SOUTH AFRICA'S MINING INDUSTRY EXPERT'S OPINION ON TECHNOLOGY IMPLEMENTATION STEPS

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ABSTRACT

SA's mining industry is moving towards implementing Industry 4.0 technology. As a developing country, circumstances surrounding the implementation of this technology need to account for the unique circumstances of developing countries. While also learning relevant lessons from developed countries. Considerations required for developing countries are how the move to Industry 4.0 technology will affect people, including addressing workers' concerns and the broad communities the mines affect. Concerns include job security, worker safety and the environmental impact of mining. This study used a survey to solicit responses from SA's mining industry experts on a technology implementation roadmap. SA's mining industry was the basis for the roadmap development. The survey measured the experts' satisfaction levels with the roadmap. Results reinforced inclusions on the roadmap that experts agree with. While also shedding light on topics the experts disagreed with. Experts also provided additional areas the roadmap needed to cover.

Keywords: technology implementation, mining, South Africa, roadmap

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1 INTRODUCTION

The mining industry is increasingly embracing technology, which offers benefits such as money-saving, time-saving and reduced risks. Adopting technological innovations minimises waste and provides a competitive edge, as noted by [1]. Despite these benefits, there has been limited research on the challenges and facilitators of technology adoption in mining, highlighting the importance of such studies.

According to [2], there has been a rapid increase in digital twin technology use, which is transforming business operations to cut costs. A 2019 survey found that 75% of companies using the Internet of Things (IoT) have adopted digital twin technology [3]. Additionally, 13% were implementing this technology already, and 62% planned to do so within a year. Digital twin technology can simulate every product, process, or service aspect, enabling faster decision-making against traditional methods.

Developing countries like South Africa are seeking the benefits of implementing these new technologies in the mining industry. This paper used a survey on the steps necessary for applying these new technologies in the South African mining context. The survey questions were from the literature from other countries with similar experiences and those leading in this pursuit.

The study aims to develop a roadmap that South African mining companies can use when introducing new technologies, accounting for the unique circumstances specific to the country.

2 LITERATURE REVIEW

2.1 Pakistan's implementation

2.1.1 Awareness of Autonomous Mining Systems

Awareness of autonomous mining systems in Pakistan primarily comes from social networks, word of mouth, and academia [4].

2.1.2 Stakeholder preparedness

Pakistan's mining industry supports semi-autonomous and fully autonomous systems due to safety improvements, productivity, and cost reductions. However, concerns about knowledge gaps and unemployment persist. Many feel prepared for autonomous systems employment, though some do not. Most are willing to undergo training, but it is currently unavailable in Pakistan [4].

2.1.3 Impact of implementing autonomous mining systems

The main concern is unemployment. Proponents believe the government will support new technology due to its positive effects on GDP and productivity. Sceptics cite potential unemployment, political risks, labour unrest, and health and safety concerns [4].

2.2 India's implementation

The study, based on [5], identified several themes for technology adoption in India's mining industry:

1. Technology adoption must be an organisational initiative.
2. Reliable emerging technology providers are crucial.
3. Mining companies seek partnerships with proven technology providers.
4. The initial step is the digitalisation of mining data.
5. Public sector companies are slow to adopt technology due to job creation goals.
6. Strategies for long-term goals and technology implementation are misaligned.

7. Difficult geographical and geological conditions hinder technology adoption.
8. A shortage of skilled employees is a barrier.
9. Improved legal environments could expedite technology adoption.
10. Natural factors limit economies of scale in the Indian mining industry.
11. Bureaucracy and legal restrictions impede new technology implementation.
12. Data analytics and cloud computing are the most feasible technologies.
13. Solutions from developed countries often do not suit India, requiring unique solutions.
14. Managers prefer extracting total value from current technology before upgrading.
15. New technology affects the entire organisation.
16. New technology requires significant initial investments.
17. New technology must enable mining activities.
18. Technology providers must understand the economic context of mining companies.
19. Providers need to comprehend the geological and geographical conditions of mining.
20. The benefits of new technology are often unclear and need a better definition.
21. Organisational culture plays a critical role in technology adoption.
22. Mining managers often lack awareness of emerging technologies.
23. If new technologies solve current problems, adoption will increase.
24. Benefits like cost reduction, faster delivery, and better quality enhance adoption likelihood.

2.3 South Africa's implementation

Key factors enabling technology implementation in South Africa include powerful political will, supportive culture, adequate funding, effective Intellectual Property Laws (IPL), robust partnership networks, market competition, high market demand, substantial R&D capacity, solid engineering capacity and access to natural resources. The absence of these factors hinders implementation [6].

2.4 Technology implementation roadmaps

Technology road mapping is identified as a well-known technique yet infrequently applied [7]. Technology implementation roadmaps are visual tools that align an organisation's technology strategy with its business strategy [8]. Successful implementation of these roadmaps requires setting clear, organisation-specific objectives that align with the company's culture [8]. The development process has three phases: Initial, Development, and Integration.

1. **Initial phase**: This phase involves gathering information for subsequent stages. Key stakeholders form a team to develop the organisation's technology implementation roadmap. Measure success by stakeholder acceptance of the customised roadmap.
2. **Development phase**: Data from internal and external sources is collected and analysed by stakeholders, who then present it in a roadmap format. This phase often requires multiple iterations. Measure success by the quality of roadmap content and the expertise contributed by stakeholders.
3. **Integration phase**: The roadmap integrates with business operations. Success measure is the roadmap's alignment with the business strategy, quality, and ongoing development.

Technology road mapping helps build consensus on technological needs, forecast technology developments, and plan future technology implementations [9]. A roadmap for Industry 4.0 technology in manufacturing with seven phases as follows [10]:

1. **DEFINE**: Identify problems and resource limitations. Develop a scope for Industry 4.0. Involve stakeholders and develop a transition team. Create detailed project plans and identify long-term, mid-term, and short-term strategies. Define skills and training needs and establish a change management strategy. Adapt the supply chain and legal framework to the new technology, including risk management strategies.

2. **MEASURE**: Gather data to understand and address the company's requirements using Quality Function Deployment (QFD) and Measurement System Analysis (MSA) to capture realistic views of process variations.
3. **EVALUATE**: Benchmark the readiness for Industry 4.0 technology, compare quality processes with market leaders, and develop new concepts using methods like FMEA and TRIZ. Use the Pugh matrix to identify the best design.
4. **OPTIMISE**: Build a detailed design using performance analysis software such as Anylogic and CAD tools like Autodesk.
5. **DEVELOP**: Build a prototype, evaluate hardware and software needs, and develop the prototype based on previous simulations without disrupting the production line.
6. **VALIDATE**: Test the prototype against the simulation model to mitigate risks and confirm expectations. Gather stakeholder feedback and conduct risk assessments.
7. **IMPLEMENT**: Implement the system, making adjustments where necessary. Focus on cost-saving, standardise processes and create a training plan for users. Continuously improve the system.

2.4.1 Roadmap of technology implementation in a generic industry

[11] developed a generic roadmap for technology adoption and divided it into three phases: analysis, goal setting, and implementation, which split further into six steps addressing production, purchasing, intralogistics, human resources, and sales.

1. Create Awareness: Involve employees and conduct a SWOT analysis.
2. Gather Data: Assess the company's capabilities to implement Industry 4.0 technologies.
3. Define Target States: Use techniques like morphological analysis and brainstorming with industry experts.
4. Draw Documents and Measure Evaluation: Evaluate differences between expectations and results, rating efforts and benefits.
5. Define Objectives: Establish the relevance and impact of objectives on the organisation.
6. Connect Projects with Budgets: Use pilot projects to gain experience and address early issues before full-scale implementation.

2.4.2 South African roadmap for Industry 4.0 implementation

[12] developed a roadmap for technology implementation in South African mines through a case study at the Wits Mining Institute (WMI). The roadmap's three phases with various challenges are as follows:

1. Pre-installation Challenges:
    - Identifying and selecting appropriate technologies
    - Budget overspending
2. Installation Phase Challenges:
    - Overspending
    - Delays in civil works
    - Poor system compatibility
    - System malfunctions
    - Unreliable communication systems
    - Faulty hardware design
    - Remote access restrictions
    - System integration issues
3. Post-installation Phase Challenges:
    - Poor after-sales support
    - Inadequate maintenance and upgradability provisions

The literature review covers technology implementation in Pakistan, India, and South Africa's mining sectors, with technology road mapping for Industry 4.0. Pakistanis and Indians show support for autonomous systems but face challenges like training availability and bureaucratic hurdles, respectively. South Africa benefits from political will and strong R&D, but some regions lack these advantages. Highlighted as critical was technology road mapping for aligning strategies and engaging stakeholders. Challenges include complex implementation phases and issues like budget overspending and system compatibility. Overall, the review stresses adapting global solutions to local contexts and continuous alignment with business strategies to maximise technology adoption benefits.

From the literature review on Industry 4.0 technology implementation and roadmaps, the researcher compiled a survey to be assessed by participants. The participants had experience with approaches suitable for South African mines. Therefore, they quantified whether the new roadmap would succeed in this context. A Appendix A: Survey questions shows the survey, and the methods used for designing this study's survey are in subsection 3.1 below.

3 METHODOLOGY

3.1 Survey design

Why surveys? Over the past 50 years, online surveys have become the most popular method for data collection in research, aligning with the rise of the internet [13]. This method is more convenient for gathering information, especially when surveyors and respondents are geographically distant. Online surveys allow respondents to participate at their convenience. This study used Google Forms for the survey, which stores responses in real-time, is free, and allows easy data export [14] - [17].

Surveys collect primary data through direct questions to respondents, measuring attitudinal data such as opinions, preferences, awareness, perceptions, and motivations. E-surveys are popular due to their autonomous data collection, low cost, wider reach, and current data [18]. They eliminate interviewer bias, give respondents more time, and ensure anonymity, resulting in more honest answers [15]; [16]; [18].

However, e-surveys have drawbacks, such as the lack of personal communication between respondents and researchers, no control over the collection procedure, low response rates, and no provision for clarity for respondents. Surveys must be simple and short, limiting the amount of data collected. There's also no control over who the final respondent is, increasing bias, and no opportunity for further probing [18]. Surveys need thorough testing before use. Researchers must ask only relevant questions, carefully considering the form, wording, and sequence of questions [13]. This study included Likert scale questions to assess respondents' views on a topic [19]. The survey was on a roadmap developed through the literature on adopting Industry 4.0 technology in the mining industry. The researcher aimed to test whether this new roadmap was sufficient for the South African mining industry. Google Forms online decimated the survey. Appendix [1] A. Ediriweera and A. Wiewiora, "Barriers and enablers of technology adoption in the mining industry," Resources Policy, vol. 73, no. 1, pp. 1–14, Oct. 2021, doi: 10.1016/J.RESOURPOL.2021.102188.

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A Appendix A: Survey questions shows the questions in the survey. Based on the literature, the recurring subdivisions were three phases in the technology implementation. The three phases were pre-installation, installation, and post-installation. These three phases also had their subdivisions that the survey roadmap was quantifying. The survey amalgamated all the roadmaps in the literature survey and redesigned them into the new roadmap.

3.2 Sampling

The study used purposive sampling, a non-random (or non-probability) sampling method based on experience, common sense, expertise, and researcher intention [20]. The study used purposive sampling because it allows the extraction of information from a particular group of individuals, in this case, people familiar with technology implementation in the mining industry.

3.2.1 Type of purposive sampling

The study employed expert sampling, which gathers data from individuals with specific expertise. This sampling is helpful in situations involving high uncertainty [20]. Participants were experts familiar with implementing new mining industry technology (all respondents worked at a single mine). The experts chosen in this study varied in professions, from plant engineers, mining engineers, managers, artisans, supervisors, superintendents and health and safety officers. Their experience ranged from 0 to more than 40 years of experience. Additional information on the participant's demographic information, such as gender, age groups, years of experience in the mining sector and type of position held, can be found in B Appendix B: Respondents demographics information.

3.2.2 Snowball sampling

Snowball sampling supplemented the purposive sampling. This study applied the s-stage k-name Snowball sampling method by asking individuals identified in the purposive sample to name k additional individuals with the necessary expertise (technology implementation in mining). This process continued in stages until an adequate sample size was reached [21].

3.3 Strategies for survey validation and verification

Emphasising validity, generalisability, and reliability ensures that observed effects honestly reflect the causes. Valid results accurately represent the phenomenon under study, reliable results remain consistent across different contexts, and generalisable results hold across various conditions [22].

3.3.1 Survey pre-testing

Environmental triangulation involves testing findings across different settings to establish validity [23]. A pilot study pre-tested the survey with a smaller participant set [19]. The pre-test confirmed the survey's clarity, readability, and consistency. It also identified grammatical or punctuation errors [24]. Five participants unfamiliar with the study were used in the pre-testing to ensure the survey's validity and reliability [15]; [17]; [25].

3.3.2 Identifying outliers in multivariate analysis

The Mahalanobis measure calculates the distance from the mean centre of the overall observations in a multidimensional space used to identify outliers in the data [26]. The levels of significance chosen were 0.05 (5%). For small samples, the $\frac{D^2}{df}$ value should be 2.5, while for larger samples, it should be between 3 and 4 [26].

3.3.3 Statistical assumptions in multivariate analysis

In multivariate analysis, the crucial assumption is normality, which compares the distribution shape to the normal distribution [26]. Examining graphed plots and statistical normality tests, namely Kurtosis and skewness, were conducted. The $z_{skewness}$ statistic calculation follows the formula:

$$z_{skewness} = \frac{skewness}{\sqrt{\frac{6}{N}}} \quad , \tag{1}$$

The used $z_{critical}$ values are ± 1.96 for a 0.05 significance level. Similarly, $z_{kurtosis}$ is determined by:

$$z_{kurtosis} = \frac{kurtosis}{\sqrt{\frac{24}{N}}} \quad , \tag{2}$$

Homoskedasticity assumes equal variance levels across predictor variables [26]. Linearity, assessed with scatter plots, is essential for correlation-based measures.

3.3.4 Measuring internal consistency: The Cronbach Alpha

Cronbach's alpha measures internal consistency in multi-item scales [27]. The alpha calculation follows the formula:

$$\alpha = \frac{N}{N-1}\left(\frac{\sigma_X^2 - \Sigma_{i=1}^{N}\sigma_{Y_i}^2}{\sigma_X^2}\right) \quad , \tag{3}$$

where N is the number of surveys in the scale, σ_X^2 is the variance of the observed total scores and $\sigma_{Y_i}^2$ is the variance of items i for person y [27].

3.4 Factor analysis

Assumptions that go along with factor analysis include linearity, no outliers in the data, no multicollinearity, homoscedastic data, interval data and correlation between variables [26]; [28].

3.4.1 Determining the number of factors to extract

In **Kaiser's Criterion**, the eigenvalue of a factor indicates the amount of variance it explains. The study retained factors with eigenvalues greater than one as they signified a more common variance than the factors' variance. This method requires careful judgment due to potential sampling errors [26]; [28]. Factor loadings with values above 0.4 represent influence considered to meet the minimum levels to represent structure [26]. **The Scree test** graphically determines factors, with eigenvalues on the vertical axis and factor numbers on the horizontal. Factor extraction stops where the plot levels off or forms an elbow [26]; [28]. Rotating Factors and Interpretation Initial factor extraction is often complex due to cross-loading. Orthogonal rotation simplifies interpretation. Varimax reduces the number of variables with high loadings on each factor [26]; [28].

3.4.2 Factor analysis

Factor analysis extracts critical factors from a large set of variables. Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA) are the main factor analysis methods. EFA, used in early research stages, examines the interrelationships among variables [26]; [28]. Steps include assessing data suitability, extracting factors, and rotating factors for interpretation. Measures like the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test for sphericity evaluate data adequacy for factor analysis [28].

$$KMO_j = \frac{\Sigma_{i\neq j} R_{ij}^2}{\Sigma_{i\neq j} R_{ij}^2 + \Sigma_{i\neq j} U_{ij}^2} \quad , \qquad \textbf{\textit{(4)}}$$

where R_{ij} is the correlation matrix and U_{ij} is the partial covariance matrix.

$$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \times ln|R| \quad , \qquad \textbf{\textit{(5)}}$$

where p is the number of variables, n is the total number of sample sizes, and R is the correlation matrix.

3.4.3 Average Variance Extracted (AVE) and Composite Reliability (CR)

AVE measures the variance a construct explains versus measurement error, indicating convergent validity. CR assesses the correlation between multiple indicators of the same construct. AVE values ≥ 0.5 confirm convergent validity, and CR values > 0.6 are acceptable. If AVE < 0.5 but CR > 0.6, convergent reliability remains adequate [28].

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n} \quad , \qquad \textbf{\textit{(6)}}$$

where λ_i are the loadings, and n is the number of items.

$$CR = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \Sigma_{i=1}^{n} Var(e_i)} \quad , \qquad \textbf{\textit{(7)}}$$

where $var(e_i)$ is the variance of error terms in the i^{th} item.

4 RESULTS

4.1 Likert scale responses

Figure 4-1 - Figure 4-3 show the respective summarised responses from the survey.

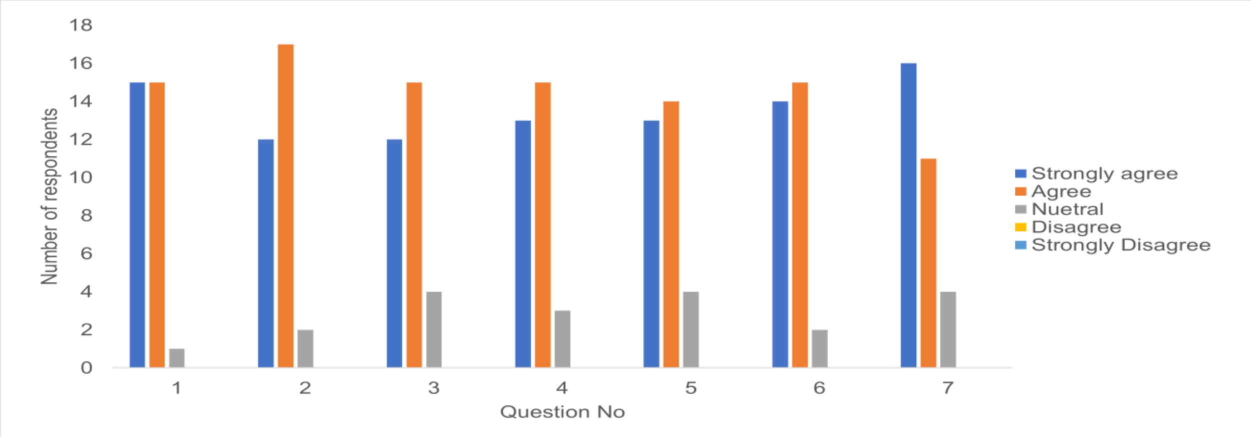

Figure 4-1: Responses to questions on the pre-installation phase.

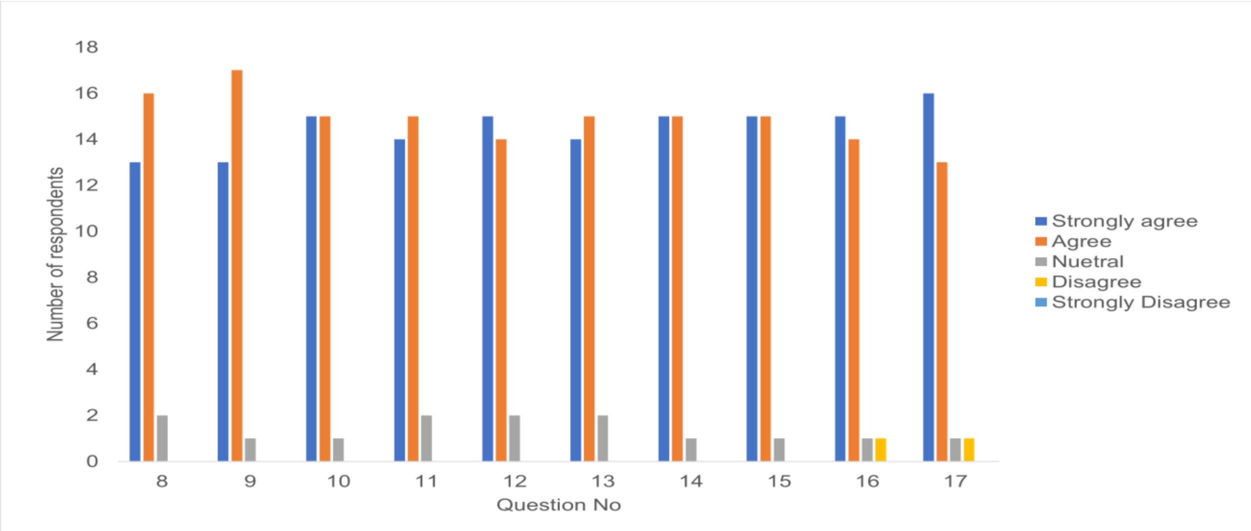

Figure 4-2: Responses to questions on the installation phase.

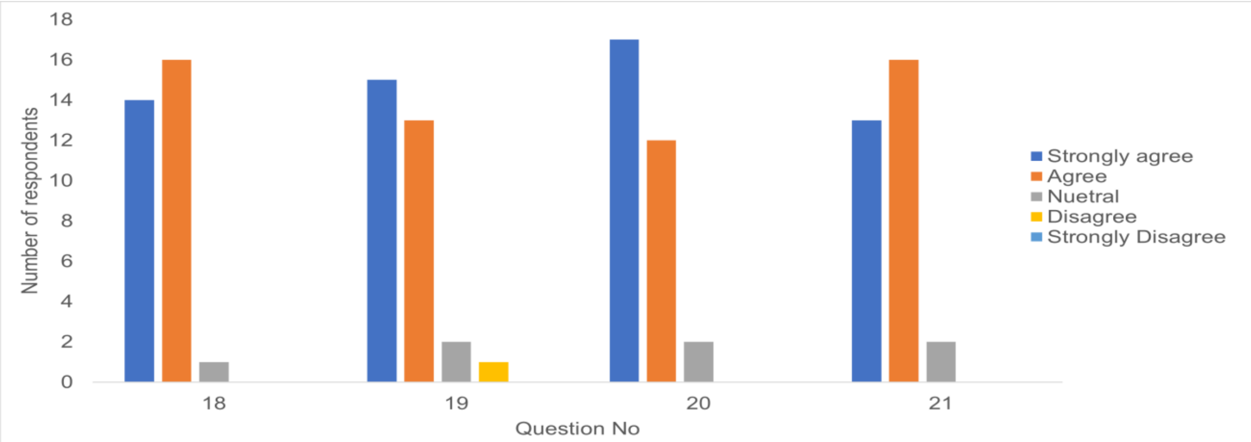

Figure 4-3: Responses to questions on the post-installation phase.

4.2 Identifying outliers in multivariate analysis

Results for the test for outliers in the survey responses are detailed in Figure 4-4 and Figure 4-5.

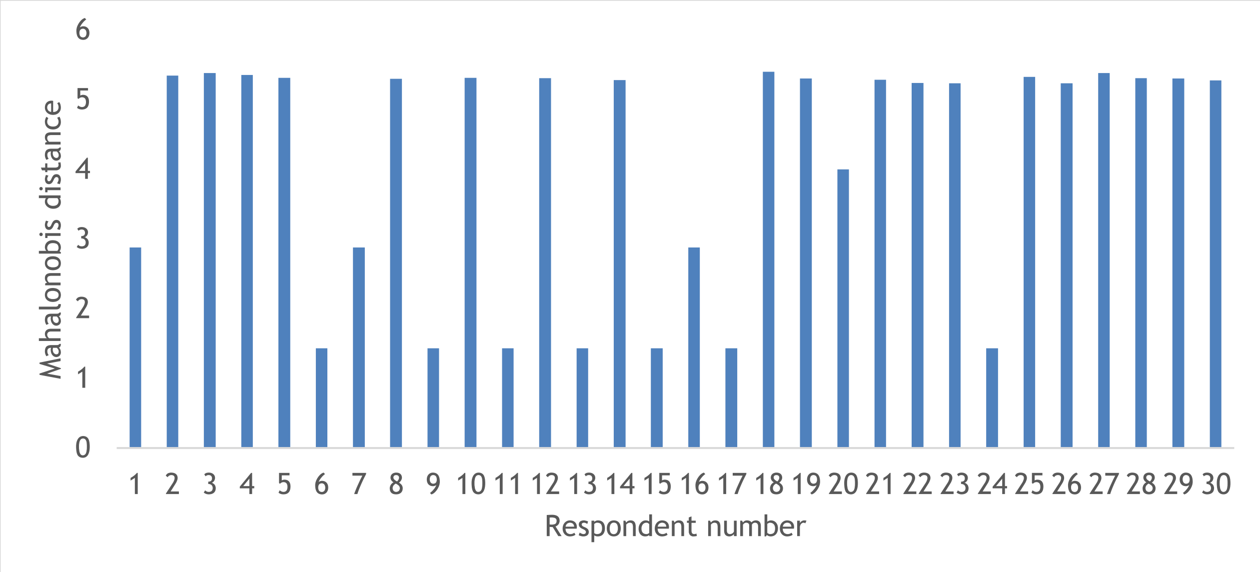

Figure 4-4: Mahalanobis Distance test for outliers.

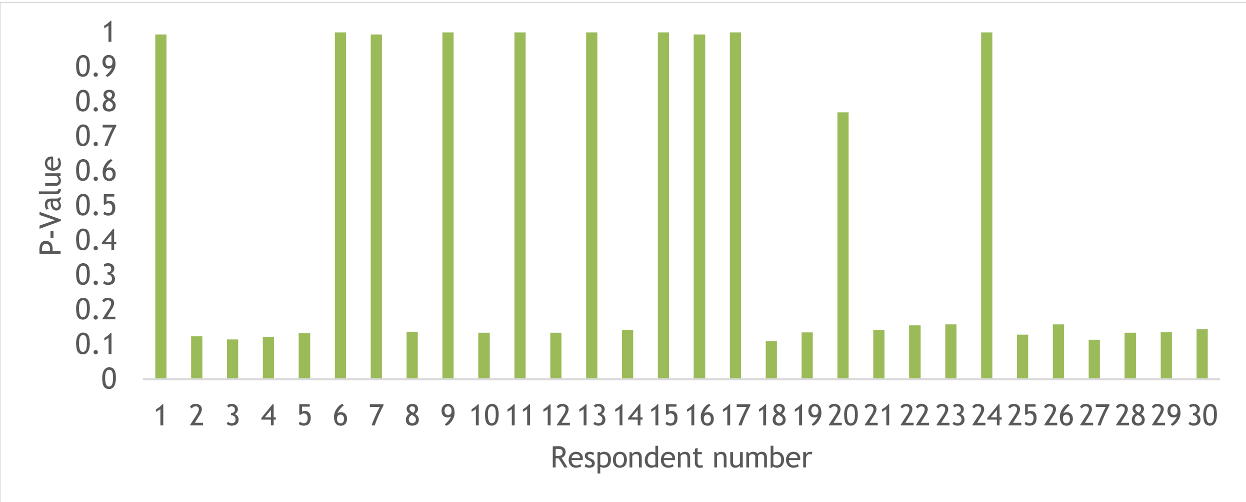

Figure 4-5: Corresponding P-values of respondents Mahalanobis Distance

Figure 4-4 and Figure 4-5 illustrate the Mahalanobis Distance and p-values of the respondents, respectively. All p-values were > 0.05, so the null hypothesis was false for all respondents.

4.3 Measuring internal consistency: The Cronbach Alpha

Table 1 lists the Cronbach Alpha values for the overall survey responses, responses relating to the pre-installation phase questions, responses relating to the installation phase questions and answers to the post-installation phase questions, respectively. The table details the confidence interval of Cronbach Alpha values at $\alpha = 0.05$.

Table 1: Cronbach alpha test for internal consistency of survey.

	Cronbach Alpha	Cronbach Alpha for pre-installation questions	Cronbach Alpha for installation questions	Cronbach Alpha for post-installation questions

Alpha value	0.976	0.944	0.970	0.874
Confidence interval	[0.961, 0.987]	[0.907, 0.970]	[0.951, 0.984]	[0.781, 0.934]

4.4 Factor analysis

4.4.1 Skewness, Kurtosis, Spearman Average correlation, Mean and Standard deviation.

Table 2 details the results for the normality in the survey responses as Kurtosis. The skewness also shows how skewed the answers were around the mean. The average correlation details the average Spearman correlation coefficients between the Likert scale question responses.

Table 2: Summary statistics for all survey question results.

Question No	Skewness	Kurtosis	Z-Skewness	Z-Kurtosis	Average correlation	Mean	Standard deviation	Variance
1	-0.433	-0.822	-0.968	-0.920	0.709	4.467	0.571	0.326
2	-0.280	-0.656	-0.625	-0.734	0.663	4.333	0.606	0.368
3	-0.307	-0.800	-0.686	-0.895	0.670	4.233	0.679	0.461
4	-0.366	-0.706	-0.818	-0.789	0.708	4.300	0.651	0.424
5	-0.474	-0.851	-1.060	-0.951	0.653	4.300	0.702	0.493
6	-0.383	-0.670	-0.857	-0.749	0.600	4.367	0.615	0.378
7	-0.657	-0.781	-1.468	-0.873	0.668	4.367	0.718	0.516
8	-0.280	-0.656	-0.625	-0.734	0.641	4.333	0.606	0.368
9	-0.070	-0.863	-0.156	-0.965	0.727	4.367	0.556	0.309
10	-0.309	-0.882	-0.691	-0.986	0.755	4.433	0.568	0.323
11	-0.383	-0.670	-0.857	-0.749	0.722	4.367	0.615	0.378
12	-0.491	-0.643	-1.098	-0.719	0.761	4.400	0.621	0.386
13	-0.383	-0.670	-0.857	-0.749	0.757	4.367	0.615	0.378
14	-0.309	-0.882	-0.691	-0.986	0.669	4.433	0.568	0.323
15	-0.309	-0.882	-0.691	-0.986	0.713	4.433	0.568	0.323
16	-1.224	2.004	-2.738	2.241	0.654	4.367	0.718	0.516
17	-1.309	2.102	-2.926	2.351	0.732	4.400	0.724	0.524

18	-0.188	-0.896	-0.421	-1.002	0.573	4.400	0.563	0.317
19	-1.109	1.200	-2.480	1.342	0.590	4.433	0.758	0.575
20	-0.720	-0.463	-1.609	-0.518	0.641	4.467	0.629	0.395
21	-0.280	-0.656	-0.625	-0.734	0.649	4.433	0.606	0.368

4.4.2 Linearity of the data

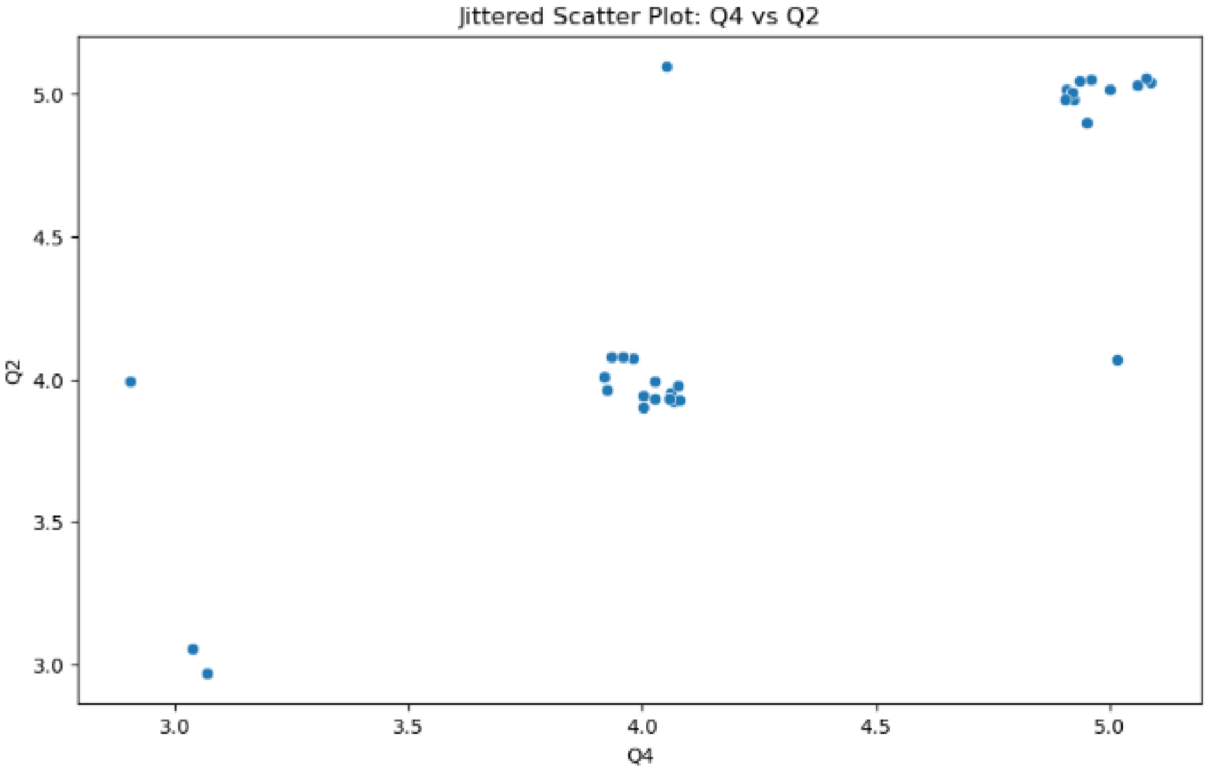

Figure 4-6: Jittered scatter plot for Q2 vs Q4.

Figure 4-6 above shows the Jitters scatter plot of Question 2 against Question 4 of the Likert survey responses. Many other plots similar to the above are available (not included because of space constraints), and the plots displayed above were selected randomly for analysis.

4.5 Factor analysis

4.5.1 KMO measure of sampling adequacy and Barlett test for sphericity

The Kaiser-Meyer-Olkin (KMO) value for the Likert scale questions in the survey, their corresponding chi-square statistic value and their p-value are in Table 3.

Table 3: KMO value for the model and significance.

KMO model value	Chi-Square value	p-value	Is p-value < 0.05
0,716	696.110	2.060×10^{-53}	Yes

4.5.2 Scree Test for Eigenvalues

The Scree plot of Eigenvalues of all factors is in Figure 4-7. This figure shows eigenvalues for each question, with questions having eigenvalues greater than 1 being influential factors.

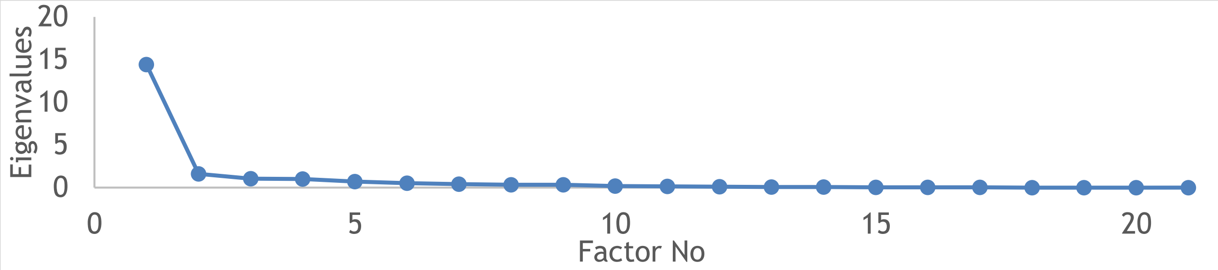

Figure 4-7: Scree plot of Eigenvalues of all factors.

4.5.3 Factor loadings

The factors loadings for Likert-scale responses having eigenvalues of more than one (>1) are detailed in Table 4 below.

Table 4: Factors, their corresponding loadings and influence on each question.

Question No	Factor1	Factor2	Factor3	Factor4	Factor 1 affects question	Factor 2 affects question	Factor 3 affects question	Factor 4 affects question
1	0.365	0.478	0.409	0.496	Yes	Yes	Yes	Yes
2	0.650	0.186	0.394	0.443	No	Yes	Yes	Yes
3	0.799	0.358	0.285	0.049	Yes	No	No	Yes
4	0.739	0.304	0.447	0.177	Yes	No	No	No
5	0.918	0.172	0.200	0.204	Yes	No	Yes	No
6	0.655	0.281	0.002	0.413	Yes	No	No	No
7	0.613	0.310	0.252	0.347	Yes	No	No	Yes
8	0.207	0.879	0.225	0.090	Yes	No	No	No
9	0.462	0.787	0.186	0.263	No	Yes	No	No
10	0.387	0.684	0.350	0.379	Yes	Yes	No	No
11	0.379	0.552	0.526	0.310	No	Yes	No	No
12	0.539	0.464	0.516	0.326	No	Yes	Yes	No
13	0.377	0.736	0.480	0.227	Yes	Yes	Yes	No
14	0.214	0.688	0.305	0.424	No	Yes	Yes	No
15	0.430	0.592	0.454	0.179	No	Yes	No	Yes
16	0.497	0.345	0.679	0.029	Yes	Yes	Yes	No

17	0.532	0.317	0.692	0.188	Yes	No	Yes	No
18	0.291	0.277	0.180	0.787	Yes	No	Yes	No
19	0.108	0.320	0.675	0.242	No	No	No	Yes
20	0.355	0.213	0.576	0.553	No	No	Yes	No
21	0.092	0.575	0.535	0.483	No	No	Yes	Yes

4.5.4 Average Variance Extracted (AVE) and Composite Reliability (CR)

Table 5 shows the variance, proportional variance, CR and cumulative variance of the factors with factor loading eigenvalues of more than one in the Scree plot.

Table 5: Factors, their variance and composite reliability.

	Factor 1	Factor 2	Factor 3	Factor 4
Variance	5.361	5.207	4.034	2.749
Proportional Variance	0.255	0.248	0.192	0.131
Cumulative Variance	0.255	0.503	0.695	0.826
Composite Reliability (CR)	4.397	4.397	4.397	4.397

5 DISCUSSION

5.1 Identifying outliers in multivariate analysis

None of the respondents were outliers because the Mahalanobis distances P-values (significance values) were all > 0.005. That meant all responses were suitable for use in the analysis. The Mahalanobis distances divided by the degree of freedom ranged between 0.068 and 0.257. That is lower than the threshold of 2.5 used to determine outliers for small samples [26].

5.2 Measuring Internal Consistency: The Cronbach Alpha

The overall Cronbach Alpha value for this study was 0.976. That meant the Likert scale questions responses internal consistency in the survey were internally consistent. In addition to the internal consistency of the overall Likert questions, the three sections, namely pre-installation, installation and post-installation, were also checked for internal consistency. Their Alpha values were 0.944, 0.970 and 0.874, respectively and were considered internally consistent.

5.3 Linearity of the data

One of the assumptions made for the factor analysis was a linear relationship between the Likert scale results. This assumption was tested by visually comparing the Jitter plots of the different questions. For example, in Figure 4-6, most of the answers were the same in Q2 and Q4, with only two exceptions where a respondent gave a 4 for Q2 and a 5 for Q4 and vice versa, leading to the assumption that a linear relationship existed between the two questions. Similar Jitter plots of a combination of questions all indicated linear relationships. It was, therefore, concluded that the Likert question in the survey had a linear relationship.

5.4 Factor analysis

5.4.1 Normality of the data

The following is a summary of the results for the normality and skewness test of the Likert scale questions in the survey. Testing was at significance values at $p < 0.05$.

- Q1 – Q6, Q8 – Q 15, Q18, Q21: Approximately symmetric. Kurtosis indicates approximately normal.
- Q7, Q20: Moderately skewed. Kurtosis indicates approximately normal.
- Q16 – Q17, Q19: Highly skewed. Kurtosis indicates a high deviation from normality.

That confirms normality for all the questions except Qs 16, 17 and 19. These questions also showed high skewness. It is safe to assume that the data follows a normal distribution.

5.4.2 KMO measure of sampling adequacy and Barlett test for sphericity

The KMO value calculated was 0.716, meaning the survey responses had adequate sampling [26]; [28]. Since the p-value corresponding to Bartlett's Test of Sphericity in Table 3 was less than 0.05, confirming Homoskedasticity, factor analysis was worth pursuing [26];[28].

5.4.3 Scree Test for eigenvalues

From Figure 4-7, only four factors had Eigenvalues > 1. That meant these four factors affected Likert scale responses significantly. Subsubsection 5.4.4 below lists the four factors.

5.4.4 Factor loadings

In factor analysis, appropriate names should reflect the underlying theme or concept that groups the questions. Based on the questions and their associated factors, the following four were the names of the factors chosen:

- Strategic Planning and Management;
- Technological Assessment and Implementation;
- Stakeholder and Expectation Management; and
- Legal and Contractual Compliance.

The reasoning behind these names is based on Table 4 factor loadings:

- **Strategic Planning and Management**: This factor encompasses questions affecting the overall planning and management processes required to ensure the project's success. The tasks involve high-level strategic decisions, risk management, and continuous oversight of the project.
- **Technological Assessment and Implementation**: This factor includes questions focusing on the technical aspects of the project, such as identifying technological needs, evaluating technical options, and implementing technology solutions.
- **Stakeholder and Expectation Management**: This factor is centred around understanding and managing the expectations and needs of various stakeholders, ensuring their requirements are met, and maintaining effective communication and support throughout the project.
- **Legal and Contractual Compliance**: This factor pertains to the legal and contractual obligations fulfilled throughout the project. It involves drafting agreements, ensuring compliance with legal requirements, and managing contracts.

These names succinctly captured the essence of the grouped questions, making it easier to understand the focus areas of each factor in the factor analysis.

5.4.5 Average Variance Extracted (AVE) and Composite Reliability (CR)

The four factors listed in the factor analysis above, accounted for 82,6% of the variance in responses.

The AVE values were 0.255, 0.248, 0.192 and 0.131 respectively. Their respective CR values were 4.397, 4.397, 4.397 and 4.397. Since all the AVE values for the factors were < 0.5, but their respective CR values were > 0.6, convergent reliability was adequate.

5.5 Likert scale responses

From Figure 4-1, Figure 4-2 and Figure 4-3, the respondents mostly agreed or strongly agreed with the implementation steps outlined on the survey's new proposed roadmap. That is also confirmed by Table 2 where the means for responses to each question range from 4.300 to 4.467, which are between agree (4) and strongly agree (5) on a Likert scale. The standard deviations also had a low range between 0.556 and 0.758 (less than a standard deviation from the mean). The variance ranged from 0.309 to 0.575, confirming the Homoskedasticity assumption.

The study conducted a rigorous analysis of data related to technology implementation in the mining sector, covering various aspects such as outlier identification, internal consistency, data linearity, and factor analysis. The Mahalanobis distances confirmed no outliers, ensuring the robustness of the dataset. High Cronbach Alpha values (0.976 overall and ranging from 0.874 to 0.970 across the three phases of Likert scale questions) indicated internal consistency among Likert scale questions. Visual inspections and statistical tests affirmed the linearity of Likert questions, supporting the assumption of a linear relationship. Factor analysis revealed four significant factors—Strategic Planning and Management, Technological Assessment and Implementation, Stakeholder and Expectation Management, and Legal and Contractual Compliance, explaining 82.6% of variance with good reliability. Most respondents agreed or strongly agreed with the implementation steps outlined, backed by low standard deviations and variance, suggesting consistent perceptions among respondents. These findings underscore the reliability and comprehensiveness of the study's data analysis methods in assessing technology adoption in the mining industry.

5.6 Limitations of the study

- A small sample size from a single mine was used for the analysis, limiting the generalisability of the findings across South African mines.
- The high Cronbach Alpha values suggest internal consistency, but they do not account for the possibility of overly homogeneous responses that might not truly reflect the diverse views of the population.
- Confirming the linearity assumption was through visual inspection of Jitter plots. However, visual inspection can be subjective and may not be as reliable as more rigorous statistical tests for linearity.
- While most questions showed approximately normal distributions, questions 16, 17, and 19 exhibited high skewness and Kurtosis deviations from normality. That indicates that the assumption of normality might not hold for all data points, potentially affecting the validity of factor analysis results.
- The study does not delve into demographic differences that could influence responses, such as gender, age, years of experience, and type of mining experience, limiting the generalisability of the findings across different demographic groups within the mining industry.
- The study relies heavily on self-reported data from survey respondents. This data type can be subject to biases such as social desirability bias, where respondents may answer in a manner they believe is more socially acceptable or favourable rather than

providing their actual opinions or experiences. That can potentially skew the results and affect the accuracy and reliability of the findings [29].

6 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusions

The study utilised quantitative methods for data collection and analysis. The survey consisted of questions based on the literature on roadmaps for technology implementation in the mining or similar industry. An online Google Form collected data. The participants purposively sampled with expertise in implementing technology in the mining industry. To ensure data validity and reliability, triangulation, pre-testing, and constant comparisons were pursued through the data collection. The researcher tested statistical assumptions made for analysis, such as linearity, normality, no outliers and correlation between the data. Statistical testing and visual inspections confirmed all assumptions. Internal consistency was measured using Cronbach's alpha. Factor analysis was employed to refine survey questions and ensure the robustness of the findings. The factor analysis yielded four factors which each question in the survey fell under, namely:

- Strategic Planning and Management
- Technological Assessment and Implementation
- Stakeholder and Expectation Management
- Legal and Contractual Compliance

These factors accounted for a majority of the variance. The actual means of the Likert scale responses ranged from 4.300 to 4.467 (four on the Likert scale meant the participant agreed with the step in the survey roadmap, and five on the Likert scale meant they strongly agreed with the step).

6.2 Recommendations

- Develop a new roadmap that includes the four identified factors (Strategic Planning and Management, Technological Assessment and Implementation, Stakeholder and Expectation Management, and Legal and Contractual Compliance). Highlight critical elements within each factor and integrate qualitative responses from experts to include necessary additional steps.
- Analyse demographic data collected from the survey, including gender, age, years of experience, and type of mining experience. Check for differences in these demographics not included in this initial study.
- Expand the participant pool to include representatives from multiple mining companies in South Africa. Ensure that the new data collection supplements the existing dataset and aims to generalise the study's conclusions to the entire South African mining industry.

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A APPENDIX A: SURVEY QUESTIONS

The following was the survey used for data collection for this study. The three sections that subdivided the survey were pre-installation, installation, and post-installation phase questions. These phases had steps that the respondents quantified by the survey respondents in terms of their applicability in the South African mining industry context. The survey consisted of 5-point Likert scales with responses allowed from strongly agree, agree, neutral, disagree, and strongly disagree. The questions were as follows.

- **Pre-installation phase (gathering and evaluating implementing entity's capacity and potential partners) questions**
  1. Define the business problem
  2. Identify the technological gap
  3. Identify the commissioning entity's expectations and capacity
  4. Evaluating information on the necessary technology and vendors
  5. Assessment and selection procedure for vendor and technology selection
  6. Compiling short-term, medium-term, long-term and risk management strategies
  7. Drafting agreements and contracts

Do you agree with the listed checklist items and their order for gathering and evaluating the information above?

- **Installation phase questions**
  8. Design and evaluate concepts for a simulation, create a numeric simulation of the technology scenario
  9. Evaluate the numeric simulation against expectations

10. Prepare prototype designs for possible implementation based on simulation separated from normal operations
11. Validate the prototype against simulation expectations, choosing optimal (if the results of the prototype are unfavourable terminate the project)
12. Gathering system requirement documents from the vendor
13. Gathering system requirements for infrastructure upgrade
14. Ensure implementation of legal agreements
15. Implement budget control measures
16. Constant checks of design and quality of civil works
17. Provide support and cooperation (communication)

Do you agree with the listed checklist items for developing a detailed project plan above?

- **Post-adoption phase (System calibration, testing, integration and after-sale service) questions**

18. System calibration, testing and integration
19. Providing training services
20. Activities required to maintain continuous system functionality
21. Exit strategy

Do you agree with the listed checklist items for system calibration, testing and integration above?

B APPENDIX B: RESPONDENTS DEMOGRAPHICS INFORMATION

There were multiple different age groups, experience levels and gender. Table 6 shows these differences among the participants.

Table 6: Sample characteristics table (demographics)

Gender	Age group						Experience level									
Male	18 - 20 years	20 - 29 years	30 - 39 years	40 - 49 years	50 - 59 years	60 years or older	0 - 2 years	3 - 5 years	6 - 10 years	11 - 15 years	16 - 20 years	21 - 25 years	26 - 30 years	31 - 35 years	36 - 40 years	More than 40 years
	0	2	9	3	3	2	2	1	1	5	1	3	4	1	1	0
Female	18 - 20 years	20 - 29 years	30 - 39 years	40 - 49 years	50 - 59 years	60 years or older	0 - 2 years	3 - 5 years	6 - 10 years	11 - 15 years	16 - 20 years	21 - 25 years	26 - 30 years	31 - 35 years	36 - 40 years	More than 40 years
	0	1	7	2	2	0	1	1	2	5	2	1	0	0	0	0

Table 7 below shows the different types of work the participants had undertaken in the mining industry.

Table 7: Sample characteristics table (types of work experiences)

Type of work experience in the mining industry	Number of respondents
General work	6
Manager or supervisor	19
Engineer	7
Senior manager	3
Junior manager	2
Specialist (e.g., boiler maker)	4
Intern	1
Professional	1