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## Article

# State of Quality 4.0 in the South African chrome mining industry: Gap analysis and priority areas for improvement

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## OPERATIONS, INFORMATION & TECHNOLOGY | RESEARCH ARTICLE

# State of Quality 4.0 in the South African chrome mining industry: Gap analysis and priority areas for improvement

Matolwandile Mzuvukile Mtotywa<sup>1\*</sup> and Thabisile Dube<sup>1</sup>

**Abstract:** The aim of the study was to understand the state of Quality 4.0 in the chrome mining industry and to use gap analysis to identify priority improvement areas. This study adopted a post-positivist paradigm, with a cross-sectional quantitative research design using a survey within the mining industry. The responses ( $n = 211$ ) represented a response rate of 74.8%. The results show a composite score,  $MID_j = 17.80$ , with  $QMI_j = 50.9\%$ , indicating that the mines were in an initial or *ad hoc* activity stage but are migrating towards an established, focused process stage. Confirmatory tetrad analysis indicates a reflective model, with an acceptable model fit,  $SRMR = 0.068$ . A one sample t-test confirmed that all dimensions of Quality 4.0 had statically significantly lower mean scores than the ideal profile of 5.0 with a large effect size.

This study provides an effective approach for quality management practitioners, process owners, and management to effectively assess the progress of Quality 4.0 implementation and identify gaps for improved performance. Identified priority areas for improvement are management commitment to technology and innovation-driven operations, technology-driven employee involvement and empowerment, and process and systems integration. The study provides a comprehensive approach to conducting gap analysis and contributes to the growing body of knowledge on Quality 4.0.

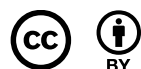
### ABOUT THE AUTHORS

Thabisile Dube is part of the MBA researchers at Tshwane School for Business and Society who focuses on quality management monitoring and evaluation of advances in Quality 2030 with application to stability in change within emergent applied systems and perspectives. Thabisile Dube formed part of the cohort which conducted research on Quality 4.0 in the mining industry with a view to improving management performance and outputs.

Dr Matolwandile Mtotywa led the research involving quality management with a particular interest in the nexus between quality management, the fourth/fifth industrial revolution, and sustainable development.

### PUBLIC INTEREST STATEMENT

This study presents guidelines that can help the ongoing effort towards transitioning technology and its use to improve the effectiveness, efficiency, and performance within the mining industry. As a critical contributor to the economic sector in South Africa, mining has to continually improve to maintain its positive contribution to South Africa and its economy and as it is one of the biggest employers in the region, it is essential that this industry has a sustainable future in South Africa and other African countries so as to curb the high levels of unemployment and poverty in the region.



**Subjects: Quality Management; Management of Technology & Innovation; Operations Management**

**Keywords: Quality 4.0; efficiency; productivity; performance; mining industry**

## 1. Introduction

Businesses are struggling with productivity, sustainability and to make a profit. Economic stresses are exacerbated by the legacy of the COVID-19 pandemic which is expected to delay business recovery (Gössling et al., 2020) and the current geopolitical tension in Europe, the Middle East, and Asia (Caldara & Iacoviello, 2022; Levy & Leaning, 2022). Segura-Salazar and Tavares (2018) explained that the mining industry faces challenges in successfully implementing sustainability principles resulting from new competitive practices that reduce environmental impacts while increasing social license. As a result, the mining business has been operating in an increasingly difficult environment over the past few decades because of rising environmental and social consciousness, as well as the need to boost output in the face of natural factors such as falling ore grades, deeper deposits, and harder rock mass—thus, the mining industry needs to constantly improve its processes across the board (Sánchez & Hartlieb, 2020). Within the ferrochrome mining sector, lower ferrochrome prices, greater output from China, and rising energy costs have impacted South Africa’s international market share and standing. Value-adding and strategic capability in the ferrochrome business is essential to keeping the country from falling behind (Department of Trade, Industry and Competition, 2020; van der Lingen & Paton, 2018). As such, there is a demand for effective quality assurance and new technology in the mining industry and change is necessary regarding aspects of management for industrial organisations to maintain competitiveness (Efimova & Briš, 2021).

Despite the industry’s importance, mining firms typically exhibit poor R&D intensity, which places them in the same category as more established, less cutting-edge industries. As vertical disintegration becomes more common, companies are increasingly focusing on their core competencies while outsourcing innovation to their suppliers and equipment manufacturers. The future of mining will be influenced by a number of current technological developments (Majstorovic et al., 2021). The first and most important is digital transformation or the introduction into the mining industry of so-called technology 4.0 linked to rapid changes associated with the fourth industrial revolution (Choi, 2023; Sánchez & Hartlieb, 2020). Technologies such as automation, robotics, remotisation of operations, the Internet of Things, analytics, and digital twinning can improve mining operations across the board. Despite digital transformation status being a top priority for many major mining firms, the industry is still only partially digitised (Sánchez & Hartlieb, 2020). This suggests that most digital potential in the mining industry has not yet been realised.

Research involving Quality 4.0 is critical within the context of mining 4.0. Jamkhaneh et al. (2021) explain that Quality 4.0 is the digitalisation of design quality, conformance quality, and performance quality using new technologies. Quality 4.0 is a new way for quality professionals to use digital tools to enhance quality and attain excellence. It has confirmed that quality management together with Industry 4.0 improves organisational and enterprise efficiency, performance, and improved business models. Several studies agree that total quality management (TQM) needs to be implemented and strengthened by leveraging the technologies of the fourth industrial revolution to provide organisations with a competitive advantage (Carvalho et al., 2021; Efimova & Briš, 2021; Maganga & Taifa, 2022). However, the importance of implementing TQM in the mining industry has been overlooked in some companies.

The aim of this study is to assess the state of technological advancement for improved quality and to improve performance in the mining industry by identifying gaps in its implementation of Quality 4.0. The results from the gap assessment will assist in better understanding the barriers that are experienced by the mining industry when it comes to implementing technological advancements in

quality management within mining management and operations. In order to stay competitive in the face of fluctuating global raw material prices, increasing safety requirements, stricter environmental regulations, and decreasing profits, the mining industry must increase its output through the implementation of smart mining systems. These systems, known as “Smart Mining” or Mining 4.0, represent the cutting edge of the current technological paradigm shift in mineral extraction; they can solve difficult operational tasks, offer big data analysis, and give a person a new role as a system integrator of all the constantly evolving mining processes (Choi, 2023). However, this innovative change in mining cannot solely focus on spreading the cutting-edge technologies of Industry 4.0. Mining is unique because of its reliance on a wide variety of performance variables, each of which can have a significant impact on the industry as a whole (Majstorovic et al., 2021). These variables include, but are not limited to, machine and equipment safety, geotechnical advancements, the scope of post-mining reclamation, worker protection, and financial losses (Zhironkin & Szurgacz, 2022). The application of Quality 4.0 is essential to development and sustainability in the mining industry and is central to smart mining (Mining 4.0).

The remainder of the paper synthesises relevant study literature, explains the methodology used in conducting the research, before it presents and discusses the results from the empirical data. It closes with conclusions that highlight the theoretical contributions, implications, and limitations of the study, and offers directions for future research.

## 2. Literature review

### 2.1. Configuration theory and profile deviation analysis

Underpinning the research was the configurational theory (Doty et al., 1993) and profile deviation analysis (Venkatraman, 1989). Configurational theory is typically informed by a logic of consistency, or the notion that all aspects of a configuration are of equal importance and are necessary for its existence or efficacy (Fiss et al., 2013). This approach is used to determine the dimensions of Quality 4.0 which collectively are equally important in ensuring the effectiveness of Quality 4.0 within an organisation to influence and improve organisational performance. The configurational theory has been investigated and applied in operations management and quality and entrepreneurial studies (Hinings, 2018; Malhotra et al., 2013; Pla-Barber et al., 2020). Meyer et al. (1993) had earlier argued that the interactions between the constituent dimensions of configurations are “non-linear,” and that there is always a possibility that two or more configurations may be “equifinal” in terms of producing performance under specific conditions, as is the case with Quality 4.0 in an organisation.

Effectiveness and sustainable performance are highly dependent on profile deviation analysis, where the greater the deviation from the ideal profile, the less effective are the collective configurations. In profile deviation analysis, it is important to understand that an ideal type is a theoretical construct, not a nominal category. Accordingly, a comprehensive multivariate strategy should be a part of any empirical test aimed at identifying the optimal type. Configurational theory is useful to evaluate the complexities of multidimensional phenomena entailed by fit or congruence relations. Malhotra et al. (2013) posit that an analysis based on configurational theory would be a significant methodological advance. When it comes to assessing fit in a way that is consistent with the multidimensional and holistic perspectives associated with marketing services, profile deviation approaches provide significant advantages over traditional approaches such as regression analysis, slope analysis, and subgroup analysis, especially involving individuals as the unit of analysis (Vorhies & Morgan, 2003). To evaluate organisations, previous research primarily used configurational theory and the profile deviation approach. Theoretical configurations typically predict improved performance for parameters that are more similar to some theoretically defined ideal profiles.

### 2.2. Technology and innovation in the mining industry

In the mining industry, work environments frequently require that compromises be made in order to find a solution to an issue. These trade-offs must be managed and navigated, but the design

and execution of technology will be constrained by the specifics of the mining industry and its environment (Majstorovic et al., 2021). These constraints have led to a lower rate of technological advancement in the mining business compared to other sectors. Mining operations have not been drastically altered by technological advancements such as automation and robotics (Lever, 2011). To better comprehend how technology affects people's health and safety, this section will delve into these aspects. The mining industry relies heavily on innovation to address its core business challenges such as geological issues, and rising public and governmental worries about the industry's impact on the environment and local communities. In relation to digital and robotic technology change within traditional geotechnology, the innovative technological transformation of mining is in its infancy. However, innovation plays a critical role in this context by supplying adequate solutions to overcome these challenges, thus guaranteeing the longevity of the mining activity (Sánchez & Hartlieb, 2020). As a result, technical concerns and design difficulties may rise to the fore during periods of technological transition.

About a decade ago, artificial intelligence (AI), machine learning, and other autonomous technologies were introduced within the mining business. This was in response to challenges related to cost, quality, safety, and environmental issues (Hyder et al., 2019). These technological advancements allow for lower operating costs, greater output, less risk to workers, nonstop production, and increased safety. However, there have been economic, financial, technological, labour force, and societal obstacles to implementing these technologies.

This, in spite of industrial technologies that are in use that are critical for effective Quality 4.0 within Mining 4.0 whose focus is on the *combination of real machines and the virtual world of the Internet into augmented reality; extraterritorial access to any information on demand; almost limitless possibilities offered by distributed cloud computing; artificial intelligence and neural networks* (Zhironkina & Zhironkin, 2023, p. 2). Fourth industrial technologies in use include autonomous machines, the Internet of Things, big data, monitoring machines in real time, the data cloud, innovative modeling software, digital mining, and virtual and augmented reality (Palka & Rizaoglu, 2019; Zhironkina & Zhironkin, 2023). Such technologies are central to the improvement in performance (Gamede & Mtotywa, 2022; Löow et al., 2019; Oliff & Liu, 2017) and support a clear pathway for transition and implementation of Quality 4.0

### **2.3. Quality 4.0 maturity index**

Technology is advancing rapidly, and quality assurance professionals must adapt—they must transition from data analyst to data wrangler by engaging with the latest technologies. Organisations are transitioning toward Quality 4.0 which used TQM with technologies of the fourth industrial revolution. This helps with improvement in information collection, analysis, management, and decision-making by connecting product, process, and system quality information. It also considers automating the process, and organisations must recognise that quality is key when preparing for sustainability of an organisation during digital transformation (Schiavone et al., 2022). This underpins the importance of technology in quality management. Studies have shown multiple dimensions of focus when analysing Quality 4.0 in the organisation (Maganga & Taifa, 2022; Mtotywa, 2022; Zulqarnain et al., 2022). Maganga and Taifa (2022) included several factors that influence the Quality 4.0 readiness and these are technology adoption, top-management support, infrastructures, Quality 4.0 training and skills, organisational culture, collaboration, and customer and supplier centeredness. These factors also overlap with those highlighted in the study of Zulqarnain et al. (2022) such as leadership, culture, management systems, and competency (knowledge and skills). Mtotywa (2022) suggested (1) describing management commitment to technology and innovation-driven operations, (2) customised customer focus, (3) technology-driven employee involvement and empowerment, (4) process and systems integration and management, (5) knowledge for decision-making and future prediction, (6) root cause analysis of operational disturbances and sustainable solutions, and (7) operational environment benchmarking and these dimensions are adopted in the study. Management commitment is regarded as those ways in which the organisation management show that they are committed to an enabling

environment by creating a culture of integrity where employees and customers feel valued within a culture that is continuously improving along with global change, a culture that says, “I care.” Dubey et al. (2018) state that organisation choices are linked to top-management beliefs, culture, and values. Top-management commitment can be shown by their values and participation in an organisation, their successful implementation of total management commitment, a most important pillar for any successful organisation. The TQM system improves the innovation process in organisations following the implementation of TQM elements such as continual improvement or customer focus. In this regard, both TQM and innovation have the same purposes and importance in an organisation’s performance, especially in the service industry, by seeking to integrate objectives and functions of an organisation to satisfy its customers (Alimohammadlou & Eslamloo, 2016).

Placing the customers’ needs as a priority is critical for satisfying the customer (Mashamba, 2015). In achieving this, customer feedback is key as an organisation can largely improve the quality of their product by getting feedback from the customer (Foster & Gardner, 2022). In addition, a customised customer focus effectively profiles the needs per customer or group of similar customers (Mtotywa et al., 2022). This can help the highest levels of Kano’s proposed needs by the customers—delighters for customer satisfaction (Lin et al., 2017). Taking into account their impact on customer satisfaction, Kano’s model is highly effective in separating diverse customer requirements into distinct groups (Kirgizov & Kwak, 2022).

Total employee involvement is an organisational TQM methodology and set of management principles that encourages individual contributions, team member, and employee participation in problem-solving and continuous improvement initiatives. Employees are the most important resource, and when implementing quality, they need to be prioritised and equipped with the correct tools to be able to identify and correct problems. In short, empowering employees means that you link their individual skills with competencies. Mashamba (2015) suggests that implementation of TQM is encouraged by the employee’s attitudes towards the organisation. As such, proposition 1 of the study is as follows:

P1. Quality 4.0 maturity index model dimensions can be used for gap analysis to determine the state of Quality 4.0 in the chrome industry ( $\bar{X} \neq \mu$ )

#### **2.4. Effects of Quality 4.0 in efficiency, productivity, and performance**

Organisations are brainstorming ways to gain a competitive advantage for their products and services so that they can sell them at a competitive price, and the new guru is digital data. Quality uses digital data to manage the quality of the product, so when the organisations are implementing their strategy, Quality 4.0 should be on their agenda so that they have a plan in place to ensure that they create a competitive advantage (Sony et al., 2021). Several studies have validated that in the long run, companies that adopt TQM achieve greater effective productivity, profitability, and market share for most kinds of products and market situations (Fundin et al., 2020, 2021; Gremyr, Elg, et al., 2021; Mas-Machuca et al., 2018). Further studies have also identified that TQM needs to be implemented within the context of the fourth industrial revolution so that the organisation moves with the new technologies to be more effective, improve customer experience, and enhance profitability (Carvalho et al., 2021; Sony et al., 2021). Carnerud and Bäckström (2021) explain that a theoretical base of TQM is needed in order to better understand the existing position of TQM. Currently, it is essential for an organisation to have a competitive advantage and so it is mandatory to follow quality standards. Many organisations use technology and adapt TQM for sustaining competitiveness (Bolatan et al., 2016). Research has determined that TQM has a positive effect on customer satisfaction and financial outcomes (Bolatan et al., 2016; Efimova & Briš, 2021) to improve growth and performance within organisations (Gremyr, Chalmers, et al., 2021). Within the context of chrome mining, it is critical that the final product of mining organisations is of the highest quality to allow them to compete with other companies worldwide and to build good relationships with customers. Thus, proposition 2 of the study was as follows:

P2. Statistical significance and strength as well as importance index (maturity level) assist in identifying those dimensions of Quality 4.0 that prioritise organisational improvement.

### 3. Methodology

This research study obtained ethics clearance from the Faculty of Management Sciences Research Ethics Committee [FCRE-ECO], reference number FCRE2022/FR/06/029-MS (2). The study adopted a post-positivist paradigm to generate knowledge in an objective manner using quantitative research measuring variables and verifying existing variables (Rahi, 2017). A cross-sectional quantitative research design was used involving the use of a survey within the mining industry (Adedoyin, 2020).

#### 3.1. Population and sample

The potential study population was 968 qualifying employees from eight different mining sites who were in management roles such as departmental managers, superintendents, specialists, or supervisors (Paterson job grading CU, D level and E-level) (Paterson, 1975). The study population was selected based on the need for effective empirical data received from employees at the management level, as the implementation of Quality 4.0 is an organisation-wide programme. In addition, this ensured that the study sample had the necessary knowledge and seniority within the industry to make judgment on the state of Quality 4.0 in the chrome mining industry (Mtotywa, 2022) as well as to bring a certain level of generalisability from the eight different mining sites. The size of the study sample was determined using Slovin's formula (Slovin, 1960; Tejda & Punzalan, 2012).

$$n = \frac{N}{Ne^2 + 1} \quad (1)$$

with  $n$  being the sample size and  $N$  the target population and  $e$  = error. For the study, the sample size was 283 and the response ( $n = 211$ ) represented a response rate of 74.8%. This was higher than the average online survey response rate of 44.1% (Wu et al., 2022). Sampling was conducted using the probability method with simple random sampling.

#### 3.2. Instrument and data collection

The research data gathering instrument was adopted from Mtotywa (2022) and focused on the maturity index for improving business operational efficiency and performance. This instrument is based on seven multidimensions of Quality 4.0 with each having four variables. As indicated in section 2.3, the seven dimensions are management commitment to technology and innovation-driven operations, customised customer focus, technology-driven employee involvement and empowerment, process and systems integration and management, knowledge for decision-making and future prediction, root cause analysis of operations disturbances and sustainable solution and operational environment benchmarking. This was a self-administered survey distributed via an email list to the selected sample where the data were collected online using an online link.

#### 3.3. Data analysis

The collected empirical data were imported to IBM Statistical Package for Social Science (SPSS) version 28 and SmartPLS version 4 for statistical analysis and to G\*Power 3.1 for sample power. Initially, the data were screened and cleaned focusing on the extreme outliers, missing values, and common method bias (CMB) (DeSimone et al., 2015; Hair et al., 2010). Harman's single test using principal axis factoring was used to determine the CMB, using 50% as the threshold (Podsakoff et al., 2003). The non-response bias was confirmed with t-test breaking the data into two groups, which comprised early response or late response, and analysing their statistical significance at 95% confidence levels ( $p < .05$ ).

The distribution profile of the respondents was analysed using frequency and percent frequency, while the central tendency was analysed with mean and median, and the spread with



standard deviation. Skewness and kurtosis were used to analyse the normality distribution of the data with values within  $\pm 2$ , indicating that the data were normally distributed (Hair et al., 2010). The maturity index was analysed using the quality maturity index score of the individual dimensions ( $MID$ ), the total composite score for all items ( $CC_j$ ) and the overall quality maturity index score for the operation ( $QMI_j$ ). A confirmatory factor analysis was conducted using partial least square structural equation modeling (PLS-SEM). The specification of the model variables was done to determine whether they were reflective or formative in nature using confirmatory tetrad analysis (CTA) (Eboli et al., 2018) and the model fit with standardised root mean square residual (SRMR) (Henseler et al., 2014). The measurement model analysed convergence validity using average variance extracted (AVE), composite reliability with composite reliability ( $\rho_a$  and  $\rho_c$ ), and Cronbach's alpha and then the discriminant validity with heterotrait-monotrait ratio of correlations (HTMT). Confirmatory tetrad analysis (CTA) compared the tetrads to test and compared how well they fit (differences in the product of pairs of covariance of observed variables) to confirm if the latent variables are reflective or formative (Gudergan et al., 2008). This was critical to confirm the type of variables as in reflective models, the latent variable affects the variables, but in formative models, the variables define it (Theodosiou et al., 2019). The gap analysis was performed using one sample t-test with level 5 (5) used as the test variable. To determine the priority for improvement, the relative importance index (RII) was computed and the correlation using Spearman's rank order.

#### 4. Results

Standardised ( $Z$ ) scores for the relevant variables were calculated, and values that were more than 3.29 standard deviations above or below the mean were flagged as outliers (Tabachnick & Fidell, 2013). Extreme outliers found in two variables were subject to the deletion procedure (Mowbray et al., 2019). The missing value analysis was found to be less than 5% (Madley-Dowd et al., 2019; Schafer, 1999). The data were analysed for common method bias (CMB) with Harman's single test, and the result for extract variance was 45.2%, which is less than 50.0%, indicating that there is no CMB and so there was no artificial inflation of relationships (Jordan & Troth, 2020; Podsakoff et al., 2003; Rodríguez-Ardura & Meseguer-Artola, 2020). There was no non-response bias, and with almost all the variables, no statistical significance using the t-test. Study respondents represented all areas of operations in the mines, with most (46.3%) from production, followed by logistics (12.9%), safety and environmental departments and finance and related resources (11.4% each), and 10.0% were from quality departments. The remainder ( $n=8$ ) were members of human resources departments. The respondents held different positions: most were supervisors (51.9%) (Paterson job grade C upper), 19.4% were specialists (Paterson job grade D lower), while 15.5% were superintendents (Paterson job grade D upper) and 13.1% were managers (Paterson job grade E lower). From a work experience perspective, most (36.9%) were in the mining industry for more than 10 years, while 23.3% were in the mining industry for fewer than 2 years and 19.9% had worked for 2–5 years or 6–10 years, respectively.

##### 4.1. Descriptive statistics

The descriptive statistics indicated in Table 1 show that the mean ( $M$ ) values for the variables are between 2.00 and 3.00. Continuous communication (EIE3) had the highest mean,  $M=2.82$  ( $SD=0.988$ ), and a median,  $Mdn=3.00$ .

This is followed by five variables including enhanced customer relationship management; levels of customer satisfaction; business sustainability benchmark; access to rich information, and statistical root-cause analysis, each with a mean value of 2.75 or higher. The variables with the lowest mean value scores equal to or less than 2.24 were customers buying behaviour changes, management-leading Gemba activities for quality 4.0, and application of artificial intelligence or other virtual technology for visual inspection and quality control. All these variables were normally distributed with skewness and kurtosis within  $\pm 2$  (Hair et al., 2010).

**Table 1. Descriptive statistics**

Variables		Mean (M)	Median (Mdn)	Standard deviation (SD)	Skewness	Kurtosis
Leadership for quality 4.0	MC1	2.40	2.00	1.055	0.115	-1.095
Investment in industry 4.0 technologies	MC2	2.32	2.00	1.177	0.552	-0.618
Enabling culture of creativity and innovation	MC3	2.62	3.00	1.161	0.325	-0.646
Management-leading Gemba' activities for Quality 4.0	MC4	2.20	2.00	1.236	0.649	-0.745
Levels of customer satisfaction	CF1	2.77	3.00	1.12	0.02	-0.602
Customised customer for satisfaction	CF2	2.69	3.00	1.079	-0.155	-1.007
Enhanced customer relationship management	CF3	2.78	3.00	1.039	-0.053	-0.637
Penalty-reward contrast analysis (PRCA)	CF4	2.35	2.00	1.19	0.374	-0.955
Continuous training and retraining	EIE1	2.41	2.00	1.004	0.25	-0.643
Increase knowledge-based technical skills	EIE2	2.54	3.00	0.913	-0.066	-0.612
Continuous communication	EIE3	2.82	3.00	0.988	-0.061	-0.678
Quality 4.0 firm culture	EIE4	2.64	3.00	1.132	0.385	-0.522
Simulation of product design improvement	PSIM1	2.31	2.00	0.987	0.44	-0.267
Application of AI (artificial intelligence or other related virtual technology) for visual inspection and quality control	PSIM2	2.24	2.00	1.006	0.406	-0.639
Real-time process performance monitoring with big data/IoT	PSIM3	2.51	2.50	1.056	0.157	-0.801
Capabilities of instant reconfiguration of process	PSIM4	2.50	2.00	1.06	0.353	-0.61
Access to rich information	KDFP1	2.75	3.00	0.944	0.05	-0.397

(Continued)

Variables		Mean (M)	Median (Mdn)	Standard deviation (SD)	Skewness	Kurtosis
Access to information analytics	KDFP2	2.68	3.00	0.969	0.143	-0.49
Availability of information for early decision-making	KDFP3	2.51	3.00	0.939	-0.018	-0.872
Early failure prediction	KDFP4	2.35	2.00	0.948	0.305	-0.331
Problem identification technologies	RCA1	2.62	3.00	0.971	0.082	-0.646
Statistical root-cause analysis	RCA2	2.75	3.00	0.924	0.105	-0.487
DOE for improvement solution	RCA3	2.45	2.00	0.974	0.426	-0.2
Process capability assessment	RCA4	2.68	3.00	1.016	0.39	-0.307
Technology in use	OEB1	2.77	3.00	0.875	-0.101	-0.199
Industry performance benchmark	OEB2	2.65	3.00	0.924	0.113	-0.489
Customers buying behaviour changes	OEB3	2.12	2.00	0.631	-0.094	-0.505
Business sustainability benchmark	OEB4	2.77	3.00	1.052	0.182	-0.652

#### 4.2. Maturity index of the mining industry

The composite score for the maturity index for Quality 4.0 in the mining industry was analysed using equation 2 (Mtotywa, 2022).

$$MID_j = \frac{\sum_{i=1}^4 QI_{ij}}{p} \tag{2}$$

where *MID* is the quality maturity index score of the individual dimensions (*MC*, *CF*, *EE*, *PS*, *KP*, *RC*, *OB*), where *QI*<sub>1</sub>, *QI*<sub>2</sub>, *QI*<sub>3</sub>, *QI*<sub>4</sub> are items used for assessing quality 4.0 maturity and *p* is the number of the items.

For the total composite score for all items, *CC*:

$$CC_j = \frac{MC_{ij} + CF_{ij} + EE_{ij} + PS_{ij} + KP_{ij} + RC_{ij} + OB_{ij}}{m} \tag{3}$$

With the overall quality maturity index score for the operation, *QMI*<sub>j</sub>, and *m* the number of the dimensions analysed, which is seven when using all dimensions of the quality 4.0 model.

$$QMI_j = \frac{CC_j}{n} \times 100\% \tag{4}$$

where  $n$  is the maximum value of maturity level—which is level 5, the level where there is return on investment from quality 4.0.

The value of the index shows that the composite score is  $MID_j = 17.80$ , with  $QMI_j = 50.9\%$  (Table 2). This indicates a maturity level of EFP ( $0.40 \leq QMI \leq 0.60$ ) meaning that the mines are in the initial or *ad hoc* activity stage but migrating towards the established focused process.

### 4.3. Measurement model

The distinction between formative and reflective measurements is essential because a measuring model must be properly specified in order to assign meaningful relationships to the model (Anderson & Gerbing, 1988; Eboli et al., 2018). The CTA was assessed with the following equation:

$$r_{1234} = cov(1, 2) \times cov(3, 4) - cov(1, 3) \times cov(2, 4) \quad (5)$$

The results of the analysis showed that more than 80% of the latent variables were not statistically significant at 5%, confirming that the variables of the measurement model were reflective, meaning that the variables were affected by the latent constructs. The measurement model was used to analyse the results of the confirmatory factor analysis to generate the values of the factor loadings, the average variance extracted (AVE) as well as the composite reliability (CR) for convergent validity, composite reliability (CR), and discriminant validity, as indicated in Figure 1.

All factor loadings were 0.70 or higher except for OEB3 which was 0.633 and was excluded in the final model (Hair et al., 2019). The overall model fit shows that with the standardised root mean square residual (SRMR), the mean absolute value of the covariance residuals based on translating the sample and anticipated covariance matrices into correlation matrices showed a good fit, with SRMR = 0.068 (better than the minimum threshold of 0.080) (Henseler et al., 2014; Hu & Bentler, 1999).

All the values of average variance extracted (AVE) were higher than 0.50 ( $AVE = 0.624\text{--}0.695$ ) indicating that there was convergence validity (Table 3). The composite reliability was confirmed with  $\rho_a$ ,  $\rho_c$ , and Cronbach's alpha, with all constructs having a value higher than 0.7 (Hair et al., 2019).

The discriminant validity was assessed with the heterotrait-monotrait (HTMT) ratio, which is based on the multitrait-multimethod matrix (Table 4). The heterotrait-monotrait ratio of correlations works better than traditional methods of discriminant validity, Fornell-Larcker criterion, or cross-loadings in a Monte Carlo simulation study (Henseler et al., 2014). The HTMT matrix analysis shows that all values within a range of 0.613–0.882 are within the threshold of 0.90 (HTMT<sub>90</sub>) (Ab Hamid et al., 2017; Teo et al., 2008).

### 4.4. Gap analysis

#### 4.4.1. One sample t-test

The one-sample t-test compares the sample mean to a given value and the comparison of the sample mean to a hypothesised mean is used to determine whether the sample is substantially different (Banda, 2018; Gerald, 2018;). The one sample t-test can be calculated using the following equation:

$$t = \frac{\bar{X} - \mu}{\hat{\sigma}_{\bar{X}}} \quad (6)$$

where  $\bar{X}$  is the mean score of the sample,  $\mu$  is the hypothesised mean value and  $\hat{\sigma}_{\bar{X}}$  denotes the standard error of the mean.  $\bar{X}$  can be determined with the following equation:

$$\bar{X} = \frac{\sum_{i=1}^n X_i}{n} \quad (7)$$

where  $n$  is the sample size, and the  $\hat{\sigma}_{\bar{X}}$  can be determined with the following formula:

**Table 2. Maturity index of quality 4.0 in mining industry**

Measure	Index
$MID_j$	17.80
$CC_j$	2.543
$QMI_j$	50.9%

$$\hat{\sigma}_{\bar{x}} = \frac{\hat{\sigma}}{\sqrt{n}} \tag{8}$$

The results of the one sample t-test with effect size is presented in Table 5. The management commitment to technology and innovation-driven operations score was statistically significantly lower by 2.628 (95% CI, 2.494 to 2.761) than the ideal profile score of 5.0,  $t(195) = -38.714$ ,  $p < .001$ . The standardised effect size was assessed with Cohen’s  $d$  (Cohen, 1988) and Hedges’  $g$  (Hedges, 1981). The  $|d| = 2.765$  indicating a large effect size. This means that the group means differ by close to three standard deviations. This was confirmed by the Hedges’  $g$  which was 2.755, where Cohen’s  $d$  differs from Hedges’  $g$  in that the latter is multiplied by a correction factor for small samples (Turner & Bernard, 2006).

Customised customer focus ( $t(195) = -35.78$ ,  $p < .001$ ), employee involvement and empowerment ( $t(198) = -40.64$ ,  $p < .001$ ), process and systems ( $t(191) = -44.24$ ,  $p < .001$ ), knowledge for decision-making and future prediction ( $t(199) = -43.70$ ,  $p < .001$ ), root cause analysis ( $t(195) = -41.97$ ,  $p < .001$ ), and operational environment benchmarking ( $t(202) = -39.35$ ,  $p < .001$ ) all have a statistically significantly lower than the ideal profile of 5.0 with large effect size. These results confirm proposition 1.

#### 4.4.2. Homogeneity analysis

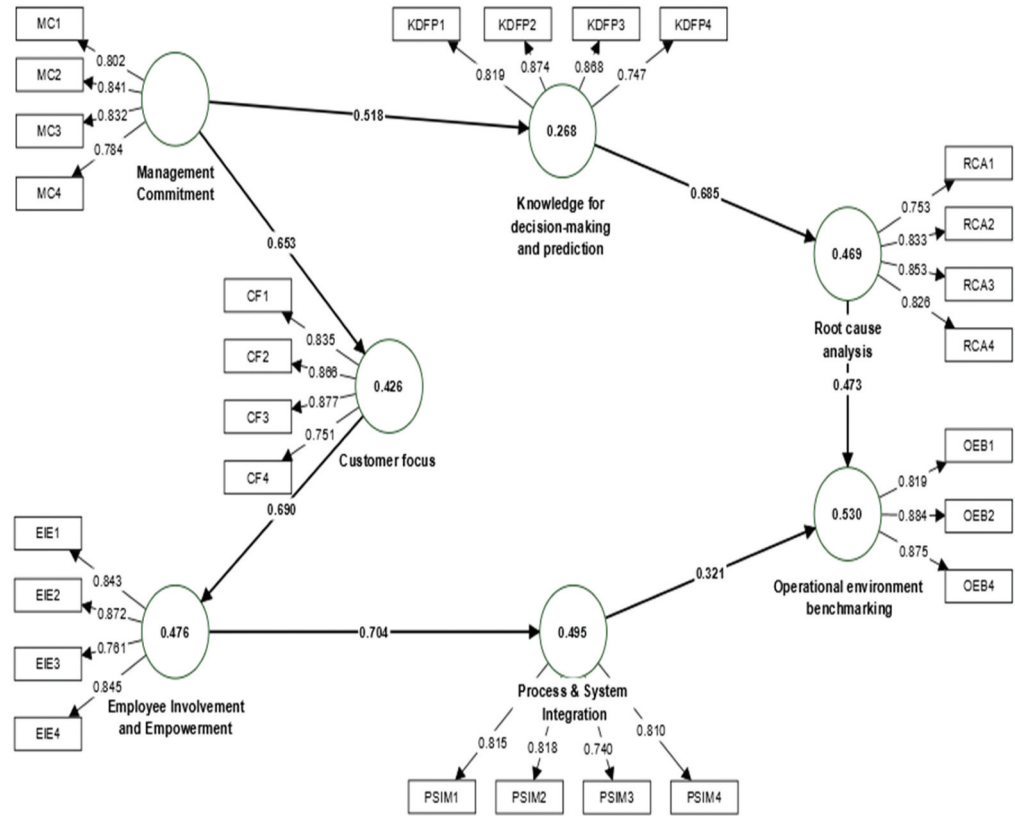
Homogeneity analysis was conducted to determine whether or not the population samples based on department, tenure in the organisation, and position have the same distribution of the dimensions of the Quality 4.0 (Table 6).

The traditional tests based on mean and the robust test based on median, median and with adjusted degrees of freedom ( $df$ ) as well as trimmed mean confirmed that Levene’s test was not statistically significant with  $p$ -value higher than 5% when comparing study participant **department**. This means that it did not matter whether the study participants were from production, logistics, safety and environmental, finance and related resources, quality or human resources, their perceptions on the Quality 4.0 dimensions and their current state in the mining industry were the same. Similar results were found for all the dimensions of Quality 4.0 in regard to the study participants’ **tenure**, from less than 2 years to more than 10 years. For their **position**, the same results were found except for technology-driven employee involvement and empowerment who had a statistically significant difference across the group ( $F = 5.124$ ,  $p < .01$ ). Despite this, it can be concluded that the sample had the same distribution on the state of the dimensions of the quality 4.0 in the chrome mining sites. This is critical as commitment and joint-task coordination between different business units, implementing proper organisational structure changes, and promoting a new cultural mindset regarding technological strategies and their continuous improvement are the primary challenges that businesses must face to achieve a successful digitisation.

#### 4.4.3. Adequacy of the sample

The achieved statistical power was determined using G\*Power 3.1. This study power is equal to (1) and represents the probability of missing a difference when one actually exists. As the likelihood of committing a Type II error decreases, the power of a study improves. Although 80% is acceptable in research indicating that on one out of five occasions, or 20% of the time, we will overlook a real distinction. In this study, we adjusted the statistical power to 90% to decrease the likelihood of

**Figure 1. Measurement model of quality 4.0 dimensions.**



a “false negative“ outcome to 10% (Kadam & Bhalerao, 2010). The statistical power was done with t-tests using means differences from constant (one sample case) with a *post hoc* test showing an achieved power based on  $\alpha$ , sample size, and the effect size. The  $\alpha$ - *err prob* which is the chosen Type I error rate was 0.01, with a sample size of 211, and the statistical power was more than 99%, confirming an adequate sample size and a good statistical power.

#### 4.5. Priority areas for improvement

With the gaps identified, there is a need to identify priority areas for improvement. Despite this, configurational theory is typically informed by a logic of consistency, or the notion that all aspects of a configuration are of equal importance and are necessary for its existence or efficacy (Fiss et al., 2013). The reality is that there is a need to prioritise as organisations do not have endless resources. To identify the priority areas within the seven dimensions, the importance index was calculated using the formula:

$$RII = \sum \frac{W}{A \times N} \tag{9}$$

where  $W$  = weight for each item,  $A$  = highest variable, and  $N$  = number of responses. This is averaged to obtain the importance index of the dimension. For effectiveness, the Spearman correlation was conducted with the following formula:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{10}$$

where  $\rho$  = Spearman’s rank correlation coefficient,  $d_i$  = difference between the two ranks of each observation,  $n$  = number of observations. This is used to determine the relationship and understand the significance and the strength of the relationship between the seven dimensions of quality 4.0 and the perceived efficiency, perceived productivity and perceived performance (Table 7).

**Table 3. Convergence validity and composite reliability**

Dimensions	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	Average variance extracted (AVE)
Management commitment to technology and innovation-driven operations (MC)	0.832	0.835	0.888	0.665
Customised customer focus (CF)	0.852	0.858	0.901	0.695
Technology-driven employee involvement and empowerment (EE)	0.851	0.863	0.899	0.691
Process and systems integration and management (PS)	0.807	0.811	0.874	0.634
Knowledge for decision-making and future prediction (KP)	0.846	0.849	0.897	0.686
Root cause analysis of operational disturbances and sustainable solutions (RC)	0.833	0.838	0.889	0.667
Operational environment benchmarking (OB).	0.794	0.822	0.867	0.624

**Table 4. Heterotrait–monotrait ratio of correlations matrix**

Dimensions	1	2	3	4	5	6	7
1. CF							
2. EE	0.804						
3. KP	0.68	0.674					
4. MC	0.771	0.800	0.613				
5. OB	0.718	0.715	0.686	0.69			
6. PC	0.882	0.837	0.733	0.787	0.764		
7. RC	0.701	0.702	0.815	0.694	0.818	0.809	

The technology-driven employee involvement and empowerment (EE) and operational environment benchmarking (OB) dimensions both have statistically significant strong relationships with perceived efficiency, perceived productivity, and perceived performance, all with  $\rho \geq 0.50$  (Cohen et al., 2003). This was followed by a management commitment to technology and innovation-driven operations (MC) and process and systems integration and management (PS) with  $\rho \geq 0.47$ . These four dimensions were contrasted with the current maturity in the mining industry, and management commitment (RII = 47.7%) and process control (RII = 47.7%) were the least mature. Based on these results on effectiveness and RII, the three dimensions that need to be prioritised for improvement in the mines were (1) management commitment, (2) employee involvement and empowerment, and (3) process and system integration. These results confirm proposition two.

**Table 5. One sample t-test with effect sizes**

Dimension	t	df	One-Sided p	Two-Sided p	Mean Difference	Lower	Upper	Mean	SD	Effect size
MC	-38.714	195	0.000	0.000	-2.62755	-2.7614	-2.4937	2.3724	0.95020	-2.765* -2.755†
CF	-35.784	195	0.000	0.000	-2.36480	-2.4951	-2.2345	2.6352	0.92519	-2.556* -2.546†
EE	-40.640	198	0.000	0.000	-2.40452	-2.5212	-2.2878	2.5955	0.83465	-2.881* -2.870†
PC	-44.237	191	0.000	0.000	-2.61719	-2.7339	-2.5005	2.3828	0.81979	-3.193* -3.180†
KP	-43.703	199	0.000	0.000	-2.42875	-2.5383	-2.3192	2.5713	0.78594	-3.090* -3.079†
RC	-41.967	195	0.000	0.000	-2.38010	-2.4920	-2.2683	2.6199	0.79399	-2.998* -2.986†
OB	-39.348	202	0.000	0.000	-2.26929	-2.3830	-2.1556	2.7307	0.82170	-2.762* -2.751†

Test value (ideal maturity) = 5.  
 95% Confidence Interval of the Difference [Lower, Upper].  
 \*Cohen's d † Hedges' correction.



**Table 6. Homogeneity analysis**

		Department		Tenure		Position	
		Levene Statistic	Sig.	Levene Statistic	Sig.	Levene Statistic	Sig.
MC	Based on Mean	0.997	0.421	0.663	0.576	2.429	0.067
	Based on Median	1.071	0.378	0.561	0.641	2.252	0.084
	Based on Median and with adjusted df	1.071	0.378	0.561	0.641	2.252	0.084
	Based on trimmed mean	1.009	0.414	0.657	0.580	2.663	0.049
CF	Based on Mean	0.849	0.517	0.179	0.911	2.212	0.088
	Based on Median	0.852	0.515	0.118	0.949	1.868	0.136
	Based on Median and with adjusted df	0.852	0.515	0.118	0.949	1.868	0.137
	Based on trimmed mean	0.870	0.502	0.165	0.920	2.187	0.091
EE	Based on Mean	0.559	0.731	1.506	0.214	5.124	0.002
	Based on Median	0.603	0.698	1.437	0.233	3.482	0.017
	Based on Median and with adjusted df	0.603	0.698	1.437	0.233	3.482	0.017
	Based on trimmed mean	0.564	0.727	1.499	0.216	5.045	0.002
PC	Based on Mean	1.860	0.103	1.218	0.304	1.953	0.123
	Based on Median	1.835	0.108	1.050	0.372	2.128	0.098
	Based on Median and with adjusted df	1.835	0.109	1.050	0.372	2.128	0.098
	Based on trimmed mean	1.912	0.094	1.179	0.319	2.024	0.112

(Continued)

**Table 6. (Continued)**

		Department		Tenure		Position	
		Levene Statistic	Sig.	Levene Statistic	Sig.	Levene Statistic	Sig.
KP	Based on Mean	1.805	0.114	1.053	0.370	1.462	0.226
	Based on Median	1.739	0.128	1.013	0.388	1.463	0.226
	Based on Median and with adjusted df	1.739	0.128	1.013	0.388	1.463	0.226
	Based on trimmed mean	1.754	0.124	1.059	0.368	1.465	0.225
RC	Based on Mean	0.464	0.803	1.320	0.269	0.223	0.881
	Based on Median	0.416	0.837	1.199	0.312	0.221	0.881
	Based on Median and with adjusted df	0.416	0.837	1.199	0.312	0.221	0.881
	Based on trimmed mean	0.473	0.796	1.294	0.278	0.207	0.892
OB	Based on Mean	0.711	0.616	1.519	0.211	2.060	0.107
	Based on Median	0.692	0.630	1.414	0.240	1.563	0.200
	Based on Median and with adjusted df	0.692	0.630	1.414	0.240	1.563	0.200
	Based on trimmed mean	0.746	0.590	1.515	0.212	2.016	0.113

Department (df1, df2 = 5, 188), Tenure (df1, df2 = 3, 190), and Position (df1, df2 = 3, 190).

## 5. Discussion

Despite several research studies conducted on the implementation of TQM in organisations to show how it improves performance, there are organisations that are unaware of its role in improving quality (Fundin et al., 2021; Gremyr, Elg, et al., 2021; Mas-Machuca et al., 2018). Mashamba (2015) posits that effective quality is about satisfying the customer by meeting his/her needs. An organisation that is driving TQM places customer needs as their priority. An understanding of such needs facilitates knowing and pleasing their customers but the organisation must be willing to spend money to build relationships with the customers and obtain a return on their investment. Customer feedback is key to organisations knowing customer needs and improving the quality of their products and services and customer research is needed when making a product that is user-friendly, attractive to customers and profitable. Thus, organisations need to continuously interact with their customers via interviews, surveys, and information sessions to be able to continuously improve the product to suit the needs of the customer.

Löw (2022) posits that the mining industry will progress positively, that is, towards a better work environment through technological interventions if it develops in an iterative way to guarantee continued suitability for the problems it intends to address and functionality within its

**Table 7. Spearman correlation and relative importance index of Quality 4.0 dimensions**

Constructs	p										RII	
	1	2	3	4	5	6	7	8	9	10		
1. Performance	—											
2. Productivity	.808**	—										
3. Efficiency	.848**	.841**	—									
4. MC	.479**	.495**	.472**	—								47.7%
5. CF	.405**	.453**	.444**	.664**	—							52.9%
6. EE	.564**	.553**	.561**	.698**	.700**	—						52.1%
7. PC	.476**	.503**	.471**	.685**	.743**	.715**	—					47.8%
8. KP	.373**	.407**	.384**	.545**	.570**	.570**	.602**	—				51.5%
9. RC	.464**	.478**	.473**	.615**	.624**	.651**	.688**	.705**	—			52.5%
10. OB	.598**	.549**	.556**	.591**	.620**	.596**	.623**	.578**	.691**	—		54.6%

\* - p < .05 \*\* - p < .01.

environment. Adaptation necessitates alterations to the context in which a technology is used, so those contexts must be flexible. The technological environment must be considered as a whole to prevent sub-optimisation and technological interventions should prioritise larger, more comprehensive interventions that take into account a variety of factors. This is what Quality 4.0 can do to provide strategic improvements in the chrome mining industry. Digital transformation influences the entire value chain, business models, as well as organisational and managerial elements (Herceg et al., 2020). Cots (2018) argues that digital technology has improved quality management and for effective implementation and in achieving desired maturity relative to quality 4.0, management must be committed to applying technology in innovation-driven operations. Thus, management within organisations must lead by example so that fellow staff members may embrace technical and personal change to improve operations and customer relations within the organisation (Efimova and Bris, 2021; Kirgizov & Kwak, 2022). The dedication of top management fosters comprehensive quality by establishing values, objectives, and processes that result in customer satisfaction and enhanced organisational performance (Jbeily, 2022; Singh et al., 2018). Involvement of top management in quality programmes, quality objectives, the relevance of quality in relation to budgets and schedules, and comprehensive quality planning are the most significant aspects of management commitment. There is a tangible connection between management commitment and employee involvement and so it is the duty of management to engage with employees and guide them regarding the mission and values of the organisation so that they are in line with sustainability goals of the organisation (Zhao et al., 2022). Employee involvement in such organisational processes improves quality and increases productivity and so employees need to know that their contribution is recognised, valued and implemented, and if not implemented, an explanation should be given to them. Operational involvement by employees also improves relationships between one another, and they become brothers' keepers (Sadikoglu & Zehir, 2010; Staniškienė et al., 2018). Employee involvement can include monthly feedback meetings with the management, team-building exercises, rewards for continuous improvement initiations, rewards for problem solving, structured suggestion systems, and quality management forums (Gremyr, Chalmers, et al., 2021).

Process management should also be based on monitoring and assessing the performance of the process, by planning, checking, organising, and continuously improving the process (van Assen, 2021). Systems management, on the other hand, manages the interaction of the elements to achieve a specific goal. Process management is based on checking all the stages of the process and making sure that the end goal is achieved. Systems and process management are important as they are the building blocks that support the organisation's growth. Total quality management (TQM) practices remain the most preferred management system tool in operations (Bon & Mustafa, 2013). Abusa (2011) highlights that TQM has become the global practical process to improve competitiveness. The TQM can be unpacked as a tool and a system that involves all levels of the organisation working together to improve the quality of the product, productivity, customer focus, employee involvement, and effectiveness, and it ensures that the organisation becomes flexible and gains a competitiveness advantage (Mas-Machuca et al., 2018). Alimohammadlou and Eslamloo (2016) suggest that this provides a holistic approach to management that tries to maintain sustainable improvement in the total performance of an organisation. This supports the contention that in order to help the world get the high-quality raw materials and energy it needs, while also minimising damage to ecosystems and speeding up their recovery, new innovations in the mining industry are needed.

The significance of the study was informed by the need for organisations to improve the quality of their product, minimise variations in results, and to ensure that customers are satisfied at all times (Lepistö et al., 2022). The introduction of the fourth industrial revolution technologies has increased competition, particularly in the mining industry, when it comes to total quality management. To be able to keep up with competition, the mining industry needs to move with the times and work with new technologies that will help them improve its customer service. As one of Deming's philosophies involves minimising variation in the product (Deming, 2013),

implementation of Quality 4.0 will assist organisations in reducing variation of the final product and help meet or exceed customer expectations and this is what the mining industry needs to focus on. Furthermore, it can help with understanding the return on investment upon introducing Quality 4.0 and enhance Crosby's philosophy of measuring quality with cost and decreasing the cost of poor quality (Evans, 2017). This is critical in the chrome industry that is suffering from lower ferrochrome prices and rising energy costs. Moreover, it is important that the organisation knows what their competition is doing so that they can align or be ahead of them in light of the increased output from China shifting the market share (Department of Trade, Industry and Competition, 2020). The effectiveness of quality management is being enhanced by the technology (Quality 4.0), and embracing this change is central for success and competitive advantage. This can be in both operational and environmental conditions. Effective quality management has a positive effect on both safety (Golan et al., 2020) and environmental management, and this is critical within the mining industry which follows stringent regulatory requirements as they operate in a generally risky environment (Agboola et al., 2020).

## 6. Conclusion

For the mining industry in South Africa to be sustainable and competitive, it needs to move with the times and implement quality management systems that are driven by new technologies. The study findings confirm the study propositions that mines were in an initial or *ad hoc* activity stage but are migrating towards the established focused process stage. As such, the Quality 4.0 maturity index model dimensions show a statistically significant difference between the current state and the ideal profile of the highest maturity level 5. The findings also conclude that management commitment, employee involvement and empowerment, as well process and system intergration and management are improvement priority areas. Increasing competition in the global market necessitates that productivity should not be considered only as a variable of efficiency, but that operational practices such as TQM provide the foundation of competitive advantage because such practices make it possible to generate and share knowledge among the members of an organisation (Alimohammadlou & Eslamloo, 2016). Companies are constantly moving ahead towards improving the quality of overall activities to prosper and serve the market in a better way.

### 6.1. Theoretical contribution of the study

The emerging literature on research regarding quality 4.0 provides a theoretical and empirical focus that has gained momentum in the past few years (Maganga & Taifa, 2022). This study makes several contributions by validating the theoretical framework of the maturity index by confirming that the variables were reflective and achieved validity (convergence and discriminant) and reliability with the measurement model. There have been numerous studies on Quality 4.0 in different industries (Maganga & Taifa, 2022; Nenadál et al., 2022; Sader et al., 2022; Sony et al., 2021; Yadav et al., 2021). However, there is a gap in the literature regarding the use of technology to increase operational efficiency within the mining industry. As such, it was prudent that this study was conducted in the mining industry to contribute towards building knowledge of the potential advantages of adopting Quality 4.0 in this industry. This is critical as the mining industry is facing many challenges when it comes to quality and the results of the study will help the mining industry to more effectively migrate to total quality management that is driven by technologies linked to the fourth industrial revolution.

This study also contributes towards the empirical evidence surrounding configurational theory and profile deviation. This affirms the study research approach regarding the dimensions of Quality 4.0 which collectively emphasises the effectiveness of quality 4.0 in an organisation and its influence on improving organisational performance. Despite this, due to resource constraints and requirement for effective implementation, it is critical to identify priority areas for improvement and systematic implementation.

## 6.2. Implication for mining industry

South Africa is one of the leading countries in the mining industry. Most mineral resources used worldwide are extracted from South Africa as it owns about 70% of the world's chrome reserves and this contributes towards economic growth (African Mining IQ, 2019; Minerals Council South Africa, 2020). The South African mining industry is currently facing difficult times with issues such as increases in electricity, safety issues, market drops, quality issues, and environmental issues (Agboola et al., 2020; Golan et al., 2020). All these factors make it currently very expensive to operate mines. Cassim et al. (2019) argue that unless the South African mining industry can improve its cost competitiveness, the situation is going to get worse. This requires an improvement in mining operational quality, ensuring an effective implementation of the Deming principles of minimising variation which can result in increased cost associated with poor quality, as well as Crosby's approach, that problems are functional in nature, that there is no optimum level of defects and zero defects is the only performance standard (Evans, 2017). Quality 4.0 affords organisations an opportunity for improvement with a holistic focus on operational processes to leverage the capabilities of the fourth industrial revolution technologies. In short, organisations should integrate Quality 4.0 into strategies and business models (Sisodia & Villegas Forero, 2019) and such integration of technologies into the chrome mining industry might alleviate many of the challenges currently facing this industry. This study can be generalised to other sectors in the mining industry such as platinum, gold, and coal as they have similar settings.

## 6.3. Limitations and suggestions for future research

The study is not without limitations. Even though the study used probability sampling methods, it only focused on the chrome mining industry and so the study results are not generalisable across all mining sectors and industries. Two suggestions are made for future research. First, it is necessary for a comparative study within different mining sectors, such as platinum, gold, and coal as to their state of Quality 4.0 so as to understand the overall performance of these sectors to allow identification of those industries that are performing well to be used as a benchmark for implementation of Quality 4.0. Second, there is a need to consider the usefulness of Multi-criteria Satisfaction Analysis (MUSA) (Ahmad & Thiruchelvam, 2014; Grigoroudis & Siskos, 2010) for prioritisation of improvement in post-gap analysis in a more comprehensive manner. This is because it accommodates double-error variable, considers both aggregate and partial measures, and conducts stability analysis of the model.

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### Author Contributions

Regarding the author contributions to the study and manuscript: Conceptualisation, TD and MMM; Methodology, MMM and TD; software, MMM and TD; Validation, MMM and TD; Formal analysis, MMM and TD; Investigation, TD; Resources, TD; Data curation, MMM and TD; Original draft preparation, MMM; Review and editing, MMM and TD; Visualisation, MMM and TD; Supervision, MMM; Project administration, TD.

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