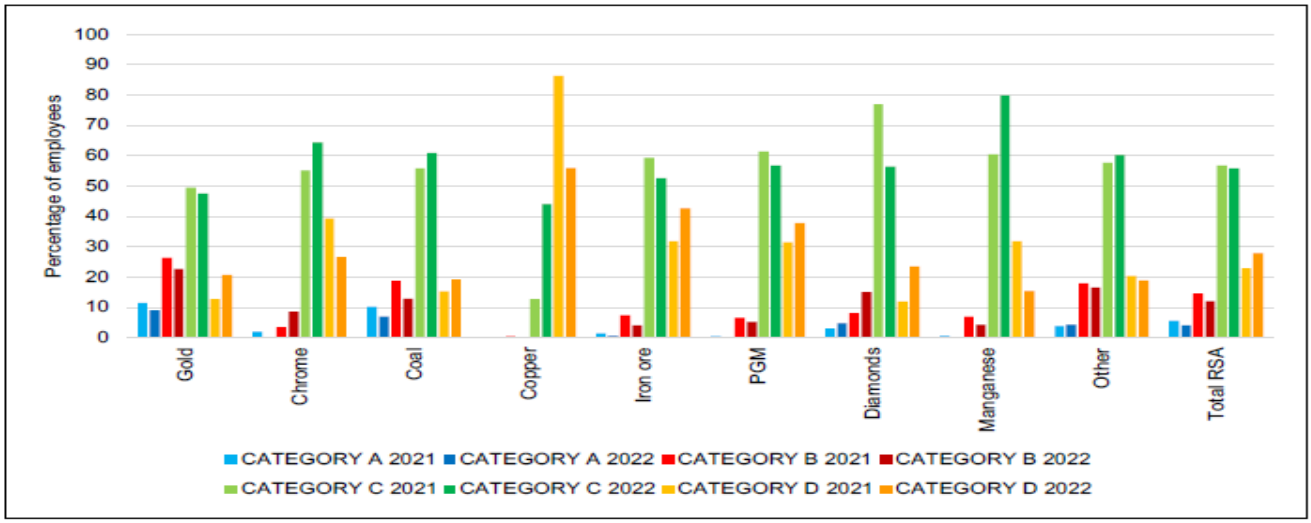
To ensure consistency across similar mining methods and commodities in South Africa, the guideline requires the establishment of HEGs to be standardized. The HEGs are established on the basis that it is currently impossible to measure every worker due to challenges with the availability of adequate equipment and human resources [7,15]. According to the guideline, a HEG comprises employees whose exposure to hazardous agents is sufficiently similar. Monitoring a representative sample can reliably reflect the exposure levels of the entire group[12]. The guideline further recommends a hierarchy for establishing HEGs, for underground mines, similar ventilation districts should be considered, followed by specific activity areas[12]. This approach supports the assumption that workers performing similar tasks, such as Stoping or Development, within the same ventilation area are likely to have comparable exposure profiles. As a result, the exposure risk profile of employees is only determined through the exposure measurements obtained within HEGs, and the differences in tasks among workers with the same job title are not considered.

To ensure representativeness in personal exposure monitoring within a HEG, the guideline requires that at least five (5) samples, or five percent (5%) of the total employees in each HEG, must be taken. The sampling must be spread randomly across all occupations within the HEG[12]. Personal exposure measurements are taken quarterly for high-risk workers (Category A: exposure levels ≥ Occupational Exposure Limit (OEL)), bi-annually for medium-risk workers (Category B: exposure levels ≥ 50% of the OEL and < OEL)[12], and annually for low-risk workers (Category C: exposure levels ≥ 10% and < 50% of the OEL). However, sampling measurements should be evenly spread out from January to December to report results every quarter of all categories to the Department of Minerals Resources Energy (DMRE).

The guideline classifies HEGs into categories A, B, or C by determining and comparing the 90th percentile concentration of airborne pollutants to the respective OELs. Both the arithmetic mean (AM) and the 90th percentile of the 8-hour time-weighted average (TWA) must fall within the same category for the classification to be statistically valid[12]. In cases where workers are exposed to multiple airborne pollutants, an Air Quality Index (AQI) is calculated, compared to an OEL of 1 (unitless as a ratio) and used to classify the HEG[12]. Then, the AM of the exposure measurements of an HEG is then required to be allocated to all individual employees within the HEG, representing exposure-dose relationships allocated to employees' medical surveillance records[12]. This approach overlooks variations in job roles within different occupations, including the inherent risks associated with specific tasks, work practices, and the

utilization of personal protective equipment. These classifications help determine the level of risk the employees face and the necessary interventions required.

Despite the guidance of legislative framework and enforcement mechanisms such as inspection, audits, and statutory reporting on compliance in place to assess and monitor occupational exposure to airborne pollutants in SAMI, occupational lung diseases persist among miners from prolonged exposure to respirable dust [16]. According to Global Data, South Africa is the world's eighth-largest producer of gold[17], employing almost 87 478 gold mine workers from a total of 443 367 mine employee's population[18]. As presented by the DMRE 2022 annual report in Figure 1 below on airborne pollutant exposure measurements per commodity, the gold commodity indicates the highest percentage of 11,40 % overexposures to airborne pollutants from 353142 of the population at risk, as compared to other commodities[18]compared to other commodities[18].



Exposure category band:
A = Exposures ≥ the OEL or mixture of exposures ≥ 1
B = 50% of the OEL ≤ exposures < OEL or 0.5 ≤ mixtures of exposures < 1
C = 10% of the OEL ≤ exposures < 50% of the OEL or 0.1 ≤ mixtures of exposures < 0.5
D = Exposures < 10% of the OEL or mixtures of exposures < 0.1

Figure 1: Percentage of HEGs falling into categories A, B, C and by commodity[18]

Mining and Dust Exposure

In mining and mineral processing operations, various activities such as crushing, grinding, and drilling release substantial amounts of dust into the air, exposing workers to hazardous levels of airborne particulates. In South Africa, gold mining operations are known to produce respirable dust often containing crystalline silica known to cause silicosis, an irreversible and often fatal lung disease. The silica content in this dust varies significantly across different mining sectors, with gold mines exhibiting silica dust concentrations ranging from 5% to 57%,

while diamond and coal mines register approximately 5%, and platinum mines less than 0.2% [15,19,20]. The quantity of dust generated during mining operations is significantly affected by the strength of activities involved in the mining process, and additionally, the silica composition within this dust is determined by geological variables present in various segments of the ore body. This means that both the mining techniques used, such as drilling, blasting, and ore processing, and the inherent geological characteristics of the mining site play crucial roles in shaping the dust's quantity and quality[19].

Exposure to RCS is a concern for miners due to causing silicosis and increasing the risk of developing Tuberculosis. The MHSA mandates that exposure to quartz (the most common form of silica) should be kept below 0.1 mg/m³ over an 8-hour work shift[21]. However, despite these regulations, cases of silicosis and other occupational lung diseases remain prevalent in the mining industry, particularly in gold mines. In 2022 alone, 218 cases of silicosis were recorded in the gold sector[18]. Given these statistics and the persistent health risks associated with respirable dust, particularly exposure to RCS dust, this study focused on evaluating the HEG approach in South African gold mines. By analysing the exposure levels of workers and comparing them to HEG averages, this research aims to assess the effectiveness of the current exposure monitoring methods and identify potential discrepancies in individual worker exposure within HEGs.

Conclusion

This research was conducted to provide a comprehensive evaluation of the HEG determination method used in South African gold mines, with a specific focus on respirable dust exposure, particularly RCS. The primary goal was to assess any significant differences in exposure levels across groups and individuals and offer insights into improving occupational exposure assessments within the mining industry. The research aimed to assess the determination of HEGs within the mining industry. This involved a detailed examination of HEGs' exposure parameters—such as central tendencies and measures of distribution—and their comparison with those of the constituent occupations and individual exposure measurements.

As Burdorf and van Tongeren[11] emphasize, that precise estimates of employee exposure levels are crucial in workplace safety strategies. These estimates help identify sources and activities that contribute to the highest exposure risks, thereby allowing for a better characterization of the exposure distribution of employees at risk. Such data is instrumental not only in developing effective mitigation strategies but also in managing the health risks posed by pollutants.

Reliable exposure data also support the evaluation of specific pollutants and implementing appropriate control measures to protect worker health.

1.3 Problem statement

Personal sampling programme of individuals exposed to airborne pollutants in a workplace poses significant challenges, in that it is impractical to assess the personal exposure of every single employee due to inadequate resources from sampling equipment to manpower. It is for this reason, that the employee population is divided into HEGs, as suggested by research studies that a potential solution is to categorize employees into groups based on their tasks and exposure environment [22,23]. Within each group, a random selection of an employee can be sampled, with the obtained results representing individuals within the group[12].

However, in SAMI the establishment of the HEGs, assumes that grouping of employees performing similar tasks will result in a similar exposure profile[12]. As a result, each employee's exposure/dose allocation is estimated using the average value within their HEG. This process overlooks the differences in occupations/job titles with the inherent risks of tasks being performed, work habits, and use of PPE.

These may lead to over-under estimating exposure results allocated to individuals within a HEG and thus limiting targeted interventions to reduce the risks[15].

1.4 Significance of the study

The allocation of individual exposure is crucial for developing and implementing the efficacy of assessing and monitoring programs in occupational health programs. Accurate exposure allocation enables the prevention of occupational diseases by identifying occupations/employees at risk and implementing appropriate targeted preventive strategies.

This study aimed to address the challenges of HEG's determination approach and estimating exposure levels including classification of employees into appropriate categories, to enhance the monitoring programs, and to reduce employee exposure to respirable dust.

The research will provide valuable insights and contribute to decision-making on regulatory guidance and developing robust strategies for individualized monitoring and protection against airborne pollutants in hazardous work environments at mines.

1.5 Research question

Can identifying a HEG and allocating its exposure measurements facilitate an accurate estimation of an individual worker's exposure or dose in a South African gold mine?

1.6 Research aim

This study explored potential HEG measurement outcomes when assigned to different occupations and individual workers within the same HEG in a South African gold mine.

1.7 Objectives

1. To review the literature and identify methodologies commonly utilized for establishing a HEG.
2. To compare HEGs' exposure parameters with those of their constituent occupations over the four (4)-years.
3. To compare individual exposure parameters with those of their occupations and the allocated HEGs over the four (4)-years.

CHAPTER 2: LITERATURE REVIEW

This literature review establishes a comprehensive framework for understanding HEGs and their significance in occupational exposure assessment, particularly within the mining industry. It examines the adverse health effects associated with RCS dust, the principles underlying HEGs, and the reliability and accuracy of grouping workers based on exposure similarities. Additionally, the review critically evaluates international methodologies for HEG establishment, highlighting challenges, limitations, and alternative approaches to improving worker health and safety.

2.1 Occupational Exposure to Airborne Pollutants in Mining

Mining operations expose workers to hazardous airborne substances, including RCS dust, which poses severe health risks. Inhalation of this particulate matter can cause silicosis, a debilitating and often fatal lung disease [24], and has been linked to lung cancer and other respiratory disorders [25,26]. Despite regulatory interventions, silicosis remains a persistent public health concern, particularly in South African gold mines, where silica content in dust can reach up to 57% [19]. Research by Knight et al[27] emphasizes that despite decades of regulatory efforts, silicosis remains a major public health concern in South African gold mines. Assessing and monitoring exposure levels is critical to inform preventative strategies in reducing occupational health risks.

2.2 Adverse Health Effects of Exposure to RCS Dust

Among the occupational diseases associated with mining, silicosis is the most prevalent [9,26]. This incurable condition results from prolonged inhalation of **RCS** dust, primarily composed of quartz, tridymite, and cristobalite [9]. Quartz, the most common polymorph, is ubiquitous in mining operations [9], increasing worker exposure risk during activities such as drilling, blasting, crushing, and transportation [9,19]. Effective exposure monitoring and control measures are imperative to reducing disease incidence and ensuring worker safety.

2.3 Reliability and Accuracy of Grouping Workers into Similar or Homogeneous Exposure Groups

Overview of Similar or Homogeneous Exposure Groupings

The concept of HEGs is fundamental in occupational exposure assessment, enabling efficient monitoring while minimizing resource constraints, [28,29]. Measuring every worker's exposure daily is impractical due to limitations in equipment and resources, necessitating a strategy that

involves measuring only a subset of workers within defined groups [7,15]. Therefore, HEGs allow for representative sampling, assuming workers performing similar tasks in comparable environments experience statistically similar exposures [30].

Various regulatory and industry guidelines define HEGs with slight variations. The South African Mining Industry (SAMI) guidelines, based on the Mine Health and Safety Act (MHSA), mandate that HEGs be established according to job roles and work environments, with at least 5% of workers sampled to ensure statistical validity[12]. Similarly, the American Industrial Hygiene Association[7] (AIHA) initially used the term HEGs but later adopted Similar Exposure Groups (SEGs) to reflect the inherent variability in workplace exposures. The British and Dutch[29] guidelines align with this perspective, emphasizing the role of materials, processes, and tasks in defining exposure groups.

While HEGs aim to categorize workers based on statistically similar exposures, the degree of homogeneity can vary due to differences in work tasks, exposure agents, and environmental factors. SAMI's guideline defines an HEG as a group of employees whose exposures to a hazardous agent are statistically similar enough to allow for the definition of exposure levels for the remaining workers [12], focusing on statistical similarity, while Mäkinen et al. and Stanton et al.[31,32], highlight the importance of aligning exposure profiles with specific tasks. This variation underscores the need for adaptable grouping strategies that balance statistical validity with practical exposure assessment.

Exposure Assessment Grouping Methods

Different methodologies for establishing exposure groups vary by industry, regulatory requirements, and workplace exposures. Early models grouped workers by job title and location, assuming stable long-term exposures [10]. However, later studies highlighted the inadequacy of job titles alone, emphasizing the need to consider work environment characteristics and exposure determinants [33,34].

In underground mining, SAMI uses a hierarchical method, first categorizing workplaces by ventilation districts and then by activity-specific areas (e.g., Stopping or Development Ends). Employees are grouped based on exposure scenarios, with statistical analysis ensuring homogeneity. This approach aligns exposure groupings with mining-specific work conditions and airflow patterns. In contrast, the SEG methodology takes a broader approach, incorporating various exposure factors, such as tasks, processes, equipment, and exposure duration [35]. SEG relies on systematic data collection, workplace observations, worker interviews, and statistical

validation to enhance the accuracy of exposure estimates and optimize resource allocation for monitoring and control.

While SAMI's model focuses on ventilation-based subdivisions, the SEG approach emphasizes a comprehensive assessment of industry exposure variability. Both methodologies aim to improve monitoring efficiency and exposure assessment accuracy, with the choice of method depending on workplace conditions and regulatory frameworks.

The CEN standard for workplace exposure measurement defines SEGs as workers with comparable exposure profiles based on tasks, environments, and control measures [36]. In contrast, the HEG approach used in SAMI categorizes workers based on ventilation districts, activity-specific areas, and shared exposure conditions [12]. Unlike general industries, underground mining's unique challenge of airflow dominance makes SAMI's HEG framework more tailored to exposure variability in these environments.

Global Approaches to Exposure Assessment Grouping Method

Various international organizations use SEG methodologies to enhance exposure assessments. In the United States, the Occupational Safety and Health Administration and National Institute for Occupational Safety and Health (NIOSH) advocate exposure grouping to facilitate representative sampling[7]. Similarly, Canada's Canadian Centre for Occupational Health and Safety (CCOHS) and the European Union, European Agency for Safety and Health at Work (EU-OSHA) prioritize statistical validation in exposure assessments [34,37]. Australia and Germany also integrate exposure determinants such as task frequency and environmental conditions, ensuring continuous reassessment for accuracy [38–40].

These global approaches to exposure grouping highlight the widespread recognition of SEGs as a critical tool for accurate exposure assessment. While methodologies vary slightly across regions, the common emphasis on statistical validation, regular monitoring, and group homogeneity ensures more effective occupational health interventions. Consistent reassessment and data-driven adjustments remain essential to maintaining accurate exposure evaluations and protecting worker health.

Variability in exposure groupings

Accurately categorizing workers based on exposure levels is a critical element in exposure assessment. The accuracy of HEG-based exposure assessment is affected by between-worker and temporal variations, including contextual factors that influence exposure assessments.

Symanski et al. [41]noted that individuals performing similar tasks often experience different exposure levels due to variations in work techniques, pace, and safety compliance. Additionally, Kromhout and Heederik[42] observed that even within similar work environments, differences in how tasks are assigned and how workspaces are structured can result in significant exposure variability that is difficult to quantify reliably. In addition to between-worker variability, temporal variation (within-worker) also hinders the efficacy of HEG-based exposure grouping. Symanski et al.[41] point out within-worker variation over time, which may be due to differences in work schedules, and task assignments, i.e., the worker may perform multiple tasks throughout a shift [35,43], and eenvironmental conditions such as airflow and location of equipment also influence exposure, as do personal behaviors such as adherence to safety regulations and the use of protective devices [10].

These variations create a challenge for stable exposure groupings since workers are likely to have varying levels of exposure in different periods. Environmental influences like seasonal and daily trends also affect exposure levels. Dispersion of airborne contaminants can be affected by changes in temperature, humidity, and workplace ventilation, which in turn can influence worker exposure [41]. Equally, Kromhout and Heederik [42]document that exposure levels vary over time because of changes in production schedules and operational conditions, further illustrating the challenge of exposure assessment.

Limitations of the SEG/HEG Approach

HEG methodologies, particularly those grouping workers based on shared air intake areas, may lead to exposure misclassification [15]. Koh et al. found that task-specific grouping provides a more accurate assessment of exposure variations, as broader classifications, such as job titles or departments, often mask significant differences. However, task-specific grouping is resource-intensive and complicated by frequent changes in job roles. Symanski et al. emphasize the necessity of granular data to address variability within groups, as overgeneralizing exposure assumptions can bias risk estimates and complicate epidemiological studies. Additionally, Kromhout and Heederik demonstrate how exposure variability undermines risk assessments, affecting regulatory compliance and health interventions.

Loomis and Kromhout further [44] highlighted the critical role of exposure variability in occupational epidemiology, emphasizing that traditional exposure assessment methods often overlook within-person variability. Excessive reliance on between-person variability can lead to measurement errors, misclassification, and weakened exposure-disease associations.

The authors advocate for improved methodologies, including repeated measurements and statistical techniques to separate intra-individual and inter-individual variations. These can enhance exposure assessments and provide a more accurate understanding of occupational risks.

To mitigate these challenges, some studies suggest a mixed approach that integrates HEG-based monitoring with individual monitoring, allowing for more targeted interventions and ensuring that high-risk workers receive adequate protection [45]

Potential Implications of Inaccurate Worker Grouping in SEGs

Inaccurately grouping workers within SEGs can seriously affect occupational health assessments, risk management, and regulatory compliance. These implications can be broadly categorized into exposure misclassification, ineffective exposure control strategies, increased errors in exposure assessments, and regulatory compliance challenges.

Misclassification of Exposure

Misclassification of exposure is a primary concern when grouping workers based on broad categories such as job titles or departments. Made et al.[15] argues that only using shared air [46]intake areas for grouping can lead to either overestimation or underestimation of actual exposure levels, distorting exposure assessments and resulting in inappropriate protective measures. This misclassification can compromise exposure-response relationships in epidemiological studies, leading to inaccurate risk assessments [33]. Furthermore, it was highlighted that job-exposure matrices, although widely used, may not fully capture variability within occupational categories across different workplaces and periods, resulting in significant exposure misclassification[46]. Loomis and Kromhout [44] reinforce these concerns by emphasizing that exposure misclassification arises when traditional assessment methods fail to distinguish between intra-individual and inter-individual variability. They argue that excessive dependence on broad exposure categories obscures true exposure patterns, leading to biased risk estimates. Addressing this issue requires methodological improvements, such as statistical modelling techniques that account for exposure variability across different workers and timeframes.

Ineffective Control of Exposure

Incorrect worker grouping can lead to ineffective exposure control strategies, where some workers receive inadequate protection while others face unnecessary restrictions. Koh et al.[47]

demonstrated that task-specific grouping is more precise than broader classifications like job titles or departments, as significant exposure variations exist among workers performing different tasks. Loomis and Kromhout [44] also highlight that without accurate exposure differentiation, workers may be subjected to inappropriate protective measures that either fail to provide adequate safety or impose unnecessary burdens.

Increased Errors in Exposure Assessments

Inaccurate grouping methods contribute to increased errors in exposure assessments, affecting the reliability of data and study conclusions. Symanski et al.[41] found that improper grouping methods introduce high within-group variability, making it challenging to detect exposure-related health effects. The lack of task-specific data further exacerbates this issue, as broad classifications fail to account for differences in work conditions. Loomis and Kromhout [44] stress that increased errors in exposure assessments stem from inefficient measurement strategies that do not properly balance within- and between-person exposure variations. The authors advocate for more comprehensive exposure assessment methods, such as repeated exposure measurements and refined exposure classification techniques, to improve the accuracy of exposure-risk relationships.

Implications for Regulatory Compliance

Misclassification and inaccurate worker grouping also have significant implications for regulatory compliance. Occupational health regulations require precise exposure monitoring to ensure adherence to safety standards. If workers are incorrectly grouped, employers may fail to identify those at higher risk, resulting in noncompliance with occupational exposure limits and potential legal penalties [41]. Inaccuracies in exposure grouping can hinder the development of effective regulatory frameworks. Loomis and Kromhout [44] further suggest that improved exposure assessment methodologies, particularly those accounting for variability, can strengthen regulatory compliance by ensuring that exposure monitoring strategies align more closely with actual workplace conditions.

2.4 Estimation of Exposure Measurements -Dose allocation of exposure measurements to employees' medical records

Estimating individual dose allocation in occupational settings is a critical aspect of exposure assessment. It is generally assumed that workers engaged in the same activity area at a given location experience uniform exposure, meaning they share the same long-term mean exposure levels [10]**.** In SAMI, an individual employee's exposure within a HEG (as a proxy of the ‘dose’)

is determined by assigning the AM of the specific pollutant/s, of that HEG's TWA(8h) concentration distribution [12].

Though Banerjee et.al highlighted that the AM is generally regarded as the most suitable metric for calculating cumulative exposure, Werner and Attfield caution that the estimate may not be truly applicable to all individuals in the group, resulting in misclassification of exposure for those employees [48]. Made et al.[15] further underscore the challenges in accurately assigning exposure levels to individual employees within HEGs, which can lead to under- or overestimation of exposure. Furthermore, Rappaport et al. [10] identify that HEGs may exhibit less homogeneity due to unobserved variations in tasks and work practices.

Various studies have explored different methodologies and metrics to achieve accurate estimations. Kromhout and Heederik [42]utilized statistical modelling, professional judgment, and deterministic models for historical exposure estimations, emphasizing the AM as the preferred metric for cumulative exposure. Stewart and Stenzel [49]point out that AM or GM can typically be used to estimate workplace exposures, or recommended for epidemiological studies, and other statistical values like the 90th percentile may also apply. But still, underlined that the accuracy of measurements depends on sampling conditions, randomness, and similarity between measured and unmeasured workers [49]. On the contrary, Crump argues that generally, using an AM to summarize exposure is often more suitable than using a GM in that the AM aligns closest with the total population risk if everyone were exposed, considering that the risk at the mean exposure equals the average risk in the population [50]. Whereas Houba et al. investigated dust exposure in agricultural settings, using both AM and GM means depending on exposure scenarios, in this context, the GM was used to describe typical exposure levels across workers, reflecting the log-normal nature of the data. Meanwhile, the AM was used for health risk evaluation and compliance comparisons, where higher exposure outliers were of concern [33]. Teschke et al. focused on exposure assessment methods in industrial settings, utilizing the AM for cumulative exposure and highlighting the necessity of reliable exposure assessment for occupational health. Ultimately, the selection of an AM for estimating exposure in a population depends on various factors, including data distribution and exposure characteristics [33]. In exposure assessment, the (AM) and (GM) serve distinct purposes. The AM is sensitive to high exposure values and aligns better with dose-response relationships, especially when assessing health risks in populations [50]. Conversely, the GM is better suited for summarizing typical exposures in log-normally distributed data, as it reflects central tendency without being skewed by outliers [51]. Therefore, selecting the AM over the GM

depends not only on the data distribution but also on the specific objective, whether the goal is to capture risk-related information or to summarize central exposure levels.

Added to the different variables, Made et al.[15] highlighted the necessity of identifying highly exposed workers for effective risk assessment and management, underscoring the importance of suitable strategies for worker grouping. These studies highlight the need to choose exposure metrics based not only on data distribution but also on the specific objective, whether for risk assessment, regulatory compliance, or epidemiological analysis. A comprehensive exposure profile should include summary statistics, exposure frequency, and variability, as well as data on atypical conditions, ensuring a more accurate evaluation of occupational health risks. The literature consistently identifies the arithmetic AM as the preferred metric for estimating cumulative exposure, crucial for chronic health risk assessments. Accurate exposure estimation is fundamental for effective risk management, regulatory compliance, and reliable epidemiological research.

2.5 Recommendation and Conclusion

The HEG approach has been widely adopted in the mining industry for its efficiency in exposure classification; however, its limitations, particularly in accounting for individual variations, highlight the need for refined assessment methods. While personal monitoring offers greater accuracy, it is often impractical due to resource constraints. The effectiveness of HEGs and SEGs depends on precise worker grouping, granular data, and continuous refinement, by retrospective evaluation of the exposure data. As Loomis and Kromhout [44] emphasize, addressing both within-person and between-person variability is essential for improving exposure assessments. A hybrid approach—integrating HEG-based sampling with targeted individual monitoring, task-specific assessments, and real-time exposure data—could enhance accuracy, ensuring better worker protection, more reliable epidemiological research, and improved regulatory compliance. These findings underscore the need for continued research and advancement in occupational exposure monitoring methods to safeguard the health and safety of mine workers in South African gold mines.

CHAPTER 3: METHODS

This chapter outlines the methodological framework used to assess RCS exposure in underground gold mines over four years (2019 to 2022). Using a cross-sectional design, the study analysed secondary data to evaluate exposure trends among HEGs and their associated occupations. The methods include detailed descriptions of the study design, sample population, data sources, pre-processing steps, statistical analyses, limitations, and ethical considerations.

3.1 Study Design

This study utilised a cross-sectional design to analyse secondary data on RCS exposure levels in two underground gold mines over four years (2019 to 2022). The secondary data was sourced from the mines' reported airborne pollutant exposure measurements (RCS and particulates not otherwise classified), which are submitted quarterly to the DMRE as mandated by the MCoP. The primary objective was to assess temporal trends and variability in exposure among individual measurements nested in their respective occupations and the allocated HEG.

3.2 Study Population

The study population consisted of individuals whose airborne pollutants exposure measurements were sampled while working in the stope and Development End areas at different levels in underground mines.

3.4 Sample Population

From the study population, HEGs with the highest number of data points and occupations that were consistently sampled over the four-year study period were selected for detailed analysis. HEGs were then further selected based on specific criteria to ensure a reliable and representative analysis of occupational exposures. The selection process focused on HEGs with the highest number of available data points.

The inclusion criteria were:

- HEGs should have consistent exposure measurements and at least more than two occupations recorded per year throughout the study period.
- The HEG should be categorized as having previous sampling results exceeding 50% of the Occupational Exposure Limit (OEL).

The study aimed to assess and analyse 20 HEGs, with inclusion limited to HEGs that had previous sampling results exceeding 50% of the OEL for the entire period under investigation

(Category B and A). However during the study as data was being assessed , it was observed that the classification of some HEGs fluctuated over time, with several that initially met the inclusion criterion subsequently falling into Category C (10% of the OEL). As a result, only 10 HEGs ultimately met the inclusion criteria: Mine 1 comprised three Development Ends and two Stoping HEGs, while Mine 2 comprised two Development Ends and three Stoping HEGs (see Appendix 2).

Applying these selection criteria, the final dataset provided a structured representation of HEGs and their associated occupations. Exposure data were further organized by year, allowing for both annual trend analysis and direct comparisons of exposure levels over the entire study period.

3.5 Data Management

a) Data Source

Permission was requested and granted from gold mines 1 and 2 to conduct a research project utilizing secondary airborne pollutant exposure data of individual measurements taken and reported from 2019 to 2023 to the Department of Mineral Resources and Energy. Both Mine 1 and 2 provided records of airborne pollutant exposure measurements from 2019 to 2023 in an Excel format. The dataset contained multiple variables across several columns, including sampling date, workplace description, employee details, and exposure metrics such as total dust, respirable silica mass, and time-weighted average quartz concentrations (TWAQCs).

b) Data Consolidation and Cleaning

The data from various years were consolidated into a master spreadsheet to facilitate efficient analysis. To maintain focus on critical variables, non-essential columns—including ventilation districts, mine overseer, subsection, organizational unit, gender (male/female sampled), and mine section/unit—were excluded. From this master dataset, records related to Development End and Stoping activities were specifically selected.

Separate spreadsheets were created for "Stoping" and "Development" activities by extracting relevant data from the master dataset. These activity-specific datasets were then analysed in detail using pivot tools to identify trends and patterns within activities and their associated HEGs. This approach highlighted the most frequently sampled occupations and individuals.

The analysis revealed that most HEGs lacked data concentrations for 2023, and occupations were not consistently represented across all five years. Additionally, most individual data points were limited, with a maximum of three entries per worker over the five years, leading to the exclusion of 2023 from further analysis.

Airborne pollutant concentration data were arranged in ascending order, revealing inconsistencies at the lower and upper extremes. Notably, some silica quartz concentration results, as expressed in percentage of respirable dust mass reported by external laboratories, exceeded 100%, with values as high as 150% and 300%[12]. These were deemed outliers, as previous studies indicate that silica content in gold mines typically ranges from 4.5% to 57% [19,26,32]. Results exceeding 100% of respirable dust mass, deemed analytically invalid, were excluded from analysis.

For extremely low or repetitive values, mines were instructed to use below-detectable limits (BDL) for pollutants that were analysed but not detected. The BDL values provided by the mines were incorporated into the Expostats NDexpo /RoS tool (accessible at https://expostats.ca/site/en/othertools.html) to generate real values for statistical analysis. NDexpo implements a rigorous censored data treatment method by labelled regression on order statistics. The rigorous data-cleaning process enhanced the accuracy and reliability of the subsequent analyses.

c) Data Transformation

The dataset was modified by adding new columns to define the sampling year and assign study-specific HEG descriptions (e.g., HEG 1 Mine 1 Development, HEG 4 Mine 1 Stoping). Occupations within HEGs were categorised under their respective HEGs (e.g., HEG 1 Mine 1 Occupation 1 Development, HEG 1 Mine 1 Occupation 1 Stoping). Individual measurements were labelled accordingly (e.g., HEG 1 Mine 1, Worker 1) for both Development and Stoping (Appendix 2). The same approach was applied to Mine 2.

d) Data Processing and Analysis

Data processing and interpretation were conducted using a combination of analytical tools, including Jeffrey's Amazing Statistics Program (JASP) version 0.19.2.0 (www.jasp-stats.org) , Expostats Tool 2 (www.expostats.ca), and Microsoft Excel.

To address the study objectives, statistical analyses were structured according to specific research questions. The following sections outline the methodologies employed for each study objective: -.

For Study Objective Two

Data preparation for statistical analysis involved log-transforming concentration values as it normalizes the data, allowing for valid statistical comparisons, reduces the impact of extreme values, and enhances the accuracy [51]. A structured approach was used in the descriptive analysis to compare HEG exposure parameters with those of their constituent occupations using JASP. Measures of central tendency and dispersion—including AM, median, standard deviation, coefficient of variation, and 95% confidence intervals—were computed to summarize exposure levels within each occupation. Additionally, the minimum, maximum, and 90th percentile values were analysed to further interpret the exposure data distribution.

Inferential statistical tests were then conducted to assess differences between occupations. For comparisons of the AMs between two occupations within a HEG, an Independent T-test was performed. Before conducting primary statistical analyses, key assumptions were evaluated:

- Normality was assessed using the Shapiro-Wilk test, with a p-value > 0.05 indicating no significant deviation from normality. If normality was violated, non-parametric tests were applied.
- Homogeneity of variances was tested using Levene's test. If the p-value was > 0.05, parametric tests (Student's t-test) were used; otherwise, non-parametric tests (Mann-Whitney U test) were applied.
- If assumptions were met, the Independent Student's T-test was used to compare AM exposure levels between the two groups. If assumptions were violated, the Mann-Whitney U test was used for differences between medians, particularly for skewed distributions or small sample sizes.

For groups with unequal variances and sample sizes, Welch's ANOVA was applied, noting that Levene's test can have low power in small and unequal samples[52,53]. P-values were compared to a significance level of 0.05. In case p > 0.05, no significant differences in exposure parameters were concluded. Additionally, effect sizes (Cohen's d) were calculated to assess the magnitude of differences, with thresholds of 0.2 (small), 0.5 (medium), and 0.8 (large).

For HEGs with three or more occupations in a single year, ANOVA was performed to determine significant differences in AM exposure levels. The F-statistic was used to compare variance between and within groups, with larger values indicating greater differences. Effect

sizes, such as omega squared (ω^2) or eta squared (η^2), quantified the proportion of variance explained by occupation groups. If parametric assumptions were violated, the Kruskal-Wallis test was used as a non-parametric alternative, to assess median exposure differences across occupation groups.

The test statistic (H) measured variability between groups, while Rank epsilon squared (ε^2) quantified the proportion of variability explained by group membership; Post Hoc Tests (Tukey HSD) were considered when ANOVA test results were significant. If the non-parametric test, the Kruskal-Wallis Test, was violated, then the post-hoc Dunnett Test was applied.

This comprehensive statistical approach ensured robustness by accounting for variations in sample size and distribution, thereby providing reliable insights into exposure differences across occupations.

For Study Objective 3

To compare individual exposure parameters with those of their occupations and allocated HEGs, time-weighted average quartz (TWAQ) concentrations were analysed for individuals having at least two data points. The difference between the HEG AM and each worker's TWAQ was then calculated.

A Linear Mixed Model (LMM) in JASP was used to analyse differences in exposure, accounting for fixed effects (occupations) and random effects (individual worker variability). This model integrates both fixed and random effects, allowing for the estimation of between-worker and within-worker variance while adjusting for fixed factors[54]. Additionally, it evaluates linear relationships between exposure determinants and exposure levels[54]. When repeated measurements are present, the model accounts for correlations within an individual's values, ensuring a more precise and reliable analysis.

The difference between the AM HEG and the individual TWAQ concentrations served as the dependent variable. Note that the relative value is used, meaning that a negative value represents a higher individual TWAQ concentration compared to the AM HEG, and vice versa. The Worker ID was included as a random effect to control for individual differences in exposure within occupations. The model was fitted using Restricted Maximum Likelihood (REML) for accurate variance estimation. Key parameters included:

- Fixed effect estimates (Estimate, Standard Error, p-value, 95% Confidence Interval) to assess occupational differences.

- Random effect variance to measure individual variability.
- Residual variance to capture unexplained variation.
- Model fit metrics: Deviance (REML), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC).
- Estimated Marginal Means (EMMs) to determine adjusted exposure levels for each occupation, with pairwise comparisons assessing statistical significance ($p < 0.05$).

Additionally, HEG classifications were validated against the MCoP by categorizing RCS exposure concentrations into established thresholds. The AM and 90th percentile were analysed to determine whether exposure levels fell within the same risk band classification.

3.6 Ethical Considerations

This study adhered to strict ethical guidelines.

- The research protocol received ethical clearance from the University of the Witwatersrand Human Research Ethics Committee (clearance certificate M240930-A-003, Appendix 3).
- Permission to access secondary data was obtained from mine management at both mines.
- Confidentiality was maintained to protect the identities of participating mines and employees.

CHAPTER 4: RESULTS

This chapter presents the results of the statistical analyses conducted to compare occupational exposure parameters of RCS across HEGs and their constituent occupations over four years (2019–2022). The results are presented in alignment with the study objectives, focusing on assessing statistical significance through tests of normality, variance, and central tendency comparisons. The analysis evaluates whether RCS exposure measurement levels differ significantly among occupations within the same HEG and whether individual RCS exposure measurement levels align with group-level assessments.

4.1 Introduction

The results provide an analysis in examining the statistical mean of occupations in HEGs where Independent t-test and ANOVA were used depending on the number of occupational groups in an HEG. The analysis included the evaluation of individual-level exposure variations within HEGs using a Linear Mixed Model, identifying deviations that may not be captured at the group level. Measures of central tendency and distribution are presented, highlighting exposure trends over time and across occupations, using GM, AM, and the 90th percentile to assess exposure variability and its implications for occupational health risk.

The results are presented according to the study objectives in the following sections :

4.2 Study Objective 2 key findings

This section addresses Study Objective 2, which compares HEGs' exposure parameters and those of their respective occupational groups. The analysis is structured by activity area for both Mine 1 and Mine 2, Independent t-tests were conducted for HEGs with two occupations, while ANOVA was used for HEGs with three or more occupations.

4.2.1 Statistical Results for HEGS with two occupations: T-Test Analysis

Before conducting inferential statistical tests, it was essential to assess whether the data met the assumptions required for parametric testing. The Shapiro-Wilk test was employed to evaluate the normality of occupational exposure data within the HEG across different years. Levene's test was further used to determine the homogeneity of variances between the occupational categories. Based on these preliminary assessments, either the Student's T-Test (for normally distributed data with equal variances) or the Mann-Whitney U Test (for non-normally distributed data or unequal variances) was applied to compare occupational exposure

levels. Additionally, the effect size was calculated to determine the magnitude of differences observed, and statistical significance was assessed at a p level of 0.05. The following sections summarize the key findings from these statistical tests.

Table 1(a): Mine 1 Development End Independent T-test

Mine1 Development End HEG				Test for Normality and Equal Variance				Comparison test of significant differences across the occupations			
HEG Number	Year	Occupations	Number of Data points	Sharpiro - Wilk p-value (Normality)	Normality Y/N	Laven's p-value (Homogeneity)	Homogeneity Y/N	Test Conducted	T-Test p - value	Effect in Size	Statistical Significant Y/N
Mine 1	2019	Team Leader Secondary Support :1	3	0.102	Y	0.311	Y	T-Test Student	0.489	-0.517	N
HEG1		Team Member Secondary Support: 2	3	0.945	Y			T-Test Mann-Whitney	0.3	-0.5	
Mine 1	2020	Team Leader Secondary Support :1	3	0.121	Y	0.352	Y	T-Test Student	0.707	-0.288	N
HEG1		Team Member Secondary Support: 2	5	0.888	Y			T-Test Mann-Whitney	1	-0.067	
Mine 1	2021	Team Leader Secondary Support :1	4	0.398	Y	0.604	Y	T-Test Student	0.465	0.518	N
HEG1		Team Member Secondary Support: 2	5	0.384	Y			T-Test Mann-Whitney	0.905	0.1	
Mine 1	2022	Team Leader Secondary Support :1	5	0.727	Y	NaN*	NaN*	T-Test Student	0.736	-0.298	N
HEG1		Team Member Secondary Support: 2	2	NaN*	NaN*			T-Test Mann-Whitney	0.571	-0.4	
Mine1	2019	Developer:1	3	0.161	Y	0.295	Y	T-Test Student	0.683	-0.313	N
HEG2		General Miner:2	5	0.336	Y			T-Test Mann-Whitney	0.571	-0.333	
Mine1	2020	Developer:1	3	0.197	Y	0.024	N	T-Test Student	0.373	-0.651	N
HEG2		General Miner:2	7	0.414	Y			Welch	0.568	-0.333	
Mine1	2021	Developer:1	4	0.662	Y	0.088	Y	T-Test Student	0.634	-0.354	N
HEG2		General Miner:2	4	0.01	Y			T-Test Mann-Whitney	0.886	-0.125	
Mine1	2022	Developer:1	4	0.968	Y	0.929	Y	T-Test Student	0.893	0.099	N
HEG2		General Miner:2	4	0.785	Y			T-Test Mann-Whitney	0.772	0.188	

Note: *NaN-Not Computed (Insufficient Data)

The results for Mine 1 HEG 1 in Table 1(a) above, indicate that for Team Leader Secondary Support and Team Member Secondary Support, normality was confirmed across all years ($p > 0.05$). Homogeneity of variance was usually maintained, except in 2022, where Levene's test results were unavailable due to a small sample size. T-test results from 2019 to 2022 revealed no statistically significant differences (p-values ranging from 0.3 to 0.872). The effect sizes were also minimal, indicating that the occupational exposure levels to RCS within HEG 1 were relatively uniform across both roles.

For Mine 1 HEG 2, which includes the Developer and General Miner occupations, normality was confirmed in most years except for General Miner in 2021 ($p = 0.01$), suggesting a non-normal distribution. Homogeneity of variance was inconsistent, as Levene's p-value fell below 0.05 in 2020. As a result, a non-parametric Welch test was applied, confirming no significant variance. Overall, the T-test and Mann-Whitney U test results showed no significant differences between these occupations (p-values ranging from 0.373 to 0.893). Effect sizes remained small, suggesting that exposure levels to RCS between Developers and General Miners were comparable with minimal variation.

Table 2(b): Mine 2 Development End Independent T-test

Min2 Development End HEG				Test for Normality and Equal Variance				Comparison test of significant differences across the occupations			
HEG Number	Year	Occupations	Number of Data points	Occupation-Sharpiro - Wilk p-value (Normality)	Normality Y/N	Laven's p-value (Homogeneity)	Homogeneity Y/N	Test Conducted	T-Test p - value	Effect in Size	Statistical Significant Y/N
Mine 2 HEG1	2019	Development Team Worker:1	6	0.052	Y	0.485	Y	T-Test Student	0.38	0.492	N
		Loco Driver :2	8	0.408	Y			T-Test Mann-Whitney	0.852	0.083	
Mine 2 HEG1	2020	Development Team Worker:1	7	0.59	Y	0.391	Y	T-Test Student	0.18	1.015	N
		Loco Driver :2	3	0.598	Y			T-Test Mann-Whitney	0.067	0.81	
Mine 2 HEG1	2021	Development Team Worker:1	4	0.376	Y	0.08	N	T-Test Student	0.757	-0.194	N
		Loco Driver :2	8	0.103	Y			Welch	0.703	-0.216	
Mine 2 HEG1	2022	Development Team Worker:1	2	NaN*	Y	NaN*	NaN*	T-Test Student	0.142	-1.579	N
		Loco Driver :2	4	0.463	Y			Welch	0.126	-1.709	

Note: *NaN-Not Computed (Insufficient Data)

The independent t-test results for Mine 2 HEG 1 (Table 1(b)), which includes Development Team Workers and Loco Drivers, indicate that normality was generally satisfied across the analysed years. However, Levene's test for homogeneity of variance showed inconsistencies, particularly in 2021 and 2022, where variance equality could not be assumed ($p = 0.08$ and NaN, respectively). Despite these inconsistencies, the t-test and Welch's test results revealed no statistically significant differences in exposure levels between the two occupational groups across all years, with p-values ranging from 0.067 to 0.852. Effect sizes remained small, suggesting that exposure levels were relatively uniform between Development Team Workers and Loco Drivers.

Table 3(a): Mine 1 Stoping Independent T-test

Mine 1 Stoping HEGs				Test for Normality and Equal Variance				Comparison test of significant differences across the occupations			
HEG Number	Year	Occupations	Number of Data points	Occupation-Sharpiro - Wilk p-value (Normality)	Normality Y/N	Laven's p-value (Homogeneity)	Homogeneity Y/N	Test Conducted	Test p -value	Effect in Size	Statistical Significant Y/N
Mine 1 HEG 4	2019	General Miner: 1	1	NaN*	NaN*	NaN*	NaN*	T-Test Student	NaN*	NaN*	NaN*
		Winch Operator: 2	4	0.177	Y			T-Test Mann-Whitney	NaN*	NaN*	
Mine 1 HEG 4	2020	General Miner: 1	3	0.871	Y	0.976	Y	T-Test Student	0.223	-1.178	N
		Winch Operator: 2	3	0.99	Y			T-Test Mann-Whitney	0.2	-0.778	
Mine 1 HEG 4	2021	General Miner: 1	1	NaN*	NaN*	NaN*	NaN*	T-Test Student	NaN*	NaN*	NaN*
		Winch Operator: 2	2	NaN*	NaN*			T-Test Mann-Whitney	NaN*	NaN*	
Mine 1 HEG 4	2022	General Miner: 1	3	0.275	Y	0.215	Y	T-Test Student	0.441	0.559	N
		Winch Operator: 2	7	0.277	Y			T-Test Mann-Whitney	0.493	0.333	
Mine 1 HEG 5	2019	General Miner: 1	2	NaN*	NaN*	NaN*	NaN*	T-Test Student	0.375	0.759	N
		Miner Stoper: 2	7	0.216	Y			T-Test Mann-Whitney	0.667	0.286	
Mine 1 HEG 5	2020	General Miner: 1	2	NaN	NaN*	NaN*	NaN*	T-Test Student	0.463	0.702	N
		Miner Stoper: 2	4	0.893	Y			T-Test Mann-Whitney	0.533	0.5	
Mine 1 HEG 5	2021	General Miner: 1	2	NaN	NaN*	NaN*	NaN*	T-Test Student	0.698	-0.344	N
		Miner Stoper: 2	5	0.645	Y			T-Test Mann-Whitney	0.857	-0.2	
Mine 1 HEG 5	2022	General Miner: 1	1	NaN*	NaN*	NaN*	NaN*	T-Test Student	NaN*	NaN*	NaN*
		Miner Stoper: 2	2	NaN*	NaN*			T-Test Mann-Whitney	NaN*	NaN*	

Note: *NaN-Not Computed (Insufficient Data)

Table 2(a) presents the independent t-test results for HEG 4 in Mine 1, comparing General Miners and Winch Operators. Statistical tests for normality, assessed using the Shapiro-Wilk test, confirmed that the occupational groups followed a normal distribution. Homogeneity of variance, tested using Levene's test, was also generally met across different years. When exposure levels to RSC were compared using independent t-tests and Mann-Whitney tests, no statistically significant differences were observed between the two occupations in any of the analysed years ($p > 0.05$).

For HEG 5, a similar analysis was conducted comparing General Miner and Miner Stoper. However, data limitations—particularly for General Miner—reduced the robustness of statistical comparisons in certain years. For years with sufficient data, independent t-tests and Mann-Whitney tests were performed, consistently showing no statistically significant differences ($p > 0.05$).

The cumulative results from 2019 to 2022 further confirmed this trend, with p-values of 0.362 for the t-test and 0.238 for the Mann-Whitney test. These findings suggest that exposure levels to RCS remained comparable between General Miner and Miner Stoper over the analysed period.

Table 4(b): Mine 2 Stoping Independent T-test

Mine 2 Stoping HEGs				Test for Normality and Equal Variance				Comparison test of significant differences across the occupations			
HEG Number	Year	Occupations	Number of Data points	Occupation-Sharpiro - Wilk p-value (Normality)	Normality Y/N	Laven's p-value (Homogeneity)	Homogeneity Y/N	Test Conducted	Test p -value	Effect in Size	Statistical Significant Y/N
Mine 2 HEG 3	2019	Miner's assistant (cheesa) :1	6	0.144	Y	0.946	Y	T-Test Student	0.144	0.819	N
		Scrapper Winch Driver: 2	9	0.828	Y						
Mine 2 HEG 3	2020	Miner's assistant (cheesa) :1	8	0.775	Y	0.294	Y	T-Test Student	0.1	-0.714	N
		Scrapper Winch Driver: 2	20	0.261	Y						
Mine 2 HEG 3	2021	Miner's assistant (cheesa) :1	8	0.775	Y	0.742	Y	T-Test Student	0.297	0.444	N
		Scrapper Winch Driver: 2	20	0.261	Y						
Mine 2 HEG 3	2022	Miner's assistant (cheesa) :1	5	0.082	Y	0.19	Y	T-Test Student	0.367	-0.469	N
		Scrapper Winch Driver: 2	17	0.041	Y			T-Test Mann-Whitney	0.704	-0.129	N
Mine 2 HEG 4	2019	Miner's assistant (cheesa) :1	21	0.424	Y	0.433	Y	T-Test Student	0.524	0.299	N
		Scrapper Winch Driver: 2	6	0.165	Y			T-Test Mann-Whitney	0.195	0.365	
Mine 2 HEG 4	2020	Miner's assistant (cheesa) :1	30	0.901	Y	0.324	Y	T-Test Student	0.957	0.018	N
		Scrapper Winch Driver: 2	13	0.775	Y			T-Test Mann-Whitney	0.948	-0.015	
Mine 2 HEG 4	2021	Miner's assistant (cheesa) :1	23	0.036	Y	0.791	Y	T-Test Student	0.059	0.696	N
		Scrapper Winch Driver: 2	12	0.748	Y			T-Test Mann-Whitney	0.079	0.37	
Mine 2 HEG 4	2022	Miner's assistant (cheesa) :1	18	0.485	Y	0.079	Y	T-Test Student	0.274	-0.441	N
		Scrapper Winch Driver: 2	10	0.069	Y			T-Test Mann-Whitney	0.588	-0.133	

Note: *NaN-Not Computed (Insufficient Data)

Table 2(b) shows that the independent t-test analysis for Mine 2 HEG 3 examined exposure levels between two occupational groups i.e. Miner's assistant and Scrapper winch driver from 2019 to 2022. The results consistently indicated no statistically significant differences between these groups across all years. Both Student's t-test and Mann-Whitney test p-values remained above 0.05, confirming that exposure levels did not vary significantly between these occupations.

The cumulative analysis from 2019 to 2022 reinforced this finding, with p-values of 0.857 and 0.865 for the t-test and Mann-Whitney test, respectively. Effect sizes were also minimal, further supporting the conclusion that exposure levels to RCS were comparable between the two occupations.

Similarly, in Mine 2 HEG 4, exposure levels to RCS between the two analysed occupations, i.e. Miner's assistant and Scrapper winch driver, showed no significant statistical difference. Across all years, p-values for both the independent t-test and Mann-Whitney test were above 0.05, and effect sizes were consistently low.

The cumulative analysis over the four years confirmed this trend, with a p-value of 0.356 for the t-test and 0.346 for the Mann-Whitney test, indicating no significant differences in occupational exposure levels to RCS.

In cases where sample sizes were unbalanced or normality assumptions were violated, post hoc analyses were conducted to improve result reliability. The Mann-Whitney test was employed in these scenarios to ensure robustness. However, results remained consistent, showing no statistically significant deviations in exposure levels to RCS between the occupations. This suggests that within each HEG, exposure parameters remained stable over time, with no meaningful differences observed between the occupational groups.

4.2.2 Statistical Results for HEGS with three or more occupations: ANOVA Analysis

For HEGs with three or more occupations in a single year, ANOVA was performed to determine significant differences in mean exposure levels to RCS. The analysis evaluates normality, homogeneity of variance, and statistical differences using ANOVA, Welch ANOVA, Kruskal-Wallis tests, and post hoc comparisons. Mine 2 Development End had fewer than three occupations for assessment; therefore, ANOVA analysis was not conducted.

Table 5: Mine 1 Development End ANOVA test

Mine1 Development End HEG				Test for Normality and Equal Variance				Comparison test of significant differences across the occupations				
HEG Number	Year	Occupations	Number of Data points	Occupation-Sharpiro - Wilk p-value (Normality)	Normality Y/N	Laven's p-value (Homogeneity)	Homogeneity Y/N	Test Conducted	F-value	p-value	Effect in size (ANOVA - η^2p; Kruskal-Wallis-Rank	Statistical Significant Y/N
Mine1 HEG3	2019	Special Team Leader Development: 1	3	0.974	Y	0.18	Y	ANOVA -None	0.101	0.904	0.011	
		Loco driver: 2	12	0.92	Y							
		Loader Driver:3	6	0.049	N			Kruskal-Wallis test		0.98	0.002	N
Mine1 HEG3	2020	Special Team Leader Development: 1	2	NaN*		0.696	Y	ANOVA -None	0.45	0.658	0.13	
		Loco driver: 2	4	0.89	Y							
		Loader Driver:3	3	0.743	Y			Kruskal-Wallis test		0.799	0.056	N
Mine1 HEG3	2021	Special Team Leader Development: 1	4	0.933	Y	1.696	Y		4.255	0.055	0.515	
		Loco driver: 2	4.5	0.931	Y			ANOVA -None				
		Loader Driver:3	5	0.477	Y			Kruskal-Wallis test		0.051	0.596	N
Mine1 HEG3	2022	Special Team Leader Development: 1	2	NaN*	NaN*	2.696	Y		0.451	0.674	0.231	
		Loco driver: 2	2	NaN*	NaN*			ANOVA -None				
		Loader Driver:3	2	NaN*	NaN*			Kruskal-Wallis test		0.651	0.171	N

Note: *NaN-Not Computed (Insufficient Data)

Table 3, shows that the ANOVA test for HEG 3 in Mine 1, which includes Special Team Leader Development, Loco Driver, and Loader Driver, indicated that normality assumptions were generally met, except for Loader Driver in 2019 ($p = 0.049$). Homogeneity of variance was confirmed for all years except 2022. ANOVA results revealed no statistically significant differences across these three occupations, with p-values ranging from 0.055 to 0.904. Effect sizes were minimal, suggesting that variations in exposure levels among these roles were negligible. To validate these findings, Kruskal-Wallis tests were conducted, which further confirmed the absence of statistically significant differences across these occupational groups.

This indicates that exposure levels to RCS remained relatively consistent among these roles during the studied period, implying similar working conditions and exposure risks.

Table 4: Mine 2 Stopping ANOVA test

Mine 2 Stoping HEGs				Test for Normality and Equal Variance				Comparison test of significant differences across the occupations					
HEG Number	Year	Occupations	Number of Data points	Occupation-Sharpiro - Wilk p-value (Normality)	Normality Y/N	Laven's p-value (Homogeneity)	Homogeneity Y/N	Test Conducted	F	p	η^2p	Post Hoc Tests	Statistical Significant Y/N
Mine 2 HEG 2	2019	Development team leader/supervisor: 1	12	0.197	Y	0.185	Y	ANOVA -None	2.127	0.148	0.191	0.255	N
		Miner's assistant (cheesa):2	3	0.761	Y			Welch ANOVA	5.883	0.021	0.191	0.259	
		Scraper winch driver:3	6	0.602	Y							0.937	
Mine 2 HEG 2	2020	Development team leader/supervisor: 1	14	0.16	Y	0.274	Y	ANOVA -None	0.396	0.678	0.035	0.974	N
		Miner's assistant (cheesa):2	2	NaN				Welch ANOVA	1.031	0.386	0.035	0.711	
		Scraper winch driver:3	9	0.439	Y							0.797	
Mine 2 HEG 2	2021	Development team leader/supervisor: 1	18	0.628	Y	Occupation 3 NaN (not valid due to n <3). Only one Observation Test could not run							N/A
		Miner's assistant (cheesa):2	11	0.027	N								
		Scraper winch driver:3	1	NaN*									
Mine 2 HEG 2	2022	Development team leader/supervisor: 1	12	0.886	Y	Occupation 3 NaN (not valid due to n <3). Only one Observation Test could not run							N/A
		Miner's assistant (cheesa):2	3	0.998	Y								
		Scraper winch driver:3	1	NaN*									
Mine 2 HEG 5	2019	Driller: hand percussion/jackhammer: 1	2	NaN*	NaN*	0.205	Y	ANOVA -None	0.518	0.602	0.037	N/A	N
		Stope team leader/supervisor: 2	20	0.13	Y								
		Stope Team Member :3	8	0.757	Y			Kruskal-Wallis Test		0.188	0.115		
Mine 2 HEG 5	2020	Driller: hand percussion/jackhammer: 1	15	0.039	N	0.662	Y	ANOVA -None	0.012	0.022	0.978	0.988	N
		Stope team leader/supervisor: 2	29	0.107	Y							0.977	
		Stope Team Member :3	15	0.573	N			Kruskal-Wallis Test		0.969	0.001	0.995	
Mine 2 HEG 5	2021	Driller: hand percussion/jackhammer: 1	13	0.053	Y	0.096	Y	ANOVA -None	1.298	1.82	0.174		N
		Stope team leader/supervisor: 2	20	0.085	Y							0.944	
		Stope Team Member :3	13	0.481	Y			Kruskal-Wallis Test		0.03	0.156	0.157	
Mine 2 HEG 5	2022	Driller: hand percussion/jackhammer: 1	9	0.224	Y	0.897	Y	Standard ANOVA	2.249	4.449	0.027	0.554	N
		Stope team leader/supervisor: 2	3	0.331	Y							0.092	
		Stope Team Member :3	9	0.468	Y			Kruskal-Wallis Test		0.06	0.282	0.042	

Note: *NaN-Not Computed (Insufficient Data)

Table 4, indicates that the statistical analysis for HEG 2 revealed that normality and homogeneity of variance were largely satisfied, though some cases were impacted by small sample sizes. The ANOVA and Welch ANOVA tests produced mixed results. In 2019, significant differences were detected ($p = 0.021$), prompting the application of post hoc tests to identify specific occupational group differences. However, all post hoc test p-values were ≥ 0.259, indicating no statistically significant differences between specific occupations.

For HEG 5, normality assumptions were met for most occupations. The ANOVA and Kruskal-Wallis tests for individual years generally revealed no significant occupational differences, except in 2022, where ANOVA results ($p = 0.027$) indicated some variation in exposure levels to RCS. A post hoc analysis determined specific group differences, yielding low significance ($p = 0.042$).

A cumulative analysis of data from 2019 to 2022 indicated a marginally significant difference in exposure levels to RCS across occupations ($p = 0.04$). However, post hoc tests showed that all pairwise comparisons exceeded the 0.05 significance threshold, suggesting that despite minor year-to-year variations, overall exposure levels to RCS remained largely comparable among occupational groups in this HEG.

4.3 Study Objective: 3 key findings

Study objective 3 compares individual exposure parameters relative to their occupational groups and HEGs. A Linear Mixed Model was used to analyse variations in RCS exposure across different worker groups and job levels. Results are presented separately for Development Ends and Stoping Activities as follows

Importantly, within the context of the model, a negative estimate means that the individual worker exposure is higher than the group (HEG) mean.

Table 5(a): Mine 1 Development Ends Activity

No.	Parameter	Fixed Effects (Occupation)	Estimated Marginal Means		Variance Component (Random Effects)(Worker (W)						
Mine1 HEG1	Occupation and Sample Size	Occupation text (1) 17 Observations	Team Leader Secondary Support O1	Team Member Secondary Support O2	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5	Worker 6	Worker 7
	ANOVA Summary	F=0.436; p=0.534									
	Estimate	0.004	0.008	0.000128	0.004	-0.021	0.002	8.742×10-5	0.004	0.005	0.006
	Standard Error	(Intercept 0.005; (O1)0.006	0.005	0.01							
	95% CI		(-0.002, 0.018)	(-0.02, 0.02)							
	p-value	Intecerpt 0.438; (O1) 0.534	0.108	0.99							
Mine1 HEG2	Occupation and Sample Size	Occupation text (1) observations 26	Developer O1	General Miner O 2	Worker 1	Worker 2	Worker 3	Worker 4			
	ANOVA Summary	F= 6.038×10-5; p=0.995									
	Estimate	Intercept -5.844×10-4 ; (O1) 3.236×10^{-5}	-6.167×10-4	-5.520×10-4	1.593×10^{-5}	-0.002	-2.818×10-5	0.002			
	Standard Error	Intercept 0.004; (O1) 0.004	0.007	0.004							
	95% CI		(-0.015, 0.013)	(-0.009: 0.008)							
	p-value	Intercept 0.905; (O1) 0.995	0.931	0.899							
Mine1 HEG3	Occupation and Sample Size	Occupation text (1)(2)(3) 42 Observations	Loader Driver O1	Loco Driver O2	Special Team Leader Development O3	Supervisor Operations O4	W1(-0.002); W2 (0.007; W3(-0.003); W4(-0.011); W5(0.005); W6(0.003); W7 (0.004); W8 (0.003); W9 (0); W10 (-0.011); W11 ('-6.878×10-4); W12 (-0.005);W13 (0.006); W14 (0.0050; W15 (6.416×10-4)					
	ANOVA Summary	F=0.435; p=0.734									
	Estimate	Intercept -0.001; (O1)0.009; (O2) -0.014; (O3)-0.002	-0.008	-0.013	-3.14×10-4	0.026					
	Standard Error	Intercept 0,110; (O1) 016;	0.016	0.014	0.017	0.033					
	95% CI		(-0.04,0.024)	(-0.041,0.016)	(-0.034,0.033)	(-0.038, 0.091)					
	p-value	Intercept 0.906; (O1) 0.566; (O2)0.371; (O3)0.922	0.615	0.383	0.985	0.422					

Table 5 (a) above presents the summary of findings for Mine 1 HEGs – Development End, showing that HEG 1 consisted of 17 observations. The ANOVA summary ($F = 0.436$, $p = 0.534$) indicated no statistically significant difference in exposure levels to RCS among occupations within this HEG. The estimated marginal means were 0.008 mg/m³ for O1 and 0.000128 mg/m³ for O2. Both values were associated with 95% confidence intervals spanning zero (O1: −0.002 to 0.018 mg/m³; O2: −0.02 to 0.02 mg/m³), and non-significant p-values of 0.108 and 0.99, respectively.

An analysis of random effects indicates relatively low variability among individual workers, ranging from −0.021 to 0.006 mg/m³. These findings support the assumption of exposure homogeneity within HEG1, validating the use of a grouped approach for monitoring and risk assessment purposes in this occupational context.

HEG2 included 26 observations from two occupational roles: Developer (O1) and General Miner (O2). The ANOVA results indicated no significant variation in exposure between these roles ($F = 6.038 \times 10^{-5}$; $p = 0.995$). The estimated marginal mean for Developer (O1) was −0.0006167 mg/m³, and for General Miner (O2) it was −0.0005520 mg/m³. Both values were near zero, with confidence intervals that encompassed zero (O1: −0.015 to 0.013 mg/m³; O2: −0.009 to 0.008 mg/m³), and p-values of 0.931 and 0.899, respectively.

Individual exposure estimates (W1–W4) similarly displayed minimal variation, ranging from −0.002 to 0.002 mg/m³, with W3 (General Miner) showing a slightly negative value of -2.818×10^{-5} mg/m³. These results indicate strong internal consistency, supporting the HEG2 classification and reinforcing its appropriateness for exposure group-based assessments.

HEG 3 comprised 42 observations across four occupational categories, as reflected in the summary of findings in Table 4(a) above. The ANOVA analysis ($F = 0.435$, $p = 0.734$) found no significant differences in exposure levels across occupations, further supporting the notion that HEGs effectively group workers with similar exposure levels to RCS. The estimated marginal means were −0.008 mg/m³ for O1 (Loader Driver), −0.013 mg/m³ for O2 (Loco Driver), −0.002 mg/m³ for O3 (Special Team Leader Development), and 0.026 mg/m³ for O4 (Supervisor Operations). Individual exposure estimates for the 15 workers (W1–W15) ranged from −0.011 mg/m³ to 0.007 mg/m³, with values such as W1 = −0.002 mg/m³, W2 = 0.007 mg/m³, and $W15 = 6.416 \times 10^{-4}$ mg/m³. These low and narrow variations suggest consistency in individual exposures within the group.

Table 5 (b): Mine 2 Development Ends Activity

HEG No.	Parameter	Fixed Effects (Occupation)	Estimated Marginal Means			Variance Component (Random Effects)(Worker (W)
Mine 2HEG 1	Occupation and Sample Size	Occupation text (1)(2) 27 observations	Developer O1	Development Team Worker O2	Loco DriverO3	(W1)0.008; (W2)-0.008; (W3)0.006; (W4)-0.021; (W5)0.016 (W6)0.001; (W7)-0.088; (W8)0.034; (W9)0.023; (W10)0.029
	ANOVA Summary	F=0.433; p=0.664				
	Estimate	Intercept '-3.393×10-4 (O1) 0.012; (O2) 0.01	0.012	0.009	-0.022	
	Standard Error	0,027; 0.029; 0.027	0.033	0.033	0.025	
	95% CI		(-0.063, 0.087)	(-0.054,0.073)	(-0.071, 0.027)	
	p-value	Intercept 0.986;(O1) 0.685;(O2) 0.725	0.756	0.774	0.372	
Mine 2 HEG2	Occupation and Sample Size	Occupation text (1) observations 70	Development team leader/supervisor O1	Miner's assistant (cheesa)O2	Scraper winch driver)3	(W1)-0.224; (W2)0.029; (W3)0.034; (W4)0.008; (W5)0.027; (W6)0.024 (W7)0.012; (W8)0.033; (W9)9.699×10-4; (W10)-0.05; (W11)0.029 (W12)0.038; (W13)0.013; (W14)-0.056; (W15)-0.003; (W16)5.983×10-4 (W17)0.016; (W18)0.021; (W19)'-1.485×10-4 ; (W20)0.005; (W21)0.028 (W22)0.027; (W23)-0.014; (W24)2.112×10-4; (W25)0.004; (W26)-0.002
	ANOVA Summary	F=0.346; p=0.71				
	Estimate	Intercept -0.007; (O1)-0.024;(O2)0.026	-0.031	0.018	-0.008	
	Standard Error	Intercept 0.027; (O1) 0.033;(O2)0.04	0.033	0.051	0.052	
	95% CI		(-0.095;0.032)	(-0.082;0.119)	(-0.111;0.094)	
	p-value	Intercept 0.792; (O1)0.464; (O2)0.528	0.335	0.72	0.873	

The ANOVA summary for Mine 2 HEG 1 in Table 5(b) comprised 27 observations The analysis found no significant differences in exposure levels to RCS across occupations (F = 0.433; p = 0.664), indicating that the exposure parameters are comparatively uniform among workers in this HEG. The confidence intervals for these estimates cross zero, the differences observed are not statistically meaningful. Furthermore, variance component analysis suggests minimal variability across individual workers, implying that exposure levels to RCS among workers within HEG 1 remain relatively stable. This supports the validity of grouping these occupations under a single HEG for exposure monitoring.

In the evaluation of Mine 2 HEG2, although the ANOVA results indicated no statistically significant differences in exposure across occupations (F = 0.346; p = 0.710), further analysis of the individual-level variance components revealed a noteworthy outlier. Specifically, Worker 1 (Development team leader/supervisor) exhibited a variance component of -0.224 mg/m³, which markedly deviates from the rest of the group, whose values largely ranged between -0.056 and 0.038 mg/m³. Importantly, within the context of the model, more negative values represent higher individual concentrations relative to the group mean. As such, W1's negative deviation suggests a significantly elevated individual exposure compared to other workers within the HEG.

Table 6(a): Mine 1 Stoping Activity

No.	Parameter	Fixed Effects (Occupation)	Estimated Marginal Means		Variance Component (Random Effects)(Worker (W)			
Mine1 HEG4	**Occupation and Sample Size**	**Occupation text (1) 6 observations**	**General Miner (O1)**	**Stoper Miner (O2)**	**Worker 1**	**Worker 2**		
	ANOVA Summary	F=0.422; p=0.552						
	Estimate	Intercept 8.435×10-4 ; (O2)-0.019	0.02	0.018	4.451×10-18	-3.296×10-17		
	Standard Error	Intercept 0.029; (O1) 0.029	-0.020;0.04	0.042				
	95% CI		(-0.099, 0.059)	(-0.065, 0.101)				
	p-value	Intercept 0.978; (O1) 0.552	0.623	0.668				
Mine1 HEG5	**Occupation and Sample Size**	**Occupation text (1) (2)(3) (4) 36 Observations**	**General Miner O1**	**Miner Stoper O2**	**Stope Labourer O3**	**Supervisor Operations O4**	**Water Jet Operator O5**	**0**
	ANOVA Summary	F=2.724; p=0.047						
	Estimate	Intercept 0.013; (O1)-0.054; (O2)'1.524×10-4;(O3)0.015; (O4)0.027	-0.041	0.013	0.028	0.04	0.026	
	Standard Error	Intercept 0.008; (O1)0.017; (O2)0.012; (O3) 0.015; (O4)0.018	0.048	0.045	0.046	0.049	0.047	
	95% CI		(-0.079, -0.003)	(-0.009,0.036)	(-0.004,0.060)	(-0.002,0.082)	(-0.009,0.060)	
	p-value	Intercept 0.101; (O1)0.003; (O2) 0.99; (O3) 0,325 (O4)0.154	0.32	0.244	0.084	0.062	0.142	

Table 6(a) gives a detailed analysis of RSC in the Stoping activity areas, Mine1 HEG4 consisted of only 6 observations covering two roles: General Miner (O1) and Stoper Miner (O2). The ANOVA results indicated no significant difference in exposure between these occupations ($F = 0.422$; $p = 0.552$). The estimated marginal means were 0.020 mg/m³ for General Miner and 0.018 mg/m³ for Stoper Miner. Both had wide 95% confidence intervals that included zero (General Miner: −0.099 to 0.059 mg/m³; Stoper Miner: −0.065 to 0.101 mg/m³), and non-significant p-values (0.623 and 0.668, respectively). The minimal random effects observed for Worker 1 and Worker 2 (4.451×10^{-18} mg/m³ and -3.296×10^{-17} mg/m³) further support the homogeneity of exposure within this HEG, suggesting that both occupational roles were exposed to similar environmental conditions.

In contrast, Mine1 HEG5, which included 36 observations across five occupational roles—General Miner (O1), Miner Stoper (O2), Stope Labourer (O3), Supervisor Operations (O4), and Water Jet Operator (O5)—showed statistically significant differences between occupational exposures ($F = 2.724$; $p = 0.047$). The estimated marginal mean for General Miner was −0.041 mg/m³, which was significantly different than the others (95% CI: −0.079 to −0.003 mg/m³; $p = 0.003$). The means for the other roles were 0.013 mg/m³ (Miner Stoper), 0.028 mg/m³ (Stope Labourer), 0.040 mg/m³ (Supervisor Operations), and 0.026 mg/m³ (Water Jet Operator), with all confidence intervals including zero, and non-significant p-values. While most individual roles did not show statistically significant differences, the significant finding for General Miners suggests heterogeneity of exposure within this HEG. This variation may imply that the current grouping under HEG5 may not fully reflect consistent exposure patterns and may require reconsideration or further stratification by task or location.

Table 6(b): Mine 2 Stoping Activity

HEG No.	Parameter	Fixed Effects (Occupation)	Estimated Marginal Means			Variance Component (Random Effects)(Worker (W)		
Mine 2 HEG 3	**Occupation and Sample Size**	**Occupation text (1)(2) 59 observations**	**Miner's assistant (cheesa)O1**	**Scraper winch driver O2**		(W1)0.002; (W2)0.018; (W3)-0.02; (W4)0.014; (W5)0.007; (W6)0.006; (W7)0.012; (W8)0.013; (W9)-0.032; (W10)0.009; (W11)8.793×10-4; (W12)0.007; (W13)0.011 (W14)-0.058; (W15)0.006; (W16)0.011; (W17)-0.001; (W18)0.011; (W19)0.007 (W20)-0.035; (W21)'3.468×10-5 ; (W22)0.01; (W23)0.004		
	ANOVA Summary	**F=0.339; p=0.556**						
	Estimate	Intercept-0.009';(O1)-0.008	-0.017	'-8.672×10-4				
	Standard Error	Intercept 0.014; (O1)0.014	0.023	0.016				
	95% CI		(-0.062;0.028)	(-0.033;0.031)				
	p-value	Intercept 0.526; (O1)0.556	0.453	0.957				
Mine 2 HRG 4	**Occupation and Sample Size**	**Occupation text (1) 89 observations**	**Miner's assistant**	**Scraper winch driver O2**		(W1)0.002; (W2)-0.003; (W3)-0.003; (W4)-0.002; (W5)-0.002; (W6)0.003 (W7)0.003; (W8)4.905×10-4; (W9)-0.004; (W10)0.009; (W11)-0.002 (W12)-0.009; (W13)-0.002; (W14)0.002; (W15)0.003; (W16)3.967×10-4; (W17)-0.002; (W18)0.004; (W19)0.001; (W20)1.620×10-4; (W21)0.002 (W22)-0.004; (W23)-0.004; (W24)0.002; (W25)0.002; (W26)0.002 (W27)0.002; (W28)-0.003; (W29)'-5.523×10-4 ; (W30)9.934×10-4; (W31)0.001		
	ANOVA Summary	**F=0.4372; p=0.0046**						
	Estimate	Intercept-0.019; (O1)0.021	-0.019	0.002				
	Standard Error	Interceptc0.008;(O1) 0.01	0.008	0.006				
	95% CI		('-0.035; -0.003)	('-0.01; 0.003)				
	p-value	Intercept-0.0025; (O2) 0.046	0.018	0.766				
Mine 2 HEG 5	**Occupation and Sample Size**	**Occupation text (1) (2)(3) (4) 119 Observations**	**Conveyor belt attendant O1**	**Driller: hand percussion/ jackhammer O2**	**Scraper winch driver O3**	**Stope team leader/supervisor O4**	**Stope team worker O5**	(W1)9.366×10-5; (W2)1.289×10-4; (W3)0.002; (W4)-45.22; (W5)0.001; (W6)4.722×10-4 (W7)0.004; (W8)0.001; (W9)-0.001; (W10)-15.59; (W11)8.362×10-4; (W12)6.551×10-4 (W13)0.003; (W14)6.824×10-4; (W15)5.892×10-4; (W16)2.914×10-4; (W17)-0.011; (W18)-81.11 (W19)0.001; (W20)4.576×10-4; (W21)6.884×10-5; (W22)3.376×10-4; (W23)-24.33 (W24)-37.02;(W25)1.214×10-4; (W26)4.697×10-4; (W27)5.892×10-4; (W28)-0.001 (W29)-0.004; (W30)1.797×10-5; (W31)-23.75; (W32)-100.92; (W33)-62.21; (W34)-65.13; (W35)6.886×10-4; (W36)8.156×10-4; (W37)8.255×10-4; (W38)1.925×10-5; (W39)0.001; (W40)5.848×10-5; (W41) 9.205×10-5; (W42)-0.001; (W43)1.895×10-4; (W44)8.928×10-4
	ANOVA Summary	**F=0.356; p=0.839**						
	Estimate	Intercept '-1.676×10-4 (O1) 0.015; (O2) 0.008; (O3) -0.001; (O4) -0.017	0.015	0.007	-0.002	-0.017	-0.005	
	Standard Error	Intercept 0.01;(O1) 0.026;(O2) 0.025;(O3)0.019;(O4)0.015	0.031	0.029	0.021	0.013	0.017	
	95% CI		(-0.046, 0.076)	(-0.05, 0.065)	(-0.042, 0.039)	(-0.043, 0.009)	(-0.038, 0.029)	
	p-value	Intercept 0.987; (O1) 0.566; (O2)0.762; (O3)0.945; (O4)0.25	0.63	0.8	0.942	0.193	0.785	

In Table 6(b), Mine 2 HEG3, which included 59 observations across two occupations—Miner's Assistant (O1) and Scraper Winch Driver (O2)—showed no statistically significant differences between occupational exposure levels (F = 0.339; p = 0.556). The estimated marginal means were −0.017 mg/m³ for O1 and −0.0008672 mg/m³ for O2, with wide 95% confidence intervals encompassing zero (O1: −0.062 to 0.028 mg/m³; O2: −0.033 to 0.031 mg/m³). P-values for both roles were non-significant (0.453 and 0.957, respectively). Individual exposure values among workers (W1–W23) ranged between −0.058 mg/m³ and 0.018 mg/m³, further supporting internal consistency within the HEG. These findings suggest a level of exposure homogeneity, validating the current HEG3 classification.

In contrast, Mine 2 HEG 4, composed of 89 observations from the same two occupations as HEG3, presented statistically significant differences in occupational exposures (F = 0.4372; p = 0.0046). The estimated marginal mean for Miner's Assistant was −0.019 mg/m³, while Scraper Winch Driver showed a slightly positive mean of 0.002 mg/m³. Notably, the confidence interval for O1 (- −0.035 to −0.003 mg/m³) did not include zero and had a significant p-value (0.018), indicating a true difference in exposure between the roles. However, individual exposure estimates (W1–W31) remained very low, mostly ranging between −0.004 mg/m³ and 0.004 mg/m³, suggesting low variability at the worker level despite occupational differences. These results imply that although the group exhibits exposure differences by occupation, individual variability remains minimal.

Whereas HEG 5, had the largest number of observations (n=119), including five different occupations. The ANOVA summary (F= 0.356; p = 0.839) indicates no statistically significant differences in exposure to RCS. The estimated marginal means were all near zero. All associated 95% confidence intervals included zero, ranging from −0.046 to 0.076 mg/m³, with p-values above 0.19 for each role, indicating that the observed differences were not statistically significant. Importantly, random effects (worker-level estimates) show relatively minor variability across the 45 workers. These ranged from −0.011 mg/m³ (Worker 17) to 0.004 mg/m³ (Worker 7), with the majority of values clustered between −0.001 and 0.001 mg/m³. No extreme outliers were identified, and the distribution appears balanced, with both slightly positive and slightly negative deviations around zero. This confirms that individual workers had exposure levels consistent with the group averages and that variability among workers was minimal.

4.4 Measures of Central Tendencies and Distribution

This section discusses the key statistics of occupational exposure levels to RCS from 2019 to 2022. Various occupational groups across different HEGs were analysed to assess trends in exposure levels to RCS by using measures of central tendency, including the AM, median, GM, 90th percentile values, and variability indicators such as standard deviation (SD) and geometric standard deviation (GSD).

Table 7(a): Mine 1 Development End Activity Measures of central tendency and distribution

HEG No	Year	Occupations	No	Mean mg/m³	SD	Median mg/m³	GM mg/m³	GSD
Mine1 HEG1	2019	HEG1	9	0.030	0.017	0.032	0.0252	1.85
		Team Leader Secondary Support :1	3	0.033	0.021	0.036	0.0255	2.3
		Team Member Secondary Support: 2	3	0.02	0.012	0.018	0.0173	1.89
	2020	HEG1	8	0.025	0.023	0.019	0.018	2.39
		Team Leader Secondary Support :1	3	0.026	0.029	0.02	0.0216	1.6
		Team Member Secondary Support: 2	5	0.023	0.012	0.017	0.0166	2.95
	2021	HEG1	9	0.029	0.043	0.017	0.0144	3.39
		Team Leader Secondary Support :1	4	0.017	0.01	0.017	0.0141	2.1
		Team Member Secondary Support: 2	5	0.041	0.056	0.017	0.0232	2.97
	2022	HEG1	8	0.015	0.009	0.014	0.0133	1.74
		Team Leader Secondary Support :1	5	0.018	0.011	0.016	0.0153	1.88
		Team Member Secondary Support: 2	2	0.013	0.003	0.013	NaN*	NaN*
Mine1 HEG2	2019	HEG2	8	0.033	0.015	0.033	0.0292	1.68
		Developer:1	3	0.028	0.009	0.032	0.0264	1.47
		General Miner:2	5	0.035	0.018	0.039	0.031	1.87
	2020	HEG2	11	*0.02*	0.013	0.015	0.0158	2.11
		Developer:1	3	0.019	0.023	0.006	0.031	1.87
		General Miner:2	7	0.02	0.01	0.015	0.0111	3.43
	2021	HEG2	8	*0.018*	0.012	0.015	0.0153	1.86
		Developer:1	4	0.018	0.017	0.013	0.0136	2.39
		General Miner:2	4	0.018	0.007	0.015	0.0172	1.38
	2022	HEG2	8	*0.012*	0.016	0.005	0.00528	4.31
		Developer:1	4	0.036	0.029	0.042	0.00573	4.83
		General Miner:2	4	0.017	0.013	0.015	0.00486	4.83
Mine 1 HEG3	2019	HEG3	21	0.076	0.059	0.056	0.0572	1.68
		Special Team Leader Development: 1	3	0.078	0.038	0.073	0.072	1.66
		Loco driver: 2	12	0.083	0.072	0.059	0.0568	2.61
		Loader Driver: 3	6	0.067	0.036	0.049	0.0606	1.57
	2020	HEG3	14	0.066	0.068	0.037	0.0417	2.05
		Special Team Leader Development:1	2	0.036	0.036	0.036	NaN*	NaN*

		Loco driver: 2	4	0.063	0.06	0.035	0.0476	2.23
		Loader Driver: 3	3	0.1	0.11	0.053	0.063	3.3
	2021	HEG3	20	0.022	0.016	0.018	0.0165	1.86
		Special Team Leader Development:1	4	0.022	0.016	0.019	0.0174	2.33
		Loco driver: 2	3	0.046	0.011	0.045	0.0459	1.27
		Loader Driver: 3	4	0.011	0.011	0.007	0.00853	2.4
	2022	HEG3	8	0.019	0.013	0.015	0.0145	4.31
		Special Team Leader Development:1	2	0.021	0.01	0.021	NaN*	NaN*
		Loco driver: 2	2	0.029	0.017	0.029	NaN*	NaN*
		Loader Driver: 3	2	0.017	0.018	0.017	NaN*	NaN*

*Note: NaN: Not Computed (Insufficient Data)

Table 7(a) presents RCS exposure levels for Mine 1 Development End, comparing three HEGs (HEG1, HEG2, and HEG3) with their nested occupations. Each HEG provides an overall exposure estimate, while nested occupations show variations in exposure levels. The AM represents the average exposure, while the SD indicates variability. The GM and GSD provide insights into the distribution and spread of exposure levels within HEGs and their nested occupations.

In HEG1 during 2019, the AM was 0.030 mg/m³ with a GSD of 1.85, indicating low variability. The median was recorded at 0.032 mg/m³, which is close to the AM, suggesting a relatively balanced distribution of exposure values. However, among the nested occupations, the Team Leader Secondary Support had an AM of 0.033 mg/m³, a SD of 0.021, a median of 0.036 mg/m³, and a GSD of 2.3, indicating slightly higher exposure and variability. In contrast, the Team Member Secondary Support had a lower AM of 0.020 mg/m³, a SD of 0.012, a median of 0.018 mg/m³, and a GSD of 1.89, showing a more stable distribution with lower exposure levels. This comparison suggests that while HEG1 provides a general estimate, individual occupations within it experience different levels of exposure risk.

HEG2 exhibited a general downward trend in mean RCS exposure levels between 2019 and 2022. The AM decreased from 0.033 mg/m³ in 2019 to 0.012 mg/m³ in 2022, indicating a 63.6% reduction over the four years, whilst the GSDs of 2.11 and 1.86, respectively, indicated moderate variability in exposure among individuals. In 2022, while the AM was the lowest across the study period (0.012 mg/m³), the GSD increased markedly to 4.31, reflecting significant inconsistency in exposure levels within the group. At the occupational level, General Miners had higher mean exposures than Developers in 2019 and 2020, but this trend reversed in 2022, where Developers recorded a substantial increase in mean exposure (0.036 mg/m³), three times higher than that of

General Miners (0.017 mg/m³). This spike among Developers coincided with a high standard deviation (0.029), highlighting elevated and highly variable exposures within this occupation.

HEG3 had the highest exposure within Mine 1 Development End, with an AM of 0.076 mg/m³, a median of 0.056 mg/m³, and a GSD of 1.68. Within HEG3, Loco Drivers experienced the highest exposure, with an AM of 0.083 mg/m³, a SD of 0.072, a median of 0.059 mg/m³, and a GSD of 2.61. Loader Drivers had lower exposure levels, with an AM of 0.067 mg/m³, a median of 0.049 mg/m³, and a GSD of 1.57.

By 2021, exposure variability had increased across HEGs. HEG1's AM remained moderate at 0.029 mg/m³, but the Team Member Secondary Support had a significantly higher AM of 0.041 mg/m³. HEG3, however, saw a reduction in exposure, with an AM of 0.022 mg/m³ and a median of 0.018 mg/m³.

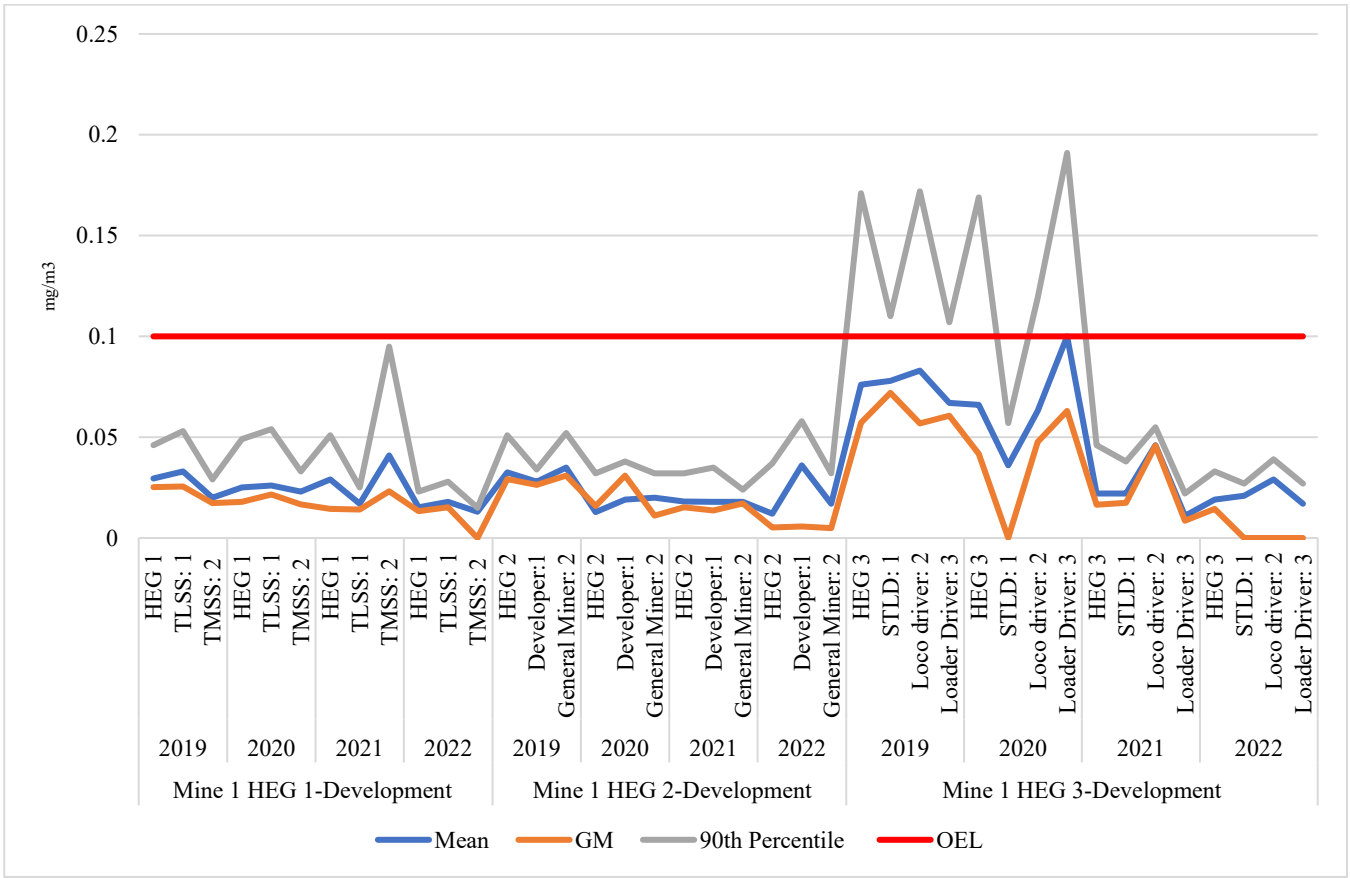


Figure 2: Mine1 Development Ends Activity -AM, GM, and 90th percentile[1]

[1] Team Leader Secondary Support = TLSS
Team Member Secondary Support = TMSS
Special Team Leader Development = STLD

Figure 2 illustrates the exposure trends for HEG 1, HEG 2, and HEG 3 in Mine 1 Development End from 2019 to 2022. The comparison between HEGs and their nested occupations highlights how exposure varies within groups.

In HEG 1, the Team Leader Secondary Support in 2019 recorded an AM of 0.033 mg/m³, a GM of 0.0255 mg/m³, and a 90th percentile of 0.053 mg/m³, placing it under Category C. The Team Member Secondary Support had a lower exposure with an AM of 0.02 mg/m³, a GM of 0.0173 mg/m³, and a 90th percentile of 0.029 mg/m³, also classified in Category C. HEG 1 itself recorded an AM of 0.030 mg/m³, a GM of 0.023 mg/m³, and a 90th percentile of 0.041 mg/m³, demonstrating that the Team Leader Secondary Support had a higher exposure than the HEG average, while the Team Member Secondary Support had a slightly lower exposure.

In 2020, HEG 1 showed a decrease in exposure levels, with an AM of 0.026 mg/m³ and a 90th percentile of 0.038 mg/m³. While the Team Leader Secondary Support followed this trend, recording an AM of 0.026 mg/m³, a GM of 0.0216 mg/m³, and a 90th percentile of 0.054 mg/m³, the Team Member Secondary Support recorded an increase in the 90th percentile to 0.033 mg/m³.

By 2021, HEG 1 recorded an AM of 0.025 mg/m³, while the Team Leader Secondary Support remained close to this value with 0.017 mg/m³. However, the Team Member Secondary Support deviated from this trend with a significant increase to an AM of 0.041 mg/m³ and a 90th percentile of 0.095 mg/m³, moving it into Category B, unlike HEG 1, which remained in Category C. In 2022, HEG 1 further reduced exposure levels to an AM of 0.021 mg/m³, aligning with the Team Leader Secondary Support at 0.018 mg/m³, while the Team Member Secondary Support recorded an AM of 0.013 mg/m³, stabilising in Category C.

HEG 2 included Developers and General Miners. In 2019, Developers had an AM of 0.028 mg/m³, a GM of 0.0264 mg/m³, and a 90th percentile of 0.034 mg/m³, while General Miners recorded higher exposure levels with an AM of 0.035 mg/m³, a GM of 0.031 mg/m³, and a 90th percentile of 0.052 mg/m³. The HEG 2 average for 2019 was an AM of 0.033 mg/m³, a GM of 0.028 mg/m³, and a 90th percentile of 0.043 mg/m³. General Miners exhibited higher exposure than the HEG 2 average, whereas Developers had exposure levels below the HEG 2 mean.

In 2020, HEG 2 exposure levels dropped to an AM of 0.024 mg/m³, following the decreasing trend in Developers and General Miners. Developers recorded an AM of 0.019 mg/m³, a GM of 0.031 mg/m³, and a 90th percentile of 0.038 mg/m³, while General Miners recorded an AM of 0.02 mg/m³, a GM of 0.0111 mg/m³, and a 90th percentile of 0.032 mg/m³. This trend continued into

2021, with HEG 2 maintaining an AM of 0.022 mg/m³. Developers saw a decline to 0.018 mg/m³, while General Miners had an AM of 0.018 mg/m³, both aligning closely with HEG 2's average. However, in 2022, Developers saw an increase in exposure, with an AM of 0.036 mg/m³ and a 90th percentile of 0.058 mg/m³, while General Miners remained stable at an AM of 0.017 mg/m³. HEG 2 as a whole reflected these changes with an AM of 0.029 mg/m³, a GM of 0.021 mg/m³, and a 90th percentile of 0.042 mg/m³.

HEG 3 contained Special Team Leaders, Loco Drivers, and Loader Drivers. In 2019, Special Team Leaders recorded an AM of 0.078 mg/m³, a GM of 0.072 mg/m³, and a 90th percentile of 0.11 mg/m³, classifying them under Category A. Loco Drivers recorded an AM of 0.083 mg/m³, a GM of 0.0568 mg/m³, and a 90th percentile of 0.172 mg/m³, while Loader Drivers recorded an AM of 0.067 mg/m³, a GM of 0.0606 mg/m³, and a 90th percentile of 0.107 mg/m³. HEG 3 itself recorded an AM of 0.076 mg/m³, a GM of 0.064 mg/m³, and a 90th percentile of 0.132 mg/m³, showing that Loco Drivers had higher exposure than the HEG 3 average.

In 2020, exposure dropped for HEG 3, with an AM of 0.036 mg/m³, placing it in Category C. Special Team Leaders recorded an AM of 0.036 mg/m³, while Loco Drivers recorded an AM of 0.063 mg/m³, and Loader Drivers recorded 0.1 mg/m³, keeping them in Category A. In 2021, exposure declined for all occupations in HEG 3, with an AM of 0.022 mg/m³ for Special Team Leaders, 0.046 mg/m³ for Loco Drivers, and 0.011 mg/m³ for Loader Drivers, classifying them under Category C. By 2022, exposure levels stabilized with an AM of 0.021 mg/m³ for Special Team Leaders, 0.029 mg/m³ for Loco Drivers, and 0.017 mg/m³ for Loader Drivers, all within Category C. HEG 3 mirrored this trend with an AM of 0.023 mg/m³, a GM of 0.018 mg/m³, and a 90th percentile of 0.029 mg/m³.

Overall, Figure 2 highlights the fluctuations in exposure levels across different occupations within HEGs. Some occupations, such as Loco Drivers and Special Team Leaders in HEG 3, consistently exceeded the occupational exposure limit (OEL) of 0.1 mg/m³, placing them in Category A, while others, such as Team Member Secondary Support in HEG 1, demonstrated varying exposure trends that required continuous monitoring and control measures.

Table 7(b): Mine 2 Development End Activity Measures of central tendency and distribution

HEG No	Year	Occupations	No	Mean mg/m³	SD	Median mg/m³	GM mg/m³	GSD
Mine 2 HEG1	2019	HEG1	32	0.041	0.027	0.034	0.0342	1.9
		Development Team Worker:1	6	0.04	0.033	0.028	0.0335	1.82
		Loco Driver:2	8	0.029	0.017	0.028	0.0241	2.01
	2020	HEG1	48	0.047	0.041	0.034	0.0362	1.99
		Development Team Worker:1	7	0.059	0.055	0.038	0.0469	1.92
		Loco Driver:2	3	0.027	0.006	0.025	0.0265	1.25
	2021	HEG1	45	0.052	0.057	0.034	0.0302	3.08
		Development Team Worker:1	4	0.063	0.054	0.042	0.0495	2.12
		Loco Driver:2	8	0.114	0.09	0.133	0.064	4.15
	2022	HEG1	21	0.054	0.059	0.038	0.0322	2.95
		Development Team Worker:1	2	0.015	0.012	0.015	NaN*	Na*
		Loco Driver:2	4	0.108	0.087	0.109	0.0729	3.2
Mine2 HEG2	2019	HEG2	51	0.06	0.074	0.04	0.0399	2.34
		Development Team leader/supervisor: 1	12	0.039	0.039	0.03	0.0264	2.5
		Miner's assistant (cheesa):2	3	0.069	0.008	0.07	0.069	1.12
		Scraper winch driver:3	6	0.095	0.126	0.05	0.0558	2.82
	2020	HEG2	61	0.077	0.11	0.049	0.0488	2.4
		Development Team leader/supervisor: 1	14	0.039	0.039	0.03	0.0625	2.57
		Miner's assistant (cheesa):2	2	0.069	0.008	0.07	NaN*	NaN
		Scraper winch driver:3	9	0.095	0.126	0.033	0.0459	2.44
	2021	HEG2	64	0.057	0.059	0.033	0.0386	2.43
		Development Team leader/supervisor: 1	18	0.069	0.067	0.038	0.0447	2.73
		Miner's assistant (cheesa):2	11	0.05	0.042	0.033	0.0401	1.9
		Scraper winch driver:3	1	0.018	NaN*	0.018	NaN*	NaN*
	2022	HEG2	24	0.111	0.262	0.055	0.0521	2.68
		Development Team leader/supervisor: 1	12	0.169	0.367	0.058	0.0626	3.46
		Miner's assistant (cheesa):2	3	0.079	0.05	0.066	0.0683	1.93
		Scraper winch driver:3	1	0.013	NaN*	0.013	NaN*	NaN*

*Note: NaN: Not Computed (Insufficient Data)

Table 7(b) presents RCS exposure levels in Mine 2 Development End for HEG1 and HEG2. In 2019, HEG1 recorded an AM of 0.041 mg/m³, which closely aligned with the Development Team Worker's AM of 0.040 mg/m³ and a median of 0.028 mg/m³. Loco Drivers had slightly lower exposure levels, with an AM of 0.029 mg/m³ and a median of 0.028 mg/m³. In HEG2, exposure

was more variable, with an AM of 0.06 mg/m³, a median of 0.04 mg/m³, and a GSD of 2.34. The highest exposure was recorded among Scraper Winch Drivers, with an AM of 0.095 mg/m³.

By 2021, HEG1's AM increased to 0.052 mg/m³, but Loco Drivers had a much higher AM of 0.114 mg/m³ and a median of 0.133 mg/m³, showing that HEG estimates do not always reflect the risks of specific occupations. HEG2's exposure remained stable, but its variability increased, with a GSD of 2.43, suggesting fluctuating exposure patterns.

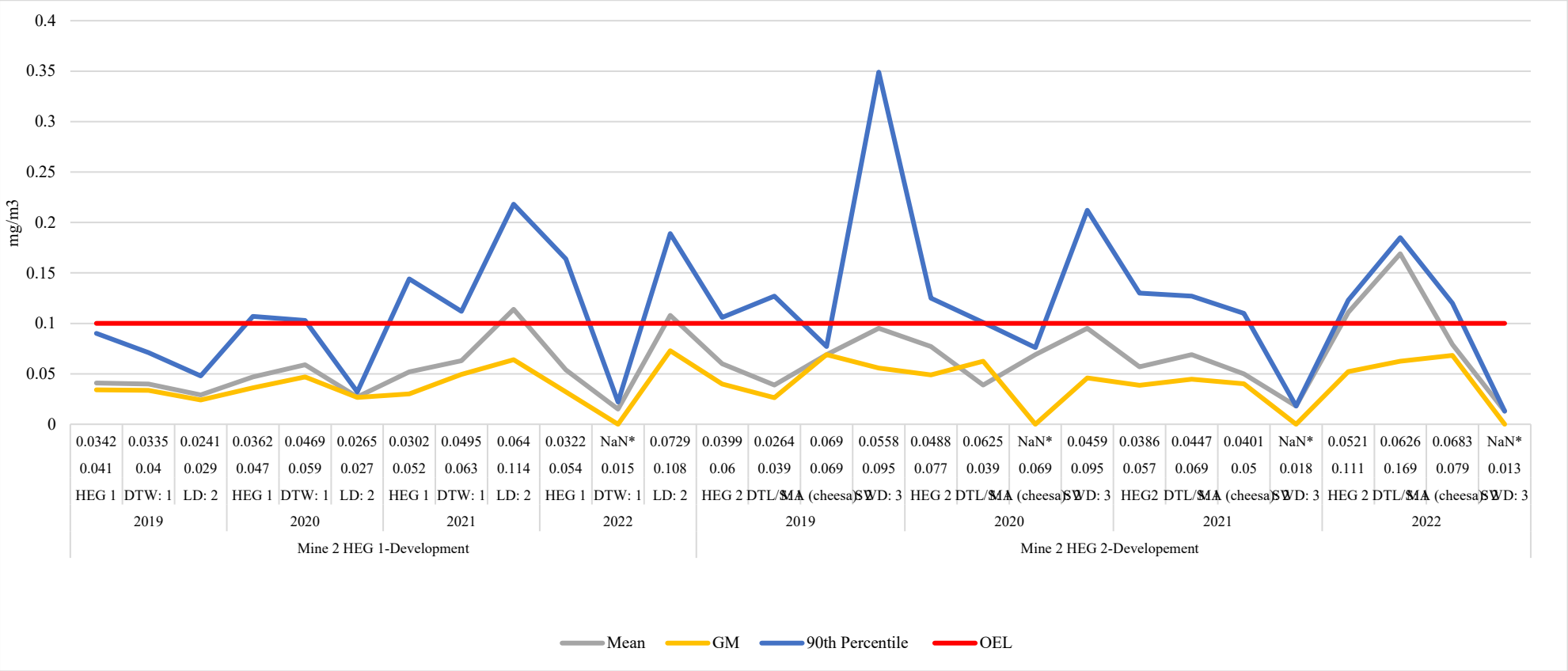


Figure 3: Mine 2 Development Ends Activity-AM, GM, and 90th percentile[2]

[2] Development Team Worker = DTW
Loco Driver = LD
Development Team Leader/Supervisor = DTL/S
Miner's assistance = MA
Scraper Winch Driver = SWD

Figure 3 illustrates the exposure trends for HEG 1 and HEG 2 in Mine 2 Development End from 2019 to 2022. The comparison between HEGs and their nested occupations highlights exposure variations within groups.

HEG 1 and HEG 2 exhibited different trends in exposure across the years. In 2019, HEG 1 recorded an AM of 0.041 mg/m³, a GM of 0.0342 mg/m³, and a 90th percentile of 0.062 mg/m³, placing it in Category C. Development Team Workers had a slightly lower exposure, whereas Loco Drivers recorded an AM of 0.029 mg/m³, a GM of 0.0241 mg/m³, and a 90th percentile of 0.048 mg/m³, also classified under Category C. HEG 2 recorded a higher AM of 0.06 mg/m³, a GM of 0.0399 mg/m³, and a 90th percentile of 0.074 mg/m³, placing it in Category B. Within HEG 2, Development Team Leaders recorded lower exposure compared to Miner's Assistants, who had an AM of 0.069 mg/m³, pushing them towards Category B.

In 2020, HEG 1 experienced an increase in AM to 0.047 mg/m³, with Development Team Workers showing elevated exposure levels, placing them in Category B. Loco Drivers, however, recorded a decrease in exposure. HEG 2 recorded an AM of 0.077 mg/m³, with the Miner's Assistants showing the highest exposure levels, maintaining Category B.

By 2021, HEG 1's exposure levels continued to rise, with an AM of 0.052 mg/m³ and a 90th percentile of 0.112 mg/m³, moving it into Category A. Loco Drivers exhibited the highest exposure, with an AM of 0.114 mg/m³ and a 90th percentile of 0.218 mg/m³, firmly in Category A. HEG 2 followed a fluctuating pattern, recording an AM of 0.057 mg/m³, with Development Team Leaders maintaining lower exposure than Miner's Assistants, keeping the latter in Category B.

In 2022, Development Team Workers in HEG 1 showed a substantial decrease in exposure, stabilizing in Category C, while Loco Drivers maintained high exposure levels, keeping them in Category A. HEG 2 recorded an AM of 0.111 mg/m³, with Miner's Assistants exhibiting elevated exposure levels that placed them in Category A.

Table 8(a): Mine 1 Stoping Activity Measures of central tendency and distribution

HEG No	Year	Occupations	No	Mean mg/m³	SD	Median mg/m³	GM mg/m³	GSD
Mine1 HEG4	2019	HEG4	**13**	0.035	0.034	0.016	0.0202	3.16
		General Miner: 1	1	0.06	NaN*	0.06	NaN*	NaN*
		Winch Operator: 2	4	0.067	0.038	0.072	0.0543	2.32
	2020	HEG4	12	0.013	0.016	0.007	0.00637	3.61
		General Miner: 1	3	0.005	0.006	0.003	0.00331	3.48
		Winch Operator: 2	3	0.025	0.027	0.015	0.015	3.73
	2021	HEG4	7	0.037	0.024	0.037	0.0289	2.39
		General Miner: 1	1	0.055	NaN*	0.055	NaN*	NaN*
		Winch Operator: 2	2	0.03	0.01	0.03	NaN*	NaN*
	2022	HEG4	11	0.022	0.021	0.015	0.0107	3.82
		General Miner: 1	3	0.036	0.029	0.042	0.0231	4.04
		Winch Operator: 2	7	0.017	0.013	0.015	0.0132	2.31
Mine1 HEG 5	2019	HEG5	9	0.07	0.078	0.032	0.0463	2.44
		General Miner: 1	2	0.141	0.165	0.141	NaN*	NaN*
		Miner Stoper: 2	7	0.049	0.037	0.032	0.0398	1.99
	2020	HEG5	18	0.083	0.169	0.029	0.0316	3.89
		General Miner: 1	2	0.064	0.044	0.064	NaN*	NaN*
		Miner Stoper: 2	4	0.041	0.035	0.029	0.0289	2.71
	2021	HEG5	21	0.021	0.018	0.017	0.0149	2.45
		General Miner: 1	2	0.022	0.027	0.022	NaN*	NaN
		Miner Stoper: 2	5	0.023	0.023	0.019	0.0158	2.57
	2022	HEG5	9	0.027	0.024	0.016	0.0152	3.22
		General Miner: 1	1	0.045	NaN*	0.045	NaN*	NaN*
		Miner Stoper: 2	2	0.008	0.008	0.1	NaN*	NaN*

*Note NaN: Not Computed (Insufficient Data)

Table 8(a) details Mine 1 Stoping exposure levels for HEG4 and HEG5. In 2019, HEG4 recorded an AM of 0.035 mg/m³, but Winch Operators had a much higher AM of 0.067 mg/m³ and a median of 0.072 mg/m³, indicating that HEG-level estimates underrepresent certain occupations' risks. Similarly, in HEG5, General Miners had an AM of 0.141 mg/m³, a median of 0.141 mg/m³, significantly exceeding HEG5's AM of 0.07 mg/m³.

By 2022, HEG4's exposure levels had dropped to an AM of 0.022 mg/m³, but General Miners still recorded an AM of 0.036 mg/m³ and a GSD of 4.04, showing high intra-group variability. HEG5's exposure remained relatively stable, with only minor fluctuations.

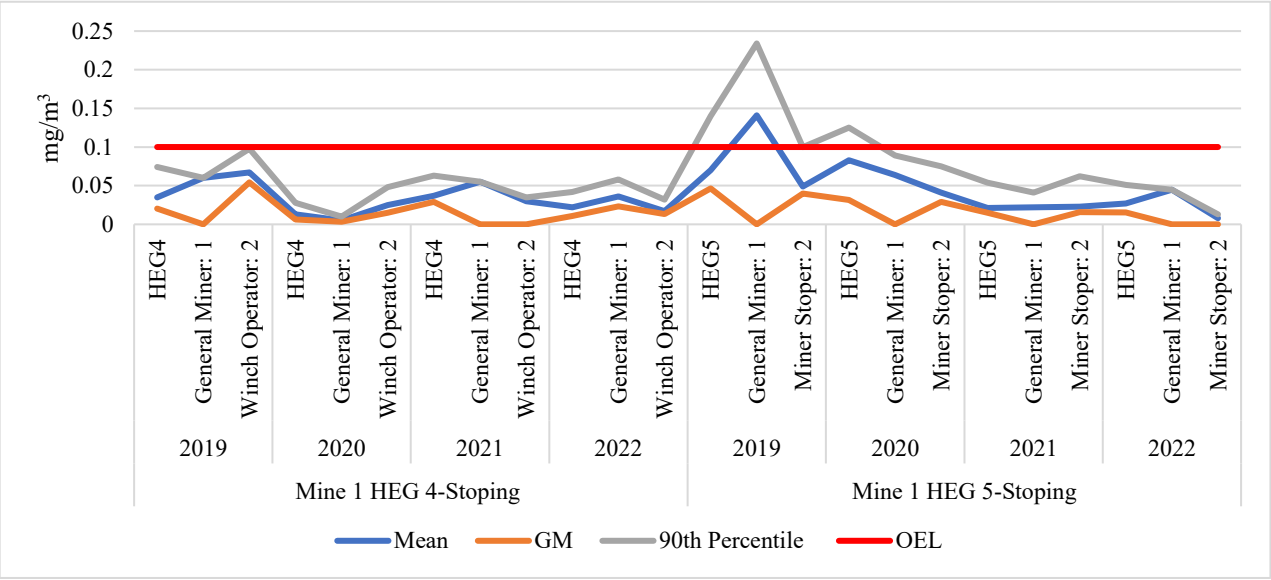


Figure 4: Mine 1 Stoping - AM, GM, and 90th percentile

Figure 4 illustrates the exposure trends for HEG 4 and HEG 5 in Mine 1 Stoping from 2019 to 2022. The comparison between HEGs and their nested occupations highlights exposure variations within groups.

HEG 4 and HEG 5 showed notable exposure variations across the years. In 2019, HEG 4 recorded an AM of 0.035 mg/m³, a GM of 0.0202 mg/m³, and a 90th percentile of 0.074 mg/m³, placing it in Category C. General Miners recorded an AM of 0.06 mg/m³, and Winch Operators had an AM of 0.067 mg/m³, placing them in Category B. HEG 5 had an AM of 0.07 mg/m³, with General Miners experiencing significantly higher exposure at 0.141 mg/m³, pushing them into Category A.

In 2020, HEG 4 saw a decline in exposure, with an AM of 0.013 mg/m³, moving all occupations into Category C. HEG 5 followed a similar trend, with exposure levels decreasing across all nested occupations, shifting General Miners into Category B.

By 2021, exposure levels in HEG 4 rebounded slightly, with an AM of 0.037 mg/m³ and a 90th percentile of 0.055 mg/m³, keeping it in Category C. General Miners and Winch Operators saw minor increases but remained in the same categories. HEG 5 recorded an AM of 0.021 mg/m³, with exposure variability increasing slightly.

In 2022, General Miners in HEG 4 experienced an increase in exposure, recording an AM of 0.036 mg/m³ and a 90th percentile of 0.058 mg/m³, maintaining Category C, while Winch Operators recorded an AM of 0.017 mg/m³, stabilizing at a lower level within the same category. HEG 5 continued to experience relatively stable exposure, with General Miners remaining in Category C.

Table 8(b): Mine 2 Stoping Measures of central tendency and distribution

HEG No	Year	Occupations	No	Mean mg/m³	SD	Median mg/m³	GM mg/m³	GSD
Mine 2 HEG3	2019	HEG3	24	0.0905	0.135	0.048	0.0489	2.86
		Miner's assistant (cheesa):1	6	0.151	0.21	0.054	0.085	2.87
		Scrapper Winch Driver: 2	9	0.056	0.054	0.044	0.0374	2.64
	2020	HEG3	71	0.0707	0.061	0.052	0.0536	2.09
	2020	Miner's assistant (cheesa):1	8	0.046	0.024	0.046	0.0403	1.81
		Scrapper Winch Driver: 2	20	0.094	0.085	0.082	0.0687	2.2
	2021	HEG3	33	0.0466	0.038	0.039	0.0341	2.33
	2021	Miner's assistant (cheesa):1	8	0.061	0.047	0.053	0.0457	2.3
		Scrapper Winch Driver: 2	20	0.043	0.039	0.032	0.0326	2.09
	2022	HEG3	24	0.045	0.023	0.049	0.0368	2.12
	2022	Miner's assistant (cheesa):1	5	0.041	0.024	0.049	0.0301	2.88
		Scrapper Winch Driver: 2	17	0.049	0.023	0.052	NaN*	NaN*
Mine 2 HEG4	2019	HEG4	46	0.0687	0.044	0.057	0.0568	1.92
	2019	Scrapper Winch Driver: 1	21	0.062	0.043	0.051	0.0512	1.95
		Miner's assistant (cheesa):2	6	0.086	0.06	0.079	0.0643	2.7
	2020	HEG4	71	0.0714	0.068	0.057	0.056	1.93
		Scrapper Winch Driver: 1	30	0.071	0.049	0.056	0.0575	1.93
		Miner's assistant (cheesa):2	13	0.067	0.04	0.056	0.0582	1.69
	2021	HEG4	66	0.0564	0.055	0.038	0.0403	2.28
		Scrapper Winch Driver: 1	23	0.047	0.03	0.04	0.0369	2.26
		Miner's assistant (cheesa):2	12	0.083	0.072	0.065	0.0639	2.09
	2022	HEG4	39	0.0573	0.044	0.045	0.0438	2.17
		Scrapper Winch Driver: 1	18	0.056	0.039	0.045	NaN*	NaN*
		Miner's assistant (cheesa):2	10	0.046	0.03	0.05	0.0335	2.62
Mine2 HEG5	2019	HEG5	67	0.081	0.085	0.059	0.0602	2.12
	2019	Driller: hand percussion/jackhammer: 1	2	0.039	0	0.039	NaN*	NaN*
		Stope team leader/supervisor: 2	20	0.1	0.127	0.071	0.0665	2.47
		Stope Team Member :3	8	0.058	0.021	0.052	0.0548	1.44
	2020	HEG5	105	0.0653	0.047	0.057	0.0505	2.14
	2020	Driller: hand percussion/jackhammer: 1	15	0.068	0.036	0.061	0.0564	2.05
		Stope team leader/supervisor: 2	29	0.074	0.047	0.071	0.0585	2.17
		Stope Team Member :3	15	0.073	0.052	0.053	0.0595	1.96
	2021	HEG5	80	0.064	0.107	0.044	0.0422	2.36
		Driller: hand percussion/jackhammer: 1	13	0.042	0.022	0.039	0.0359	1.96
		Stope team leader/supervisor: 2	20	0.089	0.205	0.042	0.0391	3.01

		Stope Team Member:3	13	0.07	0.031	0.063	0.0637	1.55
	2022	HEG5	31	0.041	0.03	0.029	0.0307	2.26
		Driller: hand percussion/jackhammer: 1	9	0.035	0.024	0.027	0.0273	2.24
		Stope team leader/supervisor: 2	3	0.02	0.017	0.012	0.0163	2.21
		Stope Team Member:3	9	0.067	0.035	0.061	0.0273	2.24

*Note: NaN: Not Computed (Insufficient Data)

Table 8(b) covers Mine 2 Stoping, detailing exposure levels for HEG3, HEG4, and HEG5. In 2019, HEG3 had an AM of 0.0905 mg/m³, with Miner's Assistants recording an even higher AM of 0.151 mg/m³ and a median of 0.054 mg/m³, highlighting a high exposure risk. HEG4 had an AM of 0.0687 mg/m³, with Scraper Winch Drivers recording a slightly lower AM of 0.062 mg/m³. HEG5 had an AM of 0.081 mg/m³, but Stope Team Leaders recorded an AM of 0.1 mg/m³, indicating a slightly elevated risk.

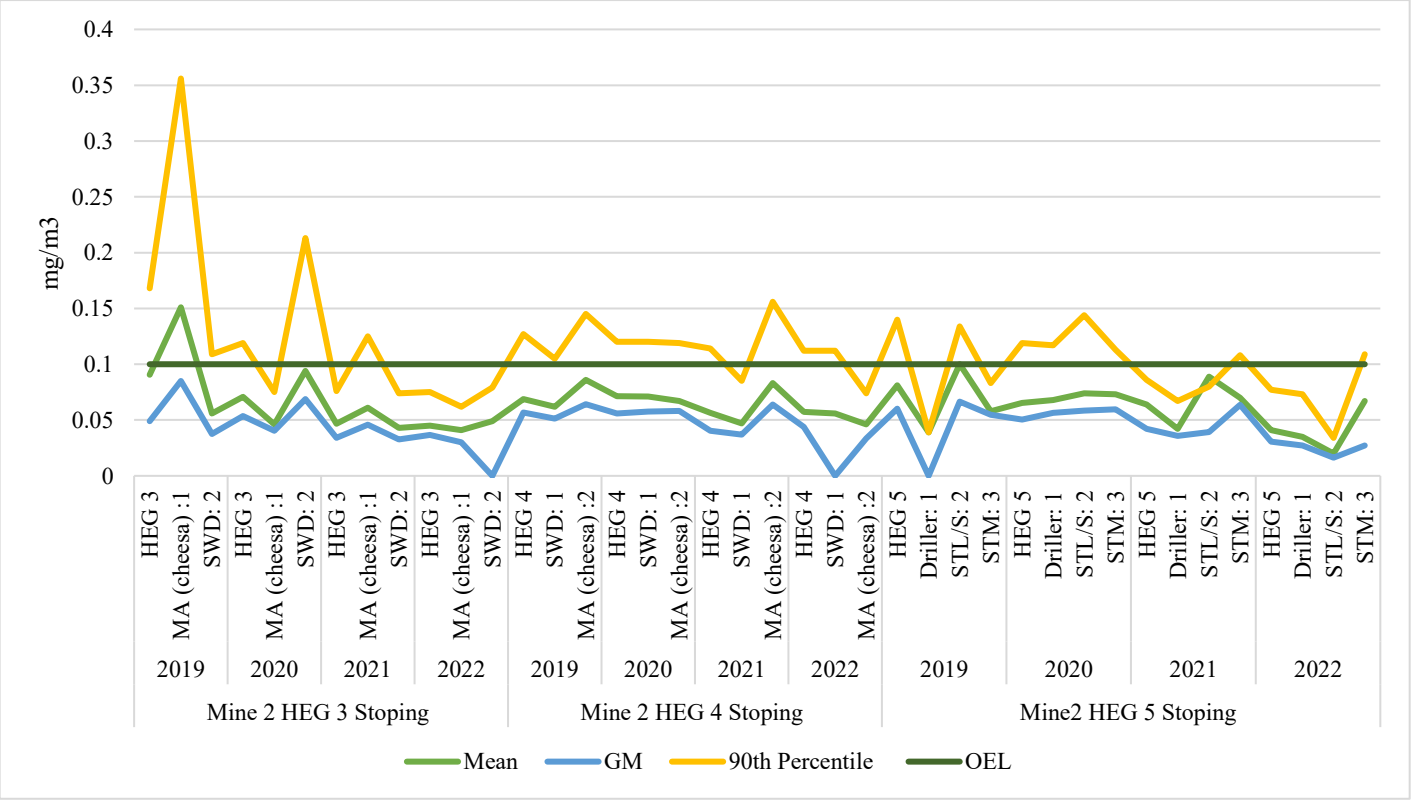


Figure 5: Mine 2 Stoping -AM, GM, and 90th percentile‡

‡ Miner's assistance = MA
Scraper Winch Driver = SWD
Driller: hand percussion/jackhammer = Driller
Stope Team Leader/Supervisor = STL/S
Stope Team Member = STM

HEG 3, HEG 4, and HEG 5 in Figure 5 above exhibited varying exposure trends across the years. In 2019, HEG 3 recorded an AM of 0.0905 mg/m³, a GM of 0.0489 mg/m³, and a 90th percentile of 0.132 mg/m³, placing it in Category B. Scraper Winch Drivers recorded an AM of 0.056 mg/m³, keeping them in Category C, while Miner's Assistants had an AM of 0.151 mg/m³, pushing them into Category A. HEG 4 recorded an AM of 0.0687 mg/m³, with Miner's Assistants showing higher exposure than Scraper Winch Drivers. HEG 5 recorded an AM of 0.081 mg/m³, with Stope Team Leaders showing significantly elevated exposure levels.

In 2020, HEG 3 saw a slight decline in exposure, recording an AM of 0.0707 mg/m³, with most nested occupations shifting into Category B. HEG 4 followed a similar trend, recording an AM of 0.0714 mg/m³, keeping most occupations in Category B. HEG 5 saw exposure stabilization, with an AM of 0.0653 mg/m³.

By 2021, HEG 3's exposure further decreased, with an AM of 0.0466 mg/m³, moving it into Category C. Miner's Assistants maintained slightly higher exposure levels but still remained within Category C. HEG 4 recorded an AM of 0.0564 mg/m³, maintaining Category C, while HEG 5 recorded an AM of 0.064 mg/m³, keeping most occupations in Category B.

In 2022, the trend continued downward, with HEG 3 recording an AM of 0.045 mg/m³, keeping both nested occupations in Category C. HEG 4 stabilized at an AM of 0.0573 mg/m³, maintaining Category C. HEG 5 recorded an AM of 0.041 mg/m³, keeping most occupations in Category C.

CHAPTER 5 DISCUSSION

This chapter provides a comprehensive discussion of the research findings concerning the three study objectives and addresses the study's limitations

5.1 Introduction

HEGs are essential for assessing occupational exposure, enabling effective policy development and monitoring within occupational health strategies. They provide a structured framework for systematic exposure assessment while optimizing resources [12,35]. However, their accuracy can be affected by inter-worker variability and temporal fluctuations [41,42], necessitating continuous reassessment to ensure reliability in dynamic work environments.

5.2 Interpretation of Results

The analysis of RCS exposure across HEGs over four years (2019–2022) provided valuable insights into occupational exposure trends. Various statistical techniques, including independent t-tests, ANOVA, and Linear Mixed Models, were used to evaluate exposure variability among workers in different roles. While HEG classification proved effective in grouping workers with similar exposure risks, specific job roles exhibited exposure variations that highlight the need for improvements in classification and monitoring strategies.

Findings indicate that, in most cases, exposure levels within HEGs were comparable across occupational groups, with no statistically significant differences. However, Stoping activities presented greater variability, reinforcing concerns that broad HEG classifications may not always accurately represent individual exposure levels[48]. Additionally, fluctuations in exposure trends over time, particularly in 2021 and 2022, suggest external factors such as operational or environmental changes influenced exposure levels[41,42]. These variations emphasize the need for periodic reassessment of HEG classifications to ensure ongoing accuracy in exposure estimation.

5.3 Reflection on Study Objectives

5.3.1 Objective 1: Reviewing Literature and Identifying HEG Methodologies

The study reaffirmed the role of HEGs as an established exposure monitoring tool. Literature findings indicated that while HEGs provide a structured approach to exposure assessment, they may overlook intra-group differences[44]. International studies suggest that integrating HEGs with individual exposure monitoring and predictive models could improve accuracy[44]. This aligns with the study’s findings, which highlight the limitations of HEG classifications in capturing individual exposure variations.

5.3.2 Objective 2: Comparing HEG Exposure Parameters with Occupational Groups

Results showed that while HEGs generally grouped workers with similar exposure risks, discrepancies were observed between certain roles within the Stoping and Development activities under investigation. The absence of statistically significant differences between occupations within the same HEG ($p > 0.05$) supports the effectiveness of HEGs. However, the observed variability in specific roles indicates that some occupations may require more refined exposure assessment. Exposure fluctuations over time suggest that HEG classifications should be dynamic, adapting to operational changes and improved dust control measures.

5.3.3 Objective 3: Comparing Individual Exposure Parameters with Occupational Groups and HEGs

The study revealed that individual workers sometimes experienced significantly different exposure levels than their HEG averages. This suggests that while HEGs are useful for general exposure assessment, individual-level monitoring is essential for high-risk workers. The findings emphasize that task-specific factors and work behaviours contribute to individual variability[42,44], which HEGs may not fully capture. Consequently, a hybrid monitoring approach that integrates HEG-based classification with individualized assessments is necessary to enhance accuracy.

5.4 Comparison of HEGs' Exposure Parameters with Those of Their Constituent Occupations

The independent t-test and Mann-Whitney U test results across Mine 1 and Mine 2 consistently revealed no statistically significant differences in exposure levels between paired occupations within the same HEG ($p > 0.05$). Effect sizes remained small, suggesting minimal practical differences in exposure conditions. This finding supports the validity of HEG classifications, as exposure levels remained comparable within each group[11].

This aligns with international methodologies for HEG establishment, which assume that workers performing similar tasks in comparable environments experience statistically similar exposures [12,36]. However, studies have highlighted the inherent variability within HEGs, emphasizing that exposure profiles may be influenced by factors beyond job title and location, such as task allocation and workplace layout [32,42].

The ANOVA and Kruskal-Wallis results indicated no significant occupational exposure differences in most HEGs, reinforcing the assumption that grouped occupations share similar exposure conditions. However, in Mine 2 HEG5 (2022), marginally significant differences ($p = 0.027$) were observed, prompting post hoc analysis. Despite initial ANOVA significance, post hoc tests failed to identify

specific occupation-level differences ($p > 0.05$), suggesting that variations were not substantial enough to warrant HEG reclassification.

5.5 Comparison of Individual Exposure Parameters with Those of Their Occupations and Allocated HEGs

5.5.1 Exposure Variability and Individual vs. Group Exposure

Linear Mixed Model results demonstrated that while HEGs captured general exposure trends, in most cases some HEGs, such as Mine 1 HEG1 and Mine 2 HEG1—individual exposure estimates were tightly grouped, with minimal random effects, supporting the assumption of exposure homogeneity as prescribed in the South African Mining Industry's statistical criteria for HEG definition[12].

However, extreme cases demonstrated that this assumption does not always hold. For example, in Mine 1 HEG5, General Miners recorded a significantly different estimated marginal mean (−0.041 mg/m³; $p = 0.003$) than other roles in the same HEG, indicating potential misclassification due to differing exposure scenarios. Similarly, in Mine 2 HEG4, Miner's Assistants had significantly different exposure levels compared to Scraper Winch Drivers ($p = 0.0046$), despite being grouped under the same HEG. A further example is evident in Mine 2 HEG2, where although ANOVA results showed no statistically significant differences across occupations ($F = 0.346$; $p = 0.710$), individual-level variance components revealed a notable different in Worker 1 (W1)—who had a variance component of −0.224 mg/m³, markedly deviating from the rest of the group whose values largely ranged between −0.056 and 0.038 mg/m³. These finding challenges the assumption of homogeneity within the HEGs and raise concerns about whether all workers' exposure profiles truly align with the group[15], potentially reflecting unique task assignments, environmental conditions, or procedural deviations. These deviations highlight a critical limitation of HEG-based assessments: while practical, they may overlook significant individual risk variability. This underscores the importance of integrating group-level and individual-level data when validating HEG classifications and supports prior studies advocating for hybrid approaches that combine HEG monitoring with targeted individual or task-based sampling to enhance accuracy and prevent underestimation of exposures[41,55].

5.5.2 Measures of Central Tendency in Comparing AMs within HEGs

Across most HEGs, GM values were consistently lower than AMs, reflecting the expected right-skewed nature of exposure data driven by sporadic high measurements. This was especially evident in groups with high variability, where a small number of elevated results disproportionately influenced the AM.

A clear example is Mine 1 HEG3 in 2020, where Loader Drivers had an AM of 0.1 mg/m³ (SD = 0.11) and a GM of 0.063 mg/m³, with a GSD of 3.3. The high SD and GSD values here indicate substantial spread and skew, confirming that the GM provides a more stable and representative measure of central tendency for this occupation. In contrast, the AM, while useful for estimating cumulative exposure burden, overstates the typical daily exposure due to the influence of extreme values.

Similarly, in Mine 2 HEG1 in 2021, Loco Drivers recorded an AM of 0.114 mg/m³, a GM of 0.064 mg/m³, and a GSD of 4.15. The large gap between AM and GM, coupled with a high SD (0.09), suggests the presence of outliers or irregular spikes in exposure. While the AM is relevant for understanding total exposure over time, the GM and GSD more accurately describe the distribution and day-to-day exposure conditions for most workers in the group.

These findings illustrate a fundamental point in exposure assessment: AM is appropriate for evaluating cumulative dose-related health outcomes, while GM is better suited for summarizing routine exposure conditions across a group[12]. The inclusion of SD and GSD further enhances interpretation, where high GSDs (e.g., >2.5) suggest considerable variability, reinforcing the need to look beyond AM when characterizing exposure patterns.

These results support previous research emphasizing the complementary use of AM and GM in occupational hygiene. While AM is central to regulatory comparisons and long-term risk estimates, GM (alongside GSD) offers a more realistic view of the distribution, especially in log-normal datasets where AM alone may misrepresent typical exposures[41,56].

5.5.3 Comparing AMs with the 90th percentile to Categorize HEGs

These results demonstrate that AM-based classification alone may underrepresent the true risk profile in HEGs with high intra-group variability or small high-exposure subgroups. The 90th percentile, by capturing upper-bound exposure levels, offers a more conservative and protective estimate—particularly critical in environments with known task- or role-specific exposure peaks.

According to South African regulatory guidance, a HEG can only be placed in a defined exposure category (A, B, or C) if both the arithmetic AM and the 90th percentile fall within the same range[12]. This ensures that typical exposures (AM) and peak conditions (90th percentile) are jointly considered in risk categorization. However, the results reveal that in several cases, especially within Mine 2 this alignment criterion was not met. These discrepancies expose a critical limitation of relying on AM values alone for exposure classification, as the 90th percentile often revealed higher, unaccounted-for risks.

A striking example is Mine 2 HEG1 in 2021, where the AM was 0.052 mg/m³, placing the group in Category B, yet the 90th percentile was 0.112 mg/m³, which falls into Category A. This mismatch indicates that while average exposure appeared acceptable, a significant proportion of workers likely experienced peak exposures well above recommended limits. Similarly, Loco Drivers in the same HEG had an AM of 0.114 mg/m³ and a 90th percentile of 0.218 mg/m³, strongly classifying them in Category A and clearly exceeding the HEG's mean.

2022, the overall HEG2 mean (0.111 mg/m³) and 90th percentile (0.123 mg/m³) surpassed the OEL, signaling a shift in exposure risk, suggesting Category A classification. The miner's assistant role illustrates a key control gap: although mean exposure sits in Category B, the 90th percentile jumps to Category A, pointing to short-term peak exposures likely tied to specific high-exposure tasks**.** However, the underlying occupational subgroup−Scraper winch driver exhibited disproportionately lower values at 0,013 mg/m³, with the 90th percentile of 10% of the OEL of 0.1 mg/m³, remains in Category C. This disparity demonstrates how HEG-level averages can obscure substantial between-worker variability, overestimating exposure for certain low-risk roles while underrepresenting high-exposure subgroups.

In Mine 1, discrepancies were also observed but were generally less severe. For example, HEG5 in 2019 showed an AM of 0.07 mg/m³ (Category B), but General Miners had individual AMs reaching 0.141 mg/m³, likely driving a 90th percentile that would fall into Category A. This implies that subgroup exposure conditions were not adequately captured by the group average.

These findings support the integration of both AM and 90th percentile metrics in exposure classification, as required by regulatory frameworks[7,36]**. Failure** to meet this dual criterion may result in undetected overexposure risks for workers, reinforcing the need for periodic re-evaluation of HEG structures and the inclusion of task-specific monitoring where necessary[12,56].

5.6 Effectiveness and Limitations of HEG Classification in Exposure Assessment

The findings of this study suggest that while HEG classification provides a structured framework for exposure estimation, it does not fully account for individual variability due to between-worker differences [15,41]. The assumption that all workers within an HEG experience similar exposures can result in misclassification, leading to under- or overestimation of individual exposures [56]. Despite these limitations, HEG-based monitoring remains a practical alternative to individualized assessments, particularly in resource-constrained environments such as South African gold mines.

5.7 Evaluating the AM in Exposure Allocation Within HEGs

While the AM is a standard metric for classifying exposures within HEGs, its appropriateness depends on the purpose of the analysis. In this study, AM values were consistently higher than GMs across most HEGs, reflecting the right-skewed distribution of RCS exposure data. This skewness is common in occupational exposure settings, where a few high-exposure events disproportionately influence the AM[56] .

As a result, the AM does not underestimate risk; rather, it can overstate average exposure if interpreted as a typical value. However, this inflation can be misleading in exposure categorization, particularly when a group's AM falls just above a regulatory threshold, while the majority of workers experience much lower exposures. In such cases, classification based solely on AM may overestimate group-wide risk while failing to identify which individuals are actually at the highest risk [7].

Conversely, the GM provides a better representation of central tendency in log-normally distributed data and is less influenced by outliers. Therefore, the GM is preferred when describing "typical" exposure conditions, whereas AM remains useful for cumulative dose estimation, relevant for long-term health risk assessments.

Additionally, Linear Mixed Model results revealed considerable between-worker variability in several HEGs (e.g., Mine 1 HEG3), indicating that group-level AMs may obscure individual exposure extremes[54]. This reinforces the need for complementary metrics, including GM, GSD, and individual-level assessments, to support accurate exposure classification and protect workers effectively.

5.8 Study limitations

Despite its strengths, the study faced several limitations. Firstly, the availability of data varied across years, resulting in missing values that reduced the robustness of statistical analyses. For example, some HEGs had limited data in specific years, which produced "Not Computed" outputs for statistical tests such as Levene's test, independent t-tests, and ANOVA.

In cases where sample sizes were too small, normality and homogeneity of variance tests could not be performed, limiting the strength of statistical comparisons. Incomplete sampling frequencies further hindered individual-level analyses, as it was difficult to identify four occupations within HEGs that had consistent annual data across the four-year period. In many cases, only two or three occupations per HEG were available for follow-up, and obtaining two individuals per occupation with sufficient yearly data was impractical. To address this, the study selected individuals with at least two data points within a HEG for analysis.

Secondly, the assumption of uniform exposure within HEGs may not have captured task-specific risks or individual work habits, contributing to variability in exposure outcomes. In Mine 2, the allocation of workers to HEGs was limited to ventilation district per activity only, which further increased HEG concentration variances.

Thirdly, the reliance on secondary data posed inherent challenges, as real-time exposure conditions were not directly observed, and the consistence method used for sampling and analysis. Although rigorous data cleaning and validation were applied to minimise errors, certain limitations in the original datasets remained. In line with the Mandatory Code of Practice for the Assessment of Personal Exposure to Airborne Pollutants exposure measurements in South African mines are required to follow internationally recognised standards, and it is therefore reasonable to assume that consistent methods for RCS sampling were applied throughout the study period [12]. Nevertheless, as with all sampling processes, potential uncertainties may have arisen from pump calibration, filter handling, laboratory analytical variability, and environmental conditions during sampling. Such systematic and random errors are well recognised in exposure assessment literature[57]. Additionally, factors such as temperature, pressure, and humidity can influence volumetric flow measurements, requiring correction with flow meters calibrated against a primary standard to ensure accuracy[58].

Finally, the use of secondary data restricted the ability to capture contextual factors influencing exposure in real time. Future research should therefore incorporate real-time exposure monitoring and individual-level assessments to strengthen the accuracy of exposure estimation methodologies.

The available HEGs were mainly classified as exposure category C. Category B HEGs, i.e., concentrations between 0.5 OEL and the OEL, would have implicitly had a larger variability compared to category C HEGs and could have resulted in different conclusions.

5.9 Conclusion

The findings highlight the need for continuous improvements in exposure monitoring strategies. While HEGs remain a useful tool for assessing occupational exposure, integrating personal monitoring and task-specific assessments would enhance accuracy. The observed exposure variability highlights the need for periodic reassessment of HEG and the adoption of technological solutions, such as real-time dust monitoring systems. By refining HEG methodologies, mining companies can enhance regulatory compliance and improve worker health outcomes.

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

This chapter provides conclusions and recommendations based on the findings from the literature review and statistical analyses regarding methodologies for establishing HEGs in mining environments. The discussion focuses on improving exposure assessment accuracy, addressing limitations of current methodologies, and optimizing worker health and safety through refined grouping strategies. The chapter concludes with key insights drawn from the literature review and statistical findings.

6.1 Conclusion

This study evaluated the accuracy of HEG classification in estimating individual worker exposure to RCS in South African gold mines. The results demonstrated that while HEGs offer a practical framework for exposure assessment and, in most cases, provide a reasonable estimate of an individual worker's exposure or dose in a South African gold mine. However, the statistical evidence of between-worker variability within HEGs suggests that this approach may not always produce fully accurate results. In some instances, reliance solely on HEG-based classification could result in underestimation or overestimation of individual exposure risks.

The study findings highlight the importance of refining HEG methodologies to improve occupational exposure assessments. A sole reliance on HEGs may misrepresent individual risks, which can impact the effectiveness of health and safety interventions. Therefore, a combination of HEG classifications and individualized exposure monitoring is recommended to ensure a more precise estimation of exposure levels and to enhance worker protection in the mining sector.

6.2 Recommendations

Enhanced monitoring strategies should be implemented to improve exposure assessments. A hybrid approach that combines HEG-based monitoring with personal exposure tracking will enhance accuracy. Real-time exposure tracking systems, such as wearable dust monitors, should be introduced to provide immediate feedback and identify exposure spikes before they become hazardous. Additionally, exposure evaluations should be tailored to specific tasks rather than broad occupational categories, ensuring that job-specific risks are accurately captured. Personalized exposure monitoring should also be considered for high-risk workers to assess individual exposure trends better and implement targeted interventions.

Policy: To strengthen regulatory compliance, regular reassessments of HEGs should be conducted to ensure their classifications reflect current operational conditions and exposure risks. Furthermore, targeted exposure reduction programs should be developed and implemented in high-exposure areas, particularly in Stoping and Development activities where exposure levels are more variable. Mandatory individual exposure assessments should also be introduced for high-risk occupations to ensure that individual workers receive adequate health protection based on their actual exposure levels.

Research: Future research should focus on expanding longitudinal studies to identify long-term exposure trends and their health impacts. Advanced statistical models, including machine learning and predictive analytics, should be explored to refine exposure assessments and develop more accurate HEG classification methods. For instance, Savic et al. [59] introduced TREXMO Plus, a self-learning model that integrates expert judgment with adaptive algorithms to classify exposure risks in real time, demonstrating that machine learning can predict high-risk exposure scenarios based on variables like task type and environmental conditions.

These innovations support the development of dynamic HEG models that can adapt to changes in mining operations and exposure conditions and will also be essential for improving occupational exposure assessments in the long term. Schinkel et al.[60] proposed a tiered HEG system responsive to real-time data, enhancing worker grouping based on both tasks and environmental variability[60,61]. Additionally, health impact studies should be conducted to establish direct correlations between exposure levels and occupational disease incidence, which will help refine exposure limits and regulatory guidelines.

6.2.1 Refining HEG Methodologies for Improved Exposure Assessment

The review of existing methodologies and statistical analysis results highlights the need for refining HEG classification approaches to enhance accuracy and reliability in exposure assessments. The following recommendations are proposed:

Adopt a Hybrid Approach: A combination of HEG-based monitoring with targeted individual monitoring can enhance exposure assessments. By integrating task-specific sampling and real-time exposure data collection, employers can reduce exposure misclassification and improve risk estimation [44].

Incorporate Task-Based Exposure Grouping: While traditional HEG methods for underground mining in SAMI focus on ventilation district and activity areas and rely on job titles and shared work environments, task-based exposure assessments allow for a more granular evaluation of exposure

variability. This approach can better account for differences in work techniques, safety compliance, and environmental influences [42].

Utilize Advanced Statistical and Computational Methods: The use of statistical modeling techniques such as mixed-effects models and Bayesian analysis can improve the identification of exposure similarities and variations within HEGs. These methods can refine exposure classification and ensure more accurate risk assessments [41].

6.2.2 Enhancing Data Collection and Monitoring Practices

Comprehensive and reliable data collection is essential for effective exposure assessment. The following strategies can strengthen data quality and monitoring processes:

Increase Frequency and Coverage of Exposure Monitoring: Current HEG methodologies often rely on periodic exposure assessments, which may not capture temporal variations. Increasing the frequency of sampling and expanding coverage across different work shifts and seasons can enhance exposure estimates [33].

Standardising exposure Assessment Protocols by aligning HEG methodologies with international best practices, such as those from the American Industrial Hygiene Association (AIHA) and the European Standard EN 689, can ensure consistency and comparability in exposure assessments. EN 689 provides a structured approach for assessing workers' inhalation exposure to chemical agents, including guidance on the formation of Similar Exposure Groups (SEGs), measurement strategies, and statistical methods for evaluating compliance with Occupational Exposure Limits [34,36].

6.2.3 Addressing Exposure Variability and Misclassification

Exposure misclassification remains a significant challenge in HEG-based assessments. To mitigate these issues, the following recommendations are suggested:

- Account for Between-Worker and Temporal Variability: Exposure grouping should consider individual worker differences, task variations, and environmental influences. This can be achieved through repeated exposure measurements and statistical adjustments[41,62].
- Improve Selection Criteria for HEGs: HEG definitions can improve accuracy, with the selection criteria refined to incorporate detailed exposure determinants such as task frequency and duration, ventilation and airflow patterns, proximity to emission sources, and control measures that can improve accuracy [10]. In line with EN 689 and AIHA exposure assessment strategies, more granular data—such as real-time exposure measurements and task-based job analysis—should be used to ensure that HEGs reflect actual exposure conditions.

6.2.4 Strengthening Regulatory Compliance and Occupational Health Interventions

Enhance Regulatory Frameworks: Regulatory agencies should provide more explicit guidelines on HEG establishment, exposure assessment methodologies, and acceptable exposure variability thresholds. Collaboration with industry stakeholders and academics can help refine these guidelines.

6.2.5 Recommendations for Study Objective 2: Comparison of HEGs' Exposure Parameters with Occupational Groups

Refine HEG Definitions to Improve Homogeneity: The statistical results indicate that certain HEGs contain occupations with significant exposure variability. Reassessing HEG definitions to ensure greater similarity among grouped occupations is necessary for accurate exposure classification [42]

Use Mixed-Effects Models for Better Variability Assessment: The results demonstrate that individual occupations within HEGs may have different exposure patterns. Implementing mixed-effect models can account for both fixed effects (job roles) and random effects (individual worker variations) to enhance exposure assessment accuracy.

Increase Sampling for Occupations with Higher Variability: The statistical analysis highlights instances where specific occupations within HEGs exhibit higher exposure variation. Targeting these occupations for increased sampling and monitoring can improve risk assessment [63].

6.2.6 Recommendations for Study Objective 3: Comparison of Individual Exposure Parameters with HEGs and Occupations

The statistical results reveal important insights about individual exposure levels compared to HEG and occupational group assessments. The following recommendations address these findings:

Reassess Exposure Categories Based on Individual Variability: The analysis found that while HEG-based exposure classification is generally effective, individual worker deviations suggest the need for flexible categorization. Adjusting exposure categories to reflect individual exposure levels can enhance protection measures [10].

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APPENDIX 1 – PLAGIARISM DECLARATION

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

FACULTY OF HEALTH SCIENCES

PLAGIARISM DECLARATION TO BE SIGNED BY ALL HIGHER DEGREE STUDENTS

SENATE PLAGIARISM POLICY: APPENDIX ONE

I Constance Titi Kekana (Student number: 81551665) am a student registered for the degree of MSc in Medicine (Exposure Science) in the academic year 2024.

I hereby declare the following:

- I am aware that plagiarism (the use of someone else's work without their permission and/or without acknowledging the original source) is wrong.
- I confirm that the work submitted for assessment for the above degree is my own unaided work except where I have explicitly indicated otherwise.
- I have followed the required conventions in referencing the thoughts and ideas of others.
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Signature:  Date: 28 March 2025

APPENDIX 2 -HEGS ANALYSED

Objective 2 Mine 1

HEG Number	Year	Occupations (O)	Number of Data points
Mine 1 HEG1 Development	2019	Team Leader Secondary Support :1	3
		Team Member Secondary Support: 2	3
	2020	Team Leader Secondary Support :1	3
		Team Member Secondary Support: 2	5
	2021	Team Leader Secondary Support :1	4
		Team Member Secondary Support: 2	5
	2022	Team Leader Secondary Support :1	5
		Team Member Secondary Support: 2	2
Mine1 HEG2 Developemnt	2019	Developer:1	3
		General Miner:2	5
	2020	Developer:1	3
		General Miner:2	7
	2021	Developer:1	4
		General Miner:2	4
	2022	Developer:1	4
		General Miner:2	4
Mine 1HEG3 Development	2019	Special Team Leader Development: 1	3
		Loco driver: 2	12
		Loader Driver:3	6
	2020	Special Team Leader Development: 1	2
		Loco driver: 2	4
		Loader Driver:3	3
	2021	Special Team Leader Development: 1	4
		Loco driver: 2	4
		Loader Driver:3	5
	2022	Special Team Leader Development: 1	2
		Loco driver: 2	2
		Loader Driver:3	2
Mine 1 HEG 4 Stoping	2019	General Miner: 1	1
		Winch Operator: 2	4
	2020	General Miner: 1	3
		Winch Operator: 2	3
	2021	General Miner: 1	1
		Winch Operator: 2	2
	2022	General Miner: 1	3
		Winch Operator: 2	7
Mine 1 HEG 5 Stoping	2019	General Miner: 1	2
		Miner Stoper: 2	7
	2020	General Miner: 1	2
		Miner Stoper: 2	4
	2021	General Miner: 1	2
		Miner Stoper: 2	5
	2022	General Miner: 1	1
		Miner Stoper: 2	2

Objective 2 Mine 2

HEG Number	Year	Occupations	Number of Data points
M2 H1 Development	2019	Development Team Worker:1	6
		Loco Driver :2	8
	2020	Development Team Worker:1	7
		Loco Driver :2	3
	2021	Development Team Worker:1	4
		Loco Driver :2	8
	2022	Development Team Worker:1	2
		Loco Driver :2	4
M2 H2 Development	2019	Development team leader/supervisor: 1	12
		Miner's assistant (cheesa):2	3
		Scraper winch driver:3	6
	2020	Development team leader/supervisor: 1	14
		Miner's assistant (cheesa):2	2
		Scraper winch driver:3	9
	2021	Development team leader/supervisor: 1	18
		Miner's assistant (cheesa):2	11
		Scraper winch driver:3	1
	2022	Development team leader/supervisor: 1	12
		Miner's assistant (cheesa):2	3
		Scraper winch driver:3	1
	2019- 2022	Loader Driver:3	17
M2 H3 Stoping		Loco Driver :2	23
	2019	Miner's assistant (cheesa) :1	6
		Scrapper Winch Driver: 2	9
	2020	Miner's assistant (cheesa) :1	8
		Scrapper Winch Driver: 2	20
	2021	Miner's assistant (cheesa) :1	8
		Scrapper Winch Driver: 2	20
	2022	Miner's assistant (cheesa) :1	5
		Scrapper Winch Driver: 2	17
M2 H5 Stoping	2019	Scrapper Winch Driver: 1	21
		Miner's assistant (cheesa) :2	6
	2020	Scrapper Winch Driver: 1	30
		Miner's assistant (cheesa) :2	13
	2021	Scrapper Winch Driver: 1	23
		Miner's assistant (cheesa) :2	12
	2022	Scrapper Winch Driver: 1	18
		Miner's assistant (cheesa) :2	10
M2H5 Stoping	2019	Driller: hand percussion/jackhammer: 1	2
		Stope team leader/supervisor: 2	20
		Scraper winch driver:3	8
	2020	Driller: hand percussion/jackhammer: 1	15
		Stope team leader/supervisor: 2	29
		Stope Team Member :3	15
	2021	Driller: hand percussion/jackhammer: 1	13
		Stope team leader/supervisor: 2	20
		Stope Team Member :3	13
	2022	Driller: hand percussion/jackhammer: 1	9
		Stope team leader/supervisor: 2	3
		Stope Team Member :3	9

Objective 3 Mine 1

HEG Number	HEG Name	Occupations (O)	Workers Nr(Individual)	Number of Data Points
1	HEG1M1DH8- Development	Team Leader Secondary Support O1		17
		Team Member Secondary Support 02	5	
2	HEG2M1DY1 -Dvelopment	Developer O1		
		General Miner O2	4	26
3	HEG5M1DM31- Development	Loader Driver O1		
		Loco Driver O2	16	42
4	HEG8M1DY40- Stoping	Special Team Leader Development O3		
		Supervisor Operations O4	2	6
5	HEG9M1D31- Stoping	General Miner O1	14	36
		Stoper Miner O2		
		General Miner O1		
		Miner Stoper O2		
		Stope Labourer O3		
		Supervisor Operations O4		
		Water Jet Operator O5		

Objective 3 Mine 2

HEG Number	HEG Name	Occupations (O)	Workers Nr(Individual)	Number of Data Points
1	H1M2SND- Development	Developer O1	10	27
		Development Team Worker O2		
		Loco Driver O3		
2	H4M2SSD Development	Development team leader/supervisor O1	26	70
		Miner's assistant (cheesa) O2		
		Scraper winch driver) 03		
3	H8M2SN1S- Stoping	Miner's assistant (cheesa) O1	23	59
		Scraper winch driver O2		
4	H10M2SSS -Stoping	Miner's assistant (cheesa) O1	31	89
		Scraper winch driver O2		
5	H11M2SS1S Stoping	Conveyer belt attendant O1	119	39
		Driller: hand percussion/jackhammer O2		
		Scraper winch driver O3		
		Stope team leader/supervisor O4		
		Stope team worker O5		

APPENDIX 3: ETHICS CLEARANCE CERTIFICATE

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

R14/49 Mrs Constance Titi Kekana

HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)

CLEARANCE CERTIFICATE NO. M240865

NAME: (Principal Investigator)	Mrs Constance Titi Kekana **DEGREE:** MSc (Med) Exposure Science
STUDENT NUMBER:	512654
DEPARTMENT:	School of Public Health/Occupational Health Division
STUDY SITES:	Sibanye Still Water – Driefontein Mine – Carletonville Harmony Gold Mine – Doornkop Mine - Johannesburg
TITLE:	Evaluation of Homogenous Exposure Grouping to Estimate Individual Worker's Exposure in South African Gold Mines, 2019-2023
DATE CONSIDERED:	30-Aug-2024
DECISION:	Approved unconditionally
CONDITIONS:	N/A
NOTE:	Original Online Application Number MED24-04-583. Subsequent Online Application Number M240930-A-0003.
SUPERVISOR:	Prof Derk Brouwer
APPROVED BY:	Ms M. Van Niekerk, Co-Chairperson, HREC (Medical)
DATE OF APPROVAL:	30-Sep-2024 **EXPIRY DATE:** 29-Sep-2029

This clearance certificate is valid for 5 years from date of approval. Extension may be applied for.

DECLARATION OF INVESTIGATOR(S)

I/we fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we undertake to ensure compliance with these conditions. Should any departure be contemplated, from the research protocol as approved, I/we undertake to resubmit the application to the Committee. **I agree to submit a yearly progress report** in the month date of convened meeting each year until study is closed. Failure to submit annual report will result in ethics clearance certificate suspension. The date for annual re-certification will be one year after the date of convened meeting where the study was initially reviewed. Unreported changes to the application may invalidate the clearance given by the HREC (Medical). Email a signed copy of ethics clearance certificate to HREC-Medical ResearchOffice@wits.ac.za

Signature of Principal Investigator

30/09/2024
Date

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