

To Analyze the Effectiveness of Data Analytics in Enhancing Strategic Decision Making in Telecommunication Companies: A Case Study of MTN Zambia

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ARTICLE INFORMATION	ABSTRACT
Article history: Published: October 2026 Keywords: Data Analytics Strategic Decision-Making Telecommunications Data Governance Competitiveness	The purpose of this study was to analyze data analytics within MTN Zambia as a way of enhancing strategic decision-making. The following departments Finance, Strategy, Customer relations and finally Data and Analytics, were engaged making a sample of 50 participants. The study was guided by three objectives mainly: (1) to assess how MTN Zambia uses data analytics in decision making, (2) to identify the limitations hindering effective analytic adoption and (3) to evaluate the effects of analytics on market competitiveness. Data collected was coded within Microsoft Excel and analyzed using Jamovi statistical tool by combining descriptive frequencies, qualitative insights and non-pragmatic methods. Findings revealed that data analytics is actively used at operational levels to support marketing, customer retention and cost management decisions, but its use at strategic and executive levels remain limited. Poor data quality, weak system integration, unclear governance structures and insufficient data literacy among decision makers were identified as major challenges. The challenges identified hold the full potential of data analytics at hold, and give strategic direction as well as long-term planning unforeseen problems. In conclusion MTN Zambia, has made great progress by simply adopting and applying data analytics in its operations. The study recommends stronger governance framework, enhanced data integration and literacy, more executive engagement and continuous capacity building as essential for translating data analytics into sustained strategic decision making, improved competitiveness and proper future forecast.

1. Introduction

Globally, firms that implement strategic decision making has boosted sales, optimised operations and streamlined marketing campaigns. This transformation is as a result of data driven decision making, especially in the digital era, where the importance of understanding your Customer base has never been so critical. The telecommunications industry, understands the importance and turns to Data Analytics, to make informed data driven decisions. Davenport and Harris (2007) emphasizes the shift from intuition-based decision making to data driven decision making results into better strategic efficiency, reduced costs and a stronger competitive position.

The progress of analytics began in the early 2000s, when firms used business intelligences tools such as big data technologies. This was further advanced to machine learning, which allowed organizations to process large amounts of information in real time which resulted in market trend anticipation, strategic data driven decision making and a competitive edge over competitors (Marr, 2016). According to the PwC report of (2019), the increased use of Mobile phones and expanding Digital services, saw the Telecommunications sector boom, in response to improve service delivery operators began using data analytics to study consumer behavior and trends. Despite the adoption and progress of data analytics in firms challenges such as weak infrastructure and limited skilled personnel became more evident.

In Zambia, Telecommunications has become a central pillar of economic development. One of the leading companies in this space is MTN Zambia, its growth reflects the continuous use of data analytics among the ever-expanding digital era. The firm's use of data analytics to provide an assorted array of services, minimised network lag, increased customer engagement and strategically plan for the future, is commendable. However, a report by the Bank of Zambia, (2020), pointed out, shortages in technical expertise, gaps in system integration and data quality problems as limiting the firm's full potential. In acknowledgement of their standing problems, a partnership between SAS training and MTN Group was formed in 2022, with the aim of training 100 young Africans in data analytics (Techtrends Zambia, 2022).

The telecommunications industry defined by rapid change, data analytics gives a competitive edge over competition. Davenport, (2013), emphasizes that firms that effectively use data, gain clear insights into market dynamics and faster responses to customer preferences. McKinsey (2018), further adds that strong infrastructure, sound governance and consistent analytical skill development breeds success at all levels. Zambia has a way to go but the progress made thus far cannot be ignored and should spark innovation for the industry to realize its full potential.

1.1 Problem Statement

The competitive nature of the Telecommunications industry cannot be understated, making timely data driven decisions is critical for organisations to succeed. According to Davenport and Harris (2007), Data analytics has become a key component in supporting

strategic data driven decision making. In Africa particularly Zambia, the telecommunications sector is operational but yet to reach its full potential, one of the leading companies at helm MTN Zambia has invested in data analytics, in order to improve customer engagement, day to day operations, poor data quality and limited analytical skill gap among employees (Bank of Zambia, 2020). This study therefore examines MTN Zambia's use of data analytics in strategic decision-making, challenges affecting its application and its contribution to the competitive realities of the Zambian Telecommunication industry.

1.2 General Objectives

To analyze the effectiveness of data analytics in enhancing strategic decision-making in telecommunications companies, using MTN Zambia as a case study.

1.2.1 Specific Objective

- To analyze MTN Zambia's data analytics practices in strategic decision making.
- To examine the effects of data analytics on MTN Zambia's market competitiveness.
- To assess the limitations of the effective use of data analytics at MTN Zambia.

1.3 Research Questions

- How does MTN Zambia utilize data analytics in its strategic decision-making processes?
- What are the effects of data analytics on MTN Zambia's market competitiveness?
- What are the limitations that hinder the effective use of data analytics at MTN Zambia?

1.4 Conceptual Framework

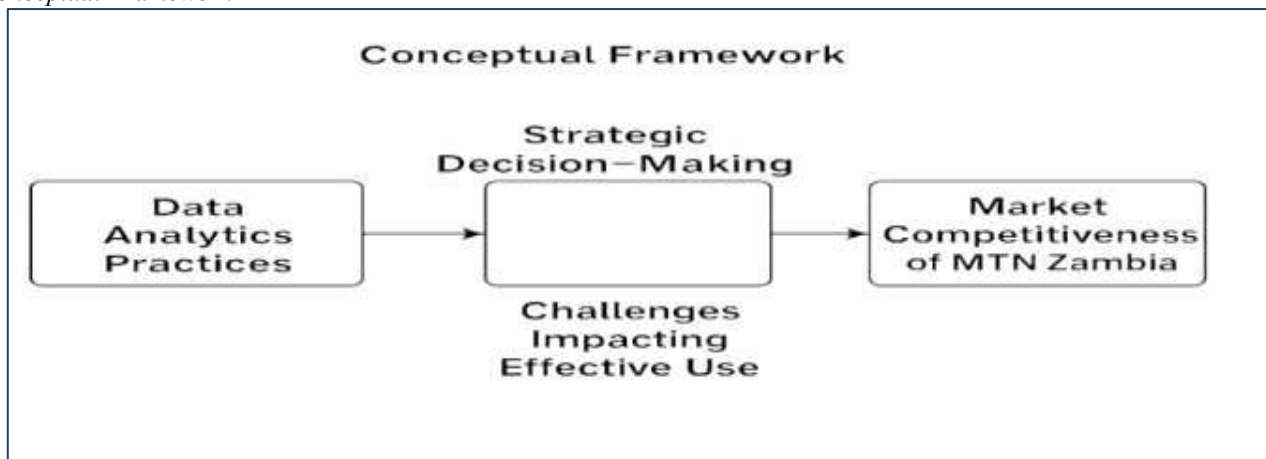


Figure 1: Conceptual Framework

In this framework, data analytics is the independent variable influencing the dependent variables Strategic decision-making and Market competitiveness. Data analytics serves as the starting point of how MTN Zambia, collects and analyses data to aid functionality to its operations. In the process challenges impacting effective use may occur, things like poor quality, skills gap and inadequate infrastructure leading to inevitable roadblocks. Akter et al, (2016), empathizes that data is powerful when aligned with strategic decision making equally Wamba et al (2017) notes that many firms have challenges converting insights from data analytics into actionable steps. Therefore, this framework maps data analytics as it feeds into strategic decision-making which boosts market competitiveness, but challenges may arise.

2. Literature Review

2.1 Data Analytics Practices in Decision-Making

LaValle et al., (2018) The progression of analytics use is descriptive reporting, predictive modeling, and later, prescriptive optimization. Organizations that go beyond ad-hoc reporting to integrated analytics tend to see productivity and revenue gains. However, realizing such gains requires organisational capability: governance, routines to turn outputs into action, leadership to embed analytics into decision cycles (Mikalef et al., 2019; Wamba et al., 2018). McAfee et al. (2019) and PwC (2020) show that better outcomes are associated with cross-functional teams, formal review cadences and senior analytics champions.

In the region of sub-Saharan Africa, operators are focusing the analytics on operational tasks that have a quick pay-off such as campaigns, churn reduction, network planning and the supply-chain forecasting because they generate value quite quickly. According to AfDB (2021) and ZDA (2024), maturity is clustered in urban, well-resourced firms. Smaller firms and those in rural areas lag due to lack of funding infrastructure and skills. The usefulness of pilots is not disputed, but effective scaling requires governance, training and budgeted follow-through (Molefe & Sibanda, 2023; Nkusu, 2020).

Various descriptive and predictive tools such as customer retention, campaign targeting and network monitoring are often used in Zambia. Meanwhile, prescriptive work is mainly pilot-based (ZICTA, 2024). Most analysts and mid-level managers utilize the uptake; however, usage level is restricted to the board (Bank of Zambia, 2020). Fragmented systems, inconsistent master data and limited senior analytic literacy all contribute to a loss of trust that slows the strategic uptake (Ministry of Technology and Science, 2023; World Bank, 2020). There are clear measurable returns on churn reduction and targeted campaigns where analytics is well applied (Mikalef et al., 2019; Ransbotham et al., 2021).

2.2 Data Analytics and Market Competitiveness

According to Mikalef et al., (2019) Analytics increases competitive advantage through enhanced consumer metrics, operational efficiency, product and price flexibility, and strategic insights (Wamba et al., 2018; McAfee et al., 2019). Results from quantitative studies show enhanced efficiency through increased productivity, reduction in forecasting errors and faster decision-making processes if companies implement analytics. Senior management support is closely associated with higher ROI (LaValle et al., 2018; McKinsey Global Institute, 2021; Ransbotham et al., 2021).

Regionally, GSMA, (2023) state telecommunications and banking industries experience positive developments in retention rates and revenues due to predictive modeling and analytics while external restrictions such as regulatory environment, infrastructure shortages, and low digital literacy limit benefits realized. The recommended way consists of three stages: showing the positive influence on operational KPIs, making rigorous measurements, and then using those to gain executive support and budgets (IFC, 2022; Namanya et al., 2024). In Zambia, a notable positive impact on competition exists, but it is usually limited to pilot projects and large companies. Wins that were achieved include lowering churn rates, high customer satisfaction, and improved operational efficiency, while one case study mentions that substantial increase in market share followed the application of analytics (MTN Zambia, 2023). However, changes in the sector remain limited due to shortages of specialists, lack of funding, and regulations (World Bank, 2020; ZDA, 2024).

2.3 Barriers to Effective Use of Data Analytics

Wamba et al., (2018) asserts the impediments encountered by organizations can be divided into five interconnected categories which include technical errors (wrong data quality, outdated systems, operational integration challenges), organizational barriers (poor governance, fragmented departments), human factors (insufficient competence in data matters), financial issues (ongoing operational expenses on training and platforms), and regulatory constraints (concerns about privacy and compliance) (PwC, 2020; McKinsey Global Institute, 2021; Deloitte, 2022). The solutions to these problems that experts propose include fixing critical problems in data quality, setting up a light governance system, embedding workflows of consumers and producers, assigning executives to supervision, and training people before scaling automation (Ransbotham et al., 2021; LaValle et al., 2018).

AfDB (2021) explains such problems become even more pronounced in the sub-Saharan region. Although organizations can find some tools, they often do not have enough resources to sustain their application or develop the necessary skills, while urban pilots face issues with scaling mainly due to connectivity issues and lack of skilled personnel. Experts suggest cost-efficient capacity development techniques for activation (GSMA, 2023; Mensah & Owusu, 2023; Tech Trends, 2022; IFC, 2022).

ZICTA (2024) notes that Zambia faces serious technical problems. The institutions that can help to address critical issues are missing records or inconsistent records, inconsistency of billing/CRM/network data and issues with governance that lead to lack of trust (Bank of Zambia, 2020; MTN Zambia, 2023). Addressing this situation is difficult when analytics outcomes contradict experience and decision-makers remain skeptical about following analytics. It is possible to develop practical solutions for solving the issues such as doing immediate master data cleanup, introducing clear metric ownership, developing a suitable reporting structure and offering relevant upskilling, while automation can be developed later when enough trust is earned (Ministry of Technology and Science, 2023).

3. Methodology

This section represents the methodology used in the study. The following were stated Research design, Target population, Sampling design, Sample size, Data collection methods and Data analysis.

3.1 Research Design

A mixed methods research design was adopted using a single Case study. The study was accompanied with a quantitative and qualitative approach to obtain both numerical and in-depth insights into how MTN Zambia applies data analytics in strategic decision making. According to Mikalef et al, (2019) and Wamba et al, (2018), using a single case study allows for a detailed rich analysis of its practices, challenges and impact while balancing numerical trends and lived experiences, using a Mixed method.

3.2 Target Population

The study targeted MTN Zambia employees engaged in data driven decision making. This included senior, mid-level employees in different departments such as Strategy, IT, Marketing, Customer Experience and Data Analytics. A number of representatives from ZICTA were also included making it a well-rounded organizational perspective.

3.3 Sampling Design

A purposive sampling design was used to select participants in the study. Palinkas et al, (2015) adds that this sampling design is best when a study seeks to produce deep insights from expertise deemed fit by the judgement of the researcher.

3.4 Sample Size Determination

The estimated population of staff directly involved in data-driven processes was around sixty (60). Using Yamane's (1967) formula with a 10% margin of error produced a sample size of thirty-eight (38):

$$n = \frac{N}{1 + N(e)^2} = \frac{60}{1 + 60(0.1)^2} = 38$$

To improve reliability, additional responses were gathered, resulting in fifty (50) completed questionnaires. This final sample covered departments such as Data & Analytics, Strategy, Finance, and Customer Relations, offering diverse organizational insights.

3.5 Data Collection Methods

Data was collected mainly by Primary and Secondary Data. Primary data consisted of Structured questionnaires sent online to staff purposely while Secondary data included Semi-Structured interviews with managers.

3.6 Data Analysis

Quantitative data was cleaned in Microsoft Excel and analyzed using Jamovi using correlation, T-test and Regression while Qualitative data analyzed interview transcripts thematically.

3.2 Limitations

The limitations observed included the single use of a case study which may not apply to other firms, Interviews and Surveys captured might have withheld sensitive information and finally Time and Resources could not allow a capture of depth in collection of data.

4. Presentation of Findings and Discussion of Results

This section presents the findings from the study, starting with the Demographic and Workplace profile, followed by the findings from each respective objective. Further, this section discusses the results inline with the reviewed literature.

4.1 Presentation of results on demographic and workplace profile

4.1.1 Department

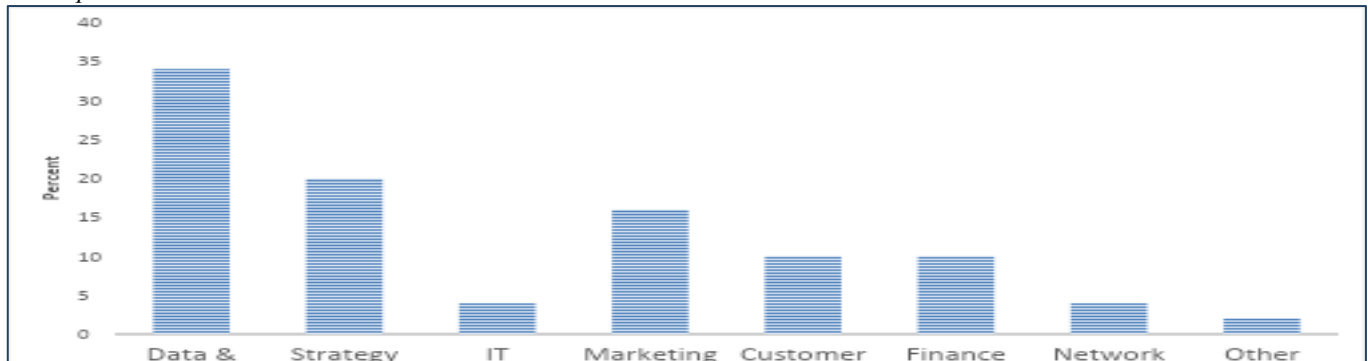


Figure 2: Department

Figure 2 shows the departments contacted, Data & analytics 34%, Strategy 20%, Marketing 16%, Customer experience 10%, Finance 10%, IT 4%, Network ops 4% and other 2%. This data suggests strong competence in data & analytics while also noting improvements in IT and Network operations.

4.1.2 Primary Analytics Roles

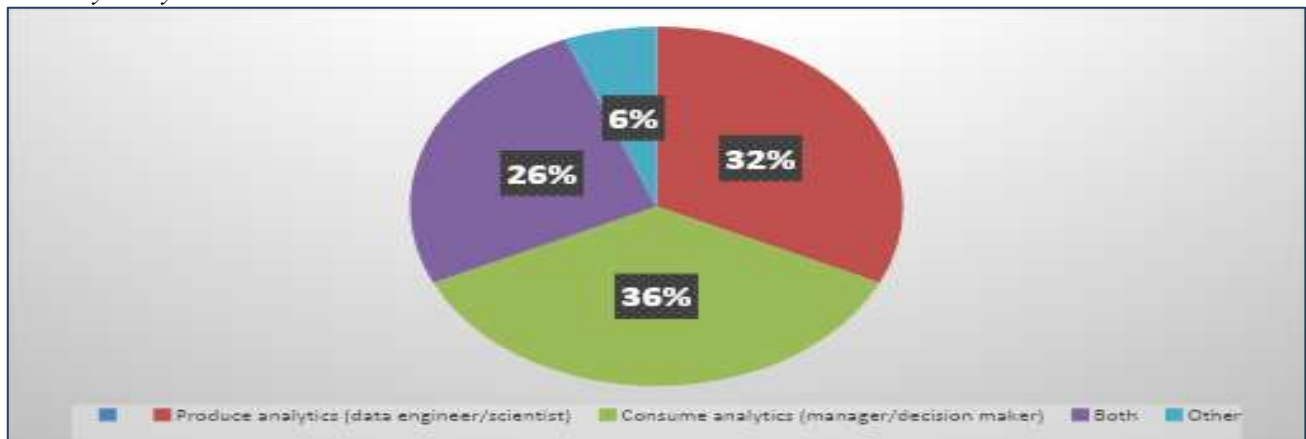


Figure 3: Primary analytic roles

Figure 3 represents the primary analytic roles in the company, 36% come from the Consume analytic role (managers/decision maker), 32% Produce analytic role (data engineer/scientist), 26% a combination of Consume analytic and Produce analytic role and lastly 6% other roles. This implies the consume analytic role as the biggest followed by the Produce analytic role, further it shows the collaboration between teams, that either produce and support information.

4.1.3 Job Level

Table 1: Job Level

job level	Counts	% of Total	Cumulative %
Analyst / Specialist	19	38.0%	38.0%
Team lead / Manager	14	28.0%	66.0%
Senior manager / Head	12	24.0%	90.0%
Executive (CxO)	5	10.0%	100.0%

Table 1 represents Job level, the following levels were Analyst/Specialist 38%, Team lead/Manager 14%, Senior manager/Head 12% and lastly the Executive (CxO) 5%. This suggest that each level of the job perspective was given on analytics while the Executive level information was not that prudent.

4.1.4 Years at MTN Zambia

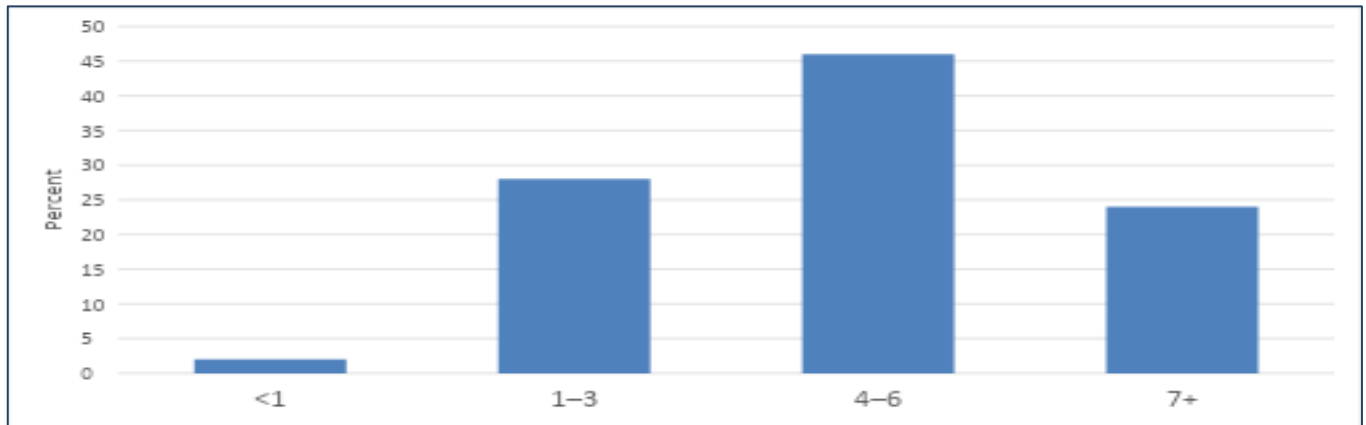


Figure 4: Years at MTN Zambia

Figure 4 represents the years at which employees have been working for MTN Zambia. 46% reported to have 4-6 years with MTN Zambia, 28% 1-3 years, 24% 7+ years and finally 2% less than a Year. The number of years employees have with MTN Zambia, show that's more than 50%, understand the importance of data and decision-making practices as reflected in its strong continuous operations.

4.1.4 Qualification

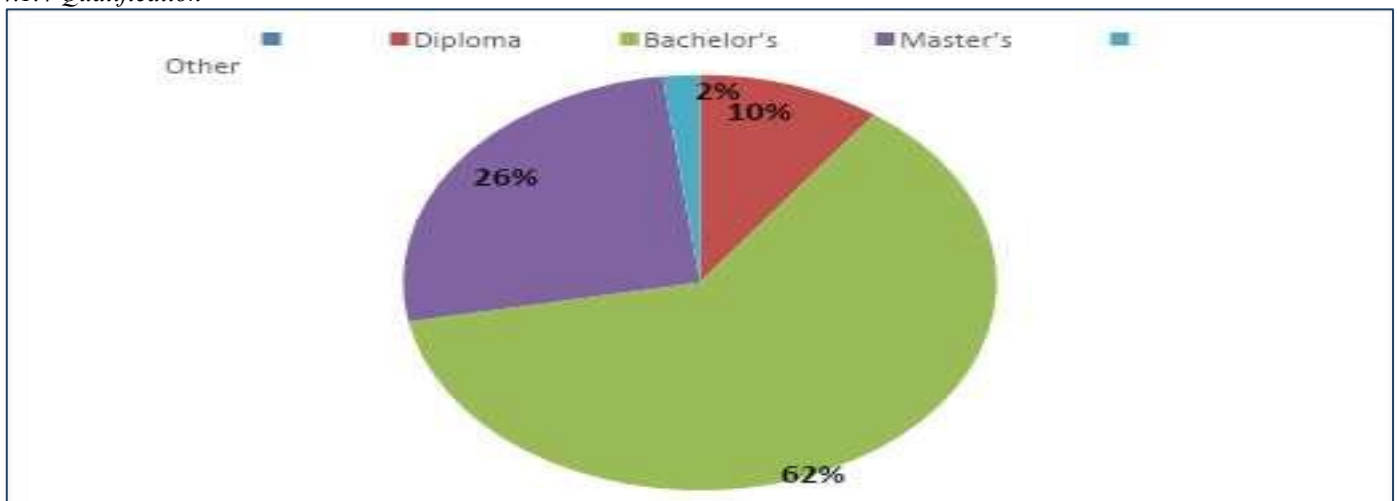


Figure 5: Qualifications

Figure 5 represents the qualifications of employees contacted at MTN Zambia. 62% had Bachelor's Degree, 26% had Master's Degree, 10% Diploma and 2% Professional certifications. It is safe to note that most of the employees have ground and theoretical competencies in data analytics while only a small number have sufficient do not qualification wise.

4.2 To analyze MTN Zambia's data analytics in strategic decision making

4.2.1 Use analytics output in work

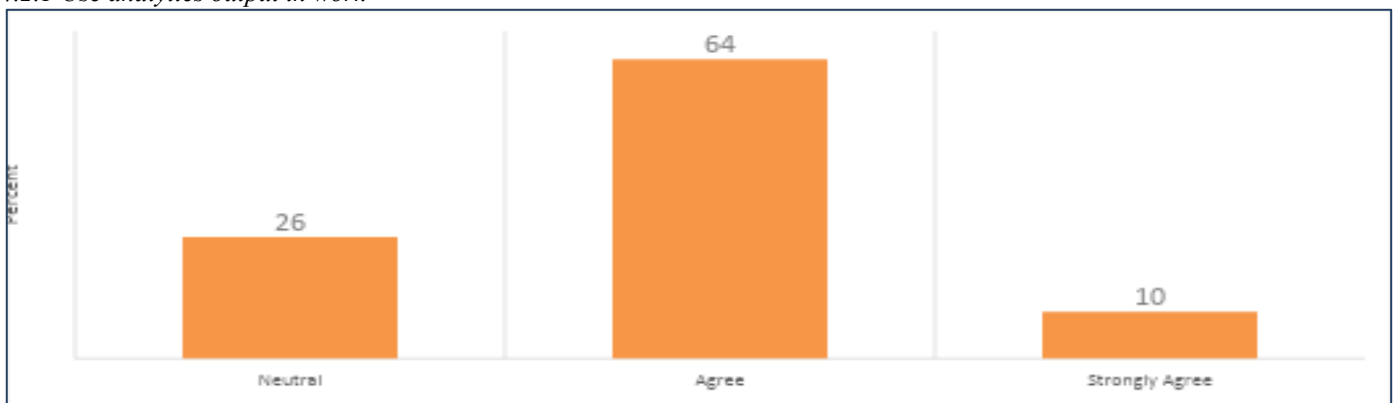


Figure 6: Analytic output in work

Figure 6 represents the analytic output in work such as dashboards, reports and model results, response came in and 64% agreed they used the analytic output in work, 26% reported being neutral on the matter and 10% strongly agreed using analytic output information. This indicates that a majority of respondents make use of analytic output in work to make informed decisions in their operations.

4.2.2 Availability and ease of access to required analytics

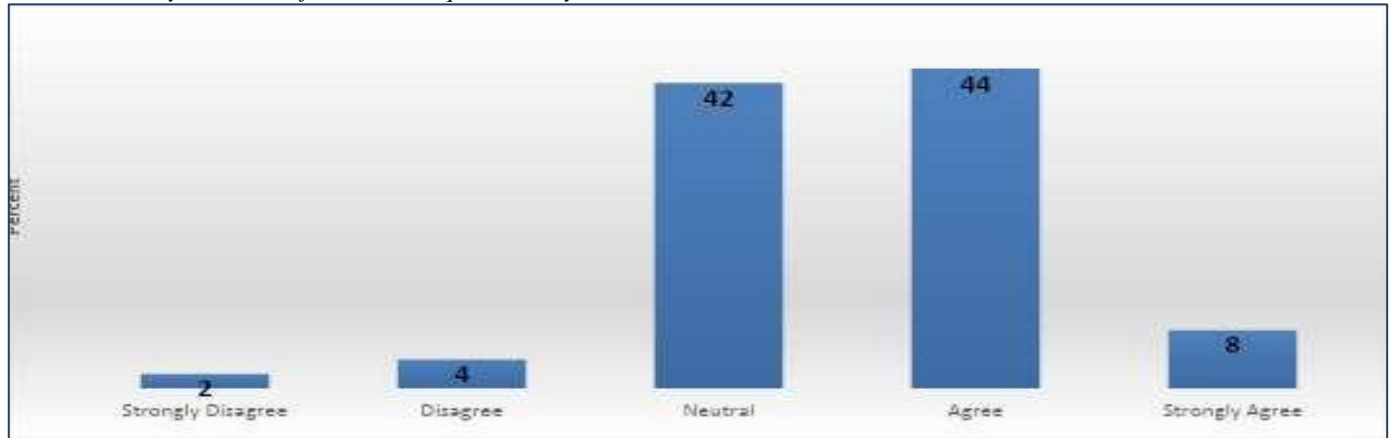


Figure 7: Availability and ease of access to required analytics

Figure 10 represents the availability and ease of access to required analytics. 44% agreed to finding analytics available and easily accessible, 42% remained neutral, 8% strongly agreed, 4% disagreed and 2% strongly disagreed. This indicates that the majority of employees find analytics available and easily accessible while the latter find issues in accessing analytics pointing to inconsistent availability.

4.2.3 Usefulness of descriptive, predictive and prescriptive analytic for decision making

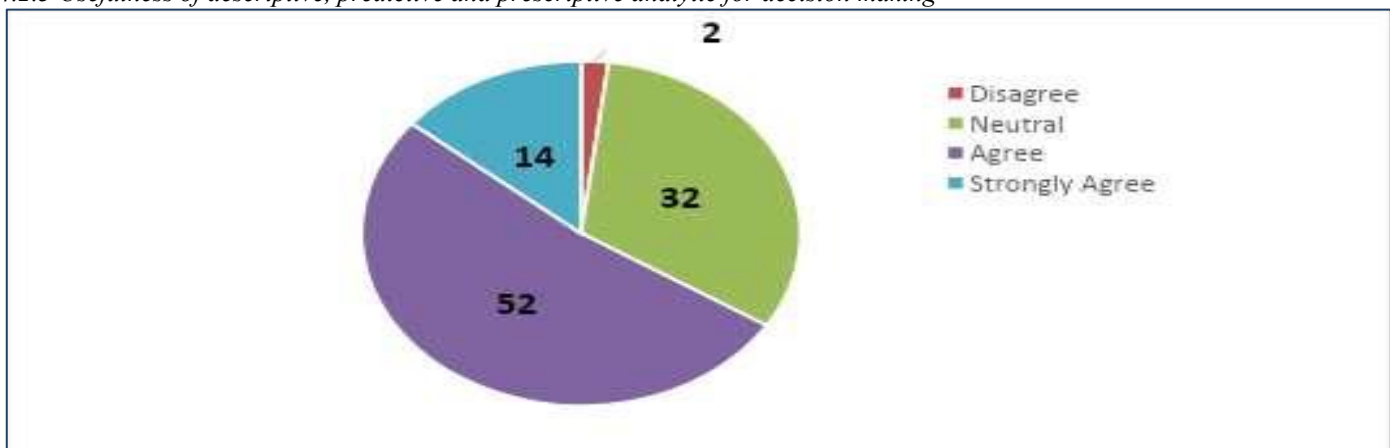


Figure 8: Usefulness of descriptive, predictive and prescriptive analytic for decision making

Figure 8 represents the usefulness of descriptive, predictive and prescriptive analytics for decision making at MTN Zambia. The respondents reported 52% agree, 32% were neutral, 14% strongly agreed and 2% disagreed. The combined majority 66% suggests the usefulness of the descriptive, predictive and prescriptive analytic for decision making at MTN Zambia while concluding that the others are slowly coming too with minimal challenges.

4.2.4 Presentation of analytics for non-technical managers



Figure 9: Presentation of analytics for non-technical managers

Figure 9 represents presentation of analytics for non-technical managers. The figure shows that output of analytics for non-technical managers is presented in a way that they understand, agree 52%, neutral 36%, strongly agree 10% and disagree 2%. The findings suggest clarity among the majority, with a sizeable number being neutral and a small notable challenge.

4.2.5 Direct engagement with analytics/data team for strategic decisions

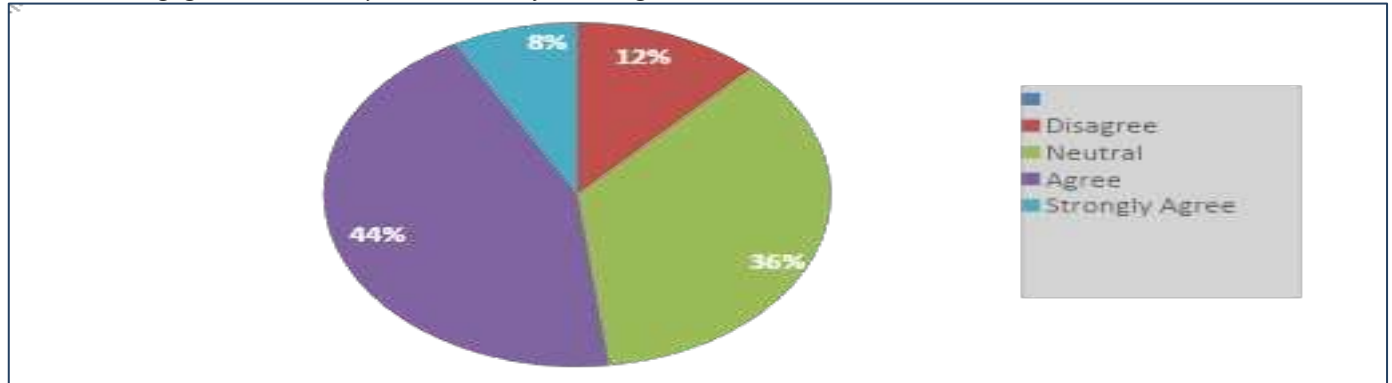


Figure 10: Direct engagement with analytics/data team for strategic decisions

Figure 10 represents Direct engagement with the Analytics/data team for Strategic decision. Findings show that 52% engaged in data analytics and the data team engaged in Strategic decisions, with 8% strongly agreeing while 36% remain completely neutral and 12% completely disagreed with the direct engagement with the strategic decision team. Finding suggested more collaboration among teams.

Table 2:

Description	Q6_use_analytics	Q7_availability	Q8_applies_analytics	Q9_presentation
N	50	50	50	50
Mean	3.84	3.52	3.78	3.70
Median	4.00	4.00	4.00	4.00
Standard deviation	0.584	0.789	0.708	0.678

Table 2 reveals Q6 (M = 3.84, M = 4, SD = 0.584), Q7 (M = 3.52, M = 4, SD = 0.789), Q8 (M = 3.78, M = 4, SD = 0.708) and Q9 (M = 3.70, M = 4, SD = 0.678). Indicating some respondents experience limited access to analytical resources.

4.2.6 Most used analytical output



Figure 11: most used analytical output

Figure 11 represents the most used analytical output. 38% represented data extracts, 22% operational dashboards, 18% scheduled reports, and Ad-hoc model output 16% and email summaries 6%. findings indicate a preference for Road data extracts over dashboarded or summary formats in this sample.

Table 3: Chi-square analysis between most used output and department

Test	χ^2	df	p	Cramer's V	N
Q11_most_used_output $\times$ Department	36.7	28	0.126	0.43	50

Table 3 represents the Chi-square test between departments and the type of Analytics output frequently used. The results showed no statistically significant association ($\chi^2 = 36.7$, $df = 28$ and $p = 0.126$). However, the effect size measured by Cramer's V is 0.43 suggests a moderate relationship, implying differences in how different departments apply Analytics. Although no statistical significance was found, employees emphasize the need for concise decision ready output, below include some common responses given within the company.

"Analytics must answer top-line questions quickly - give me the one slide that shows impact, not 20 tables." Senior management - Head/Executive

"Give us a single source of truth for Churn and ARPU Anglican standard days outputs across teams." Data analyst/Bi engineers

"A One-line insight with the dashboard changes everything. Tell me what to do with this number." Middle-level decision maker

4.2.7 Suggested changes

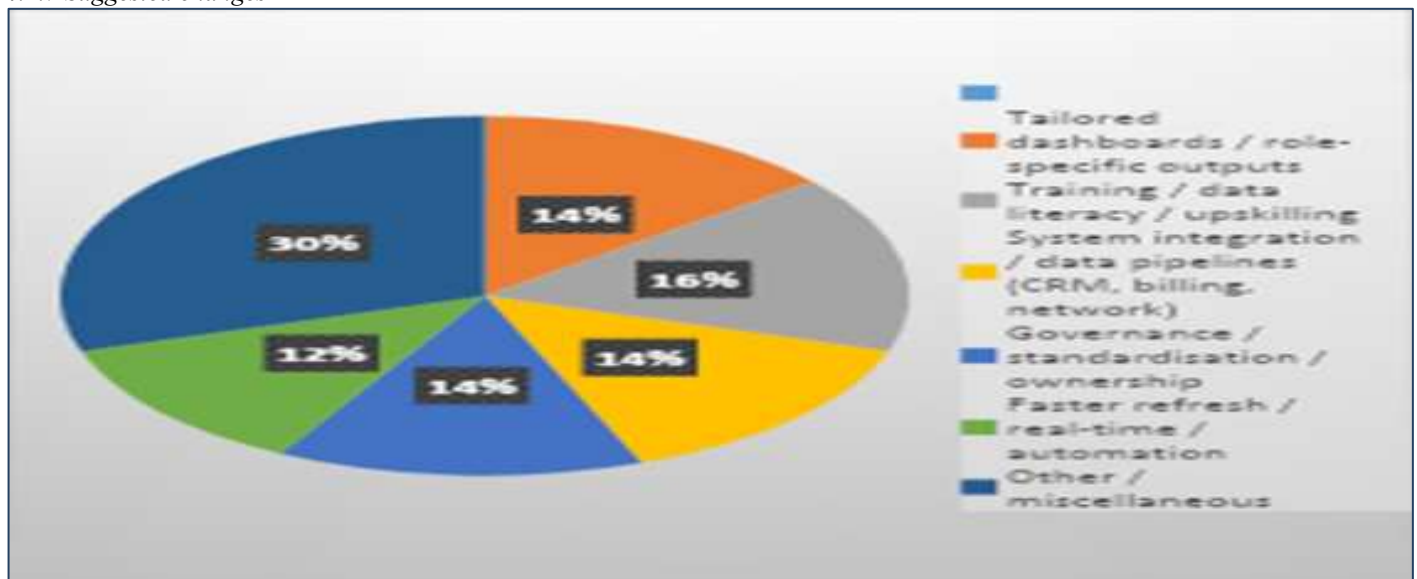


Figure 12: suggested changes

Figure 12 represents suggested changes. Other/ miscellaneous 30%, literacy / upskilling 16%, training/data 14%, governance/standardization/ownership 14%, system integrations / data pipeline (CRM, billing, network) 14%, tailored dashboard/row specific output 14% and refresh real-time/automation 12%. Findings suggest that there's a need for additional needs hence other/miscellaneous with the largest proportion in the pie chart in terms analytical capability and delivery.

4.3 To assess the effect of data analytics on MTN Zambia's market competitiveness.

4.3.1 Operational or Financial improvements from analytics

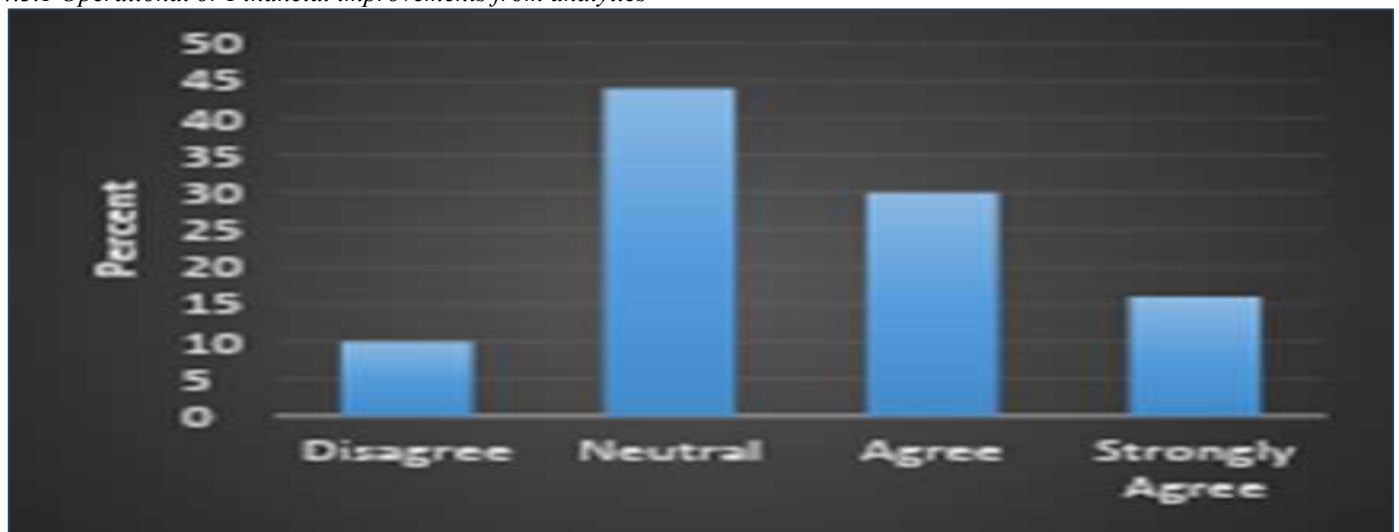


Figure 13: Operational or financial improvements from analytics

Figure 13 represents the operational or financial improvements from analytics. 44% remain neutral, 30% agree, 16% strongly agree and 10% disagree. Findings suggest that there is yet more to benefit as a result majority remain neutral.

4.3.2 Analytics reducing time to make well informed decisions

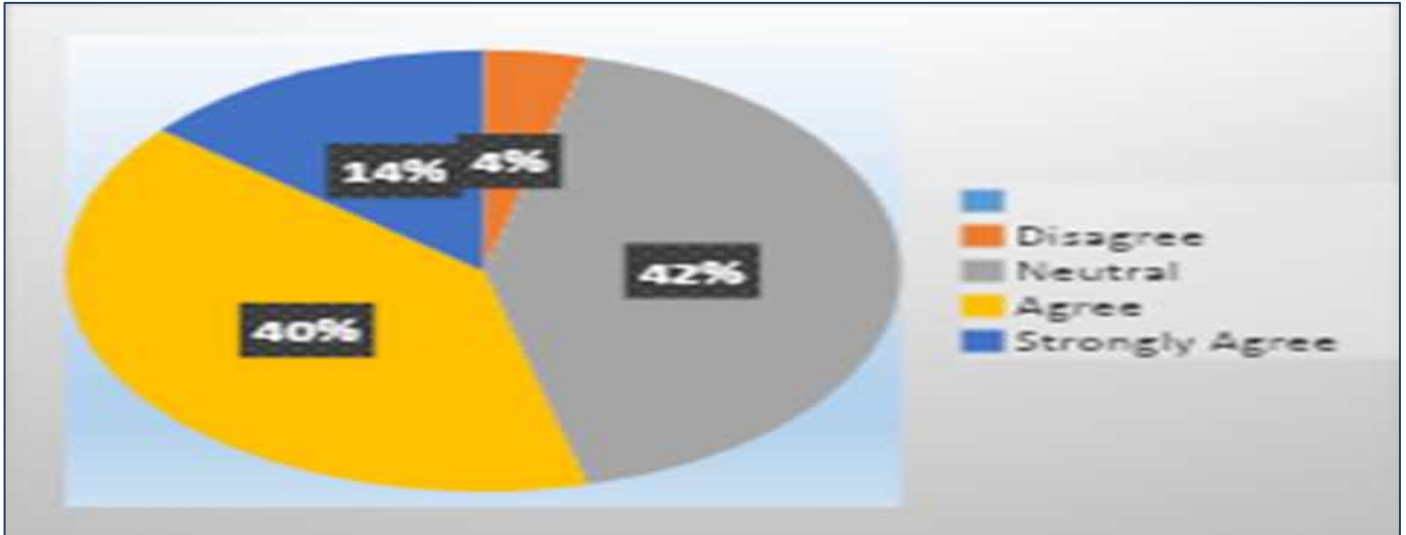


Figure 14: Analytics reducing time to make well informed decisions

Figure 14 represents analytics reducing time to make well informed decisions. 42% remain neutral, 40% agree, 14% strongly agree and 4% disagree. Findings indicate some time savings benefit from Analytics but not yet consistent among all departments.

4.3.3 Analytics contributing to competitive advantage

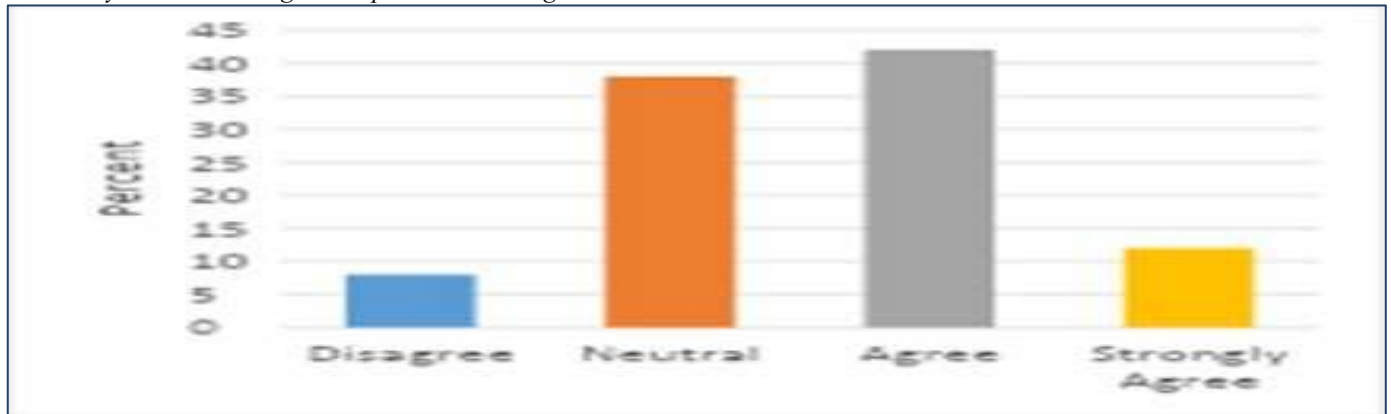


Figure 15: Analytics contributing to competitive advantage

Figure 15 represents analytics contributing to competitive advantage. 42% agree, 38% neutral, 12% strongly agree and 8% disagree. Findings indicate a combined 54% agreement that they see the benefit of Analytics while a large neutral share does not see the advantages yet or consistency across the board.

4.3.4 When analytics recommendations and managerial judgement conflict, analytics is usually followed.

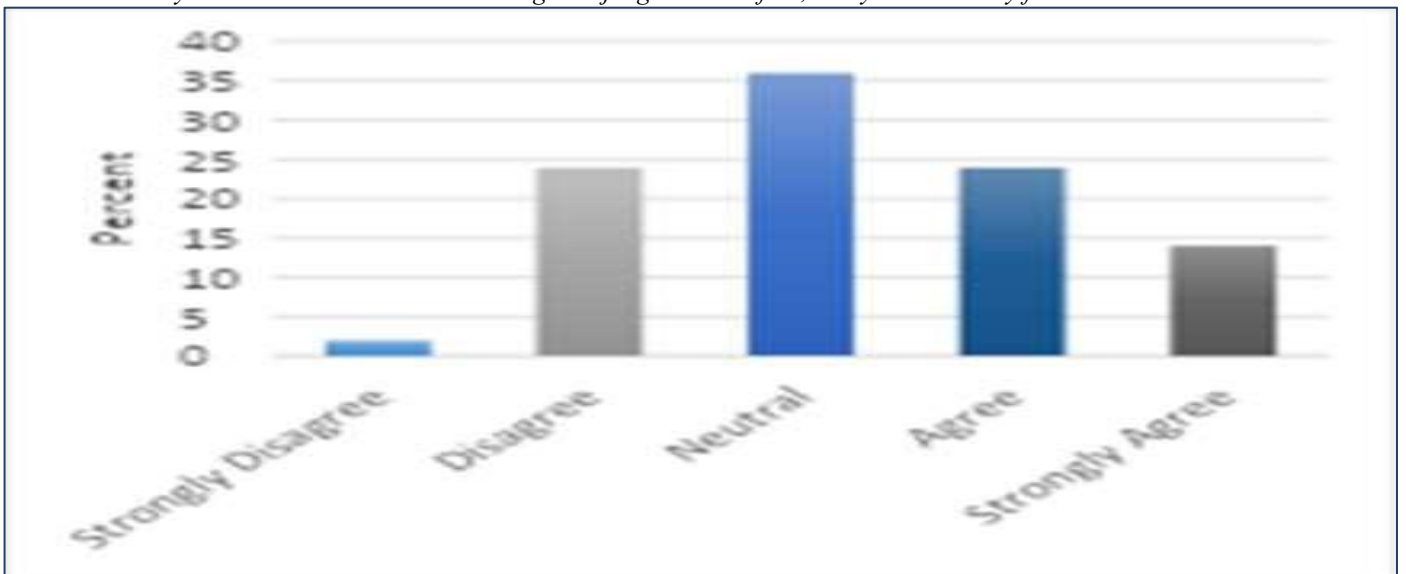


Figure 16: analytical recommendations and managerial judgement conflict analytics is usually followed

Figure 16 represents analytical recommendations and managerial judgement conflict analytics is usually followed. 36% remain neutral, 24% disagree, 24% agree, 14% strongly agree and 2% strongly disagree. Findings suggest that although the 38% combined agreement versus the 26% disagreement, Analytics are followed in some cases but not consistently giving room for managers in certain situations to please judgement.

4.3.5 Affirmative use of analytics

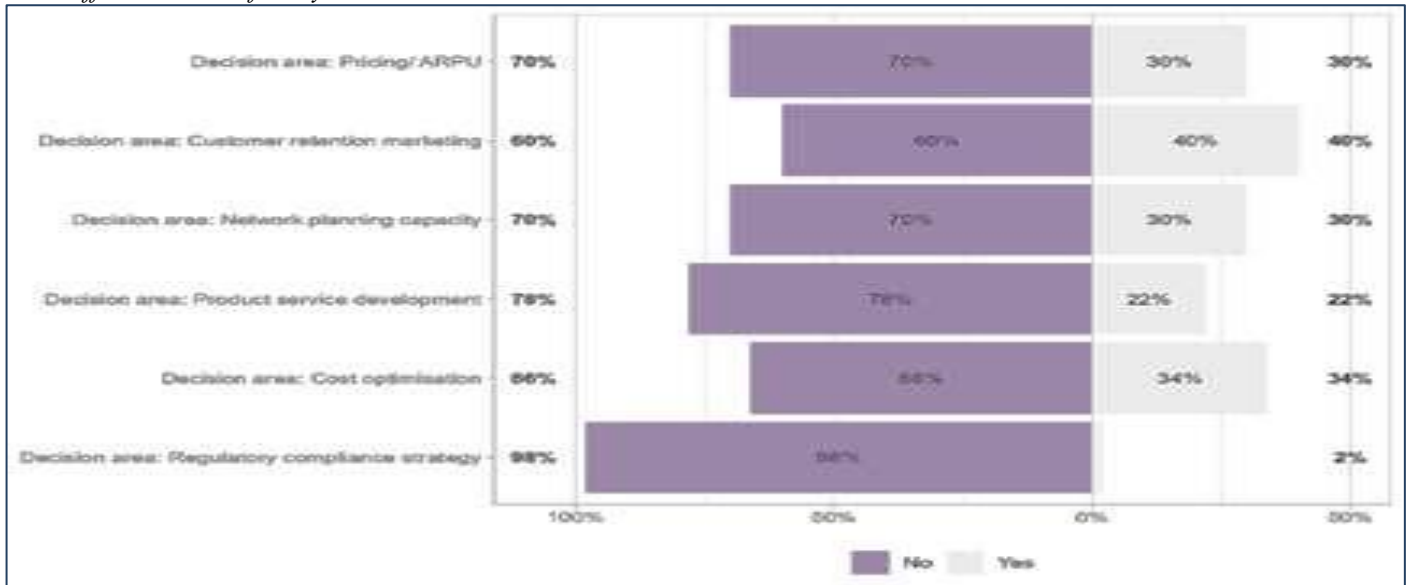


Figure 17: Affirmative use of analytics

Figure 17 represents affirmative use of analytics. Pricing ARPU yes 30% no 70%, customer retention marketing yes 40% no 60%, network planning capacity yes 30% no 70%, Product service development yes 22% no 78%, cost optimization yes 34% no 66%, regulatory compliance strategy yes to present you know 98%. findings indicate that Analytics are mostly used for market customer retention, cost optimization and regulatory compliance strategy.

4.3.6 Examples of long term benefits or harm from analytics



Figure 18: Examples of long term benefits or harm from analytics

Figure 18 represents examples of long term benefits or harm from analytics. 46% retention/target (Churn reduction) Common 18% others/mixed, 14% customer service/operational improvement (AHT, NPS), 12% Network / operations optimization and 10% price/revenue/ARPU uplift. Finding suggested customer retention is a superior reported success of Analytics.

4.4 To assess the limitations of the effective use of data analytics at MTN Zambia.

4.4.1 Perceived accuracy and reliability of analytical data

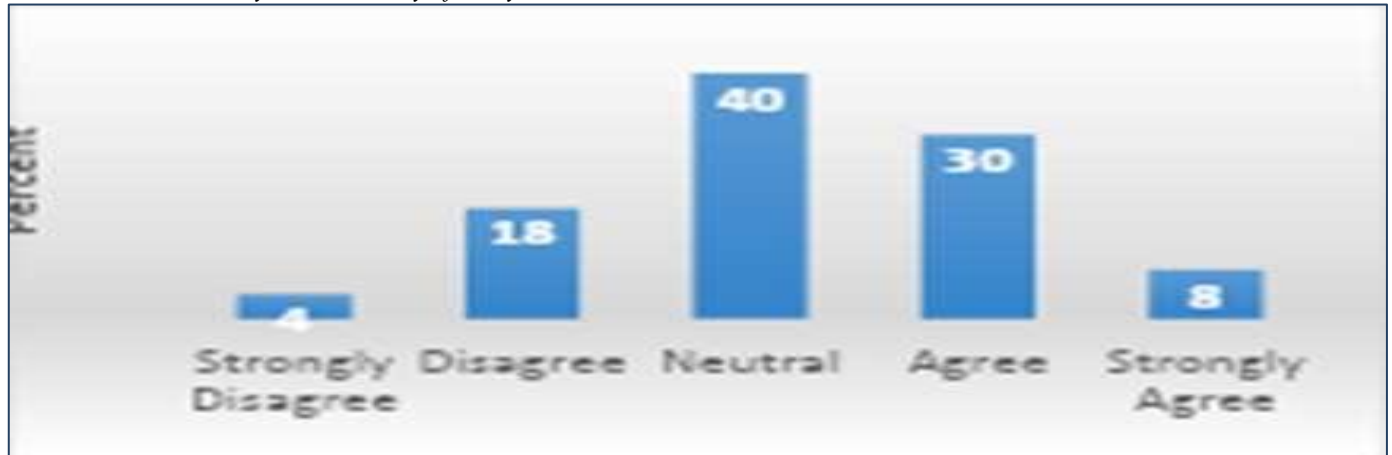


Figure 19: Perceived accuracy and reliability of analytics

Figure 19 represents Perceived accuracy and reliability of analytics. 40% remain neutral, 30% agree, 18% disagree, 8% strongly agree and 4% strongly disagree. Findings indicate that there is more to be done on accuracy and reliability analytics obtained within the company. Respondents described operational challenges that limited analytical impact below.

“We spend 40 to 60% of our time cleaning and aligning data before we can even model anything.” (Data analysis/BI engineers)

“Missing or duplicate records make it hard to trust the outputs; we often have to cross check manually.” (Middle-level decision -maker)

4.4.2 Integration of data across systems for trustworthy analysis (Billing, CRM, Network)

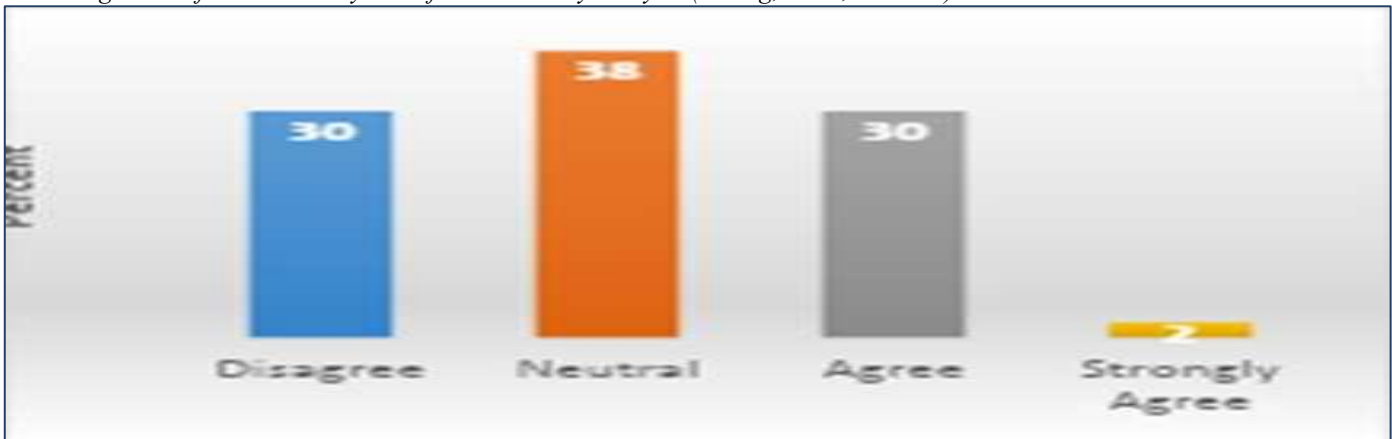


Figure 20: Integration of data across systems for trustworthy analytics

Figure 20 represents Integration of data across systems for trustworthy analytics. 38% remain neutral, 30% agree and disagree, and lastly 2% strongly. Findings suggest inconsistency in system integration that undermines trust and cross system Analytics reliability within the company. Respondents described operational constraints that limit Analytics impact, stated below.

“When a business asks for a quick model, they often want immediate answers; without proper integration, that would yield shaky results.” (Data analysts/BI engineers)

4.4.3 Clarity and enforcement of data governance



Figure 21: Clarity and enforcement of data governance

Figure 21 represents Clarity and enforcement of data governance. 42% remain neutral, 28% agree, 20% disagree, 8% strongly agree and 2% strongly disagree. Finding suggest governance and clarity is unclear or inconsistently enforced which limits the reliability of analytics, respondents described challenges listed below limit the impact.

“If the CFO and the CMO see different churn numbers, we do not make decisions; we debate numbers.” (Senior management - Head/Executive)

“Investment decisions will follow; show cost-benefits and we will find it. But governance must be fixed first.” (Senior management - Head/Executive)

4.4.4 Trust in analytics outputs to act without repeated confirmation

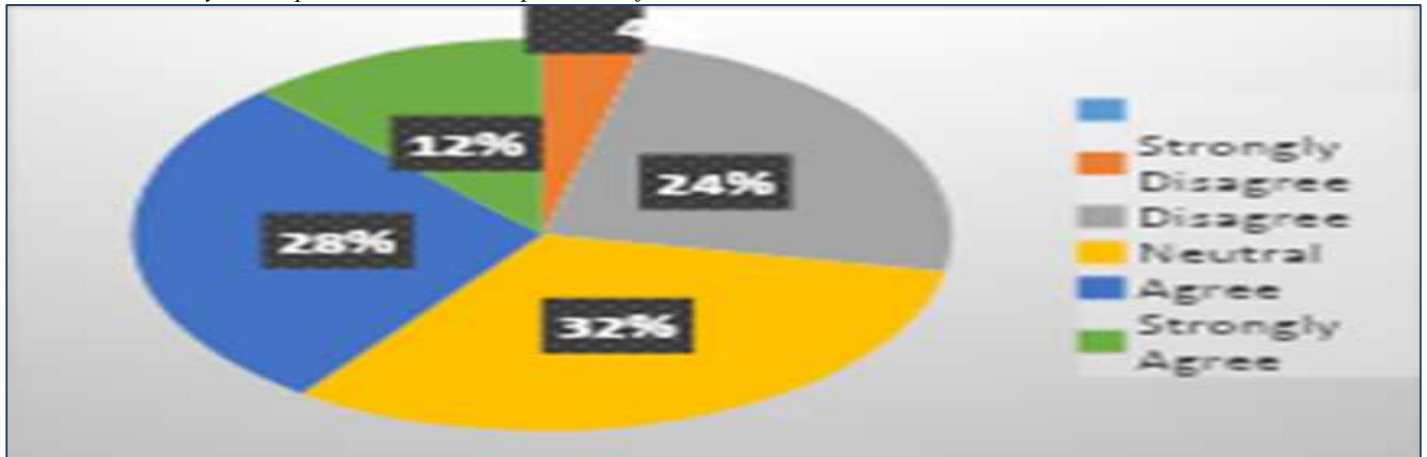


Figure 22: Trust analytics outputs to act without repeated confirmation

Figure 22 represents Trust analytics outputs to act without repeated confirmation. 32% remain neutral, 28% disagree, 24% disagree, 12% strongly agree and 4% strongly disagree. Findings suggest that stronger quality is needed for employees to have confidence in Analytics produced within the company.

4.4.5 Frequency that missing/inconsistent data blocked decisions (past 12 months)



Figure 23: Frequency that missing/inconsistent data blocked decisions (past 12 months)

Figure 23 represents Frequency that missing/inconsistent data blocked decisions in the past 12 months. 30% sometimes, 26% often, 22% rarely, 14% always and 8% never. Findings point to delays in decision making and operational risk from data gaps.

4.4.5 Barriers to effective analytical use

Table 4: Barriers to effective analytical use

Q18_major_limitation	Counts	% of Total	Cumulative %
Data integration issues between systems (CRM, billing, network)	7	14.0%	14.0%
Data quality (missing, duplicates, inconsistent)	21	42.0%	56.0%
Weak governance / unclear ownership of metrics	14	28.0%	84.0%
Skills / data literacy gaps among staff	6	12.0%	96.0%
Regulatory or privacy constraints limiting data use	2	4.0%	100.0%

Table 5

Kruskal-Wallis	χ^2	df	p	ε^2
Q14_integration	8.91	7	0.259	0.182

Respondents indicated different obstacles to effective usage of analytics (See Table 5). The barrier that occurred most frequently was not quality of data (missing values, duplicates, conflicting records), namely 42%, after that weak governance/unclear ownership 28% and problems of data integration 14% occurred. Kruskal-Wallis test showed that there are no significant differences in the severity of the problem of data integration perceived by departments $\chi^2(7) = 8.91$, $p = .259$, $\varepsilon^2 = 0.182$. The analysis of pairwise differences showed that there are no significant associations between departments' differences. To summarize, data quality and governance are seen as top barriers in general, however the sample does not show significant differences in these views among departments.

4.5 Discussion of results

4.5.1 How MTN Zambia uses data analytics in strategic decision making

Analytics is often applied at operational and middle-management levels. The research shows that Data & Analytics is the most important discipline at 34%, followed by Strategy 20%. 36% use analytics, with many companies doing both. The most common cases of analytics usage are in customer retention and targeted marketing reported by 46% of the respondents; the least popular area is regulatory strategy at 2% and limited pricing/ARPU 30% said yes and 70% engaged in no analytics. In conclusion, analytics is used at various operational and tactical levels but is not widely incorporated into strategic management (LaValle et al., 2018; Mikalef et al., 2019; PwC, 2020). MTN has analytics tools and interacts with both producers and consumers, but it should create processes that channel analytics into executive decision-making so that operational benefits contribute to the overall strategy of the company.

4.5.2 Effects of analytics on market competitiveness

The findings indicate a positive outlook: 54% of respondents (42% agree and 12% strongly agree) believe that analytics provide a competitive edge whereas 38% remain neutral. Benefits can be classified as customer retention, cost control, and operational performance measures. Concrete long-term benefits are reported but are applied mostly at the unit levels instead of the enterprise level (Mikalef et al., 2019; Wamba et al., 2018). The challenge is to convert tactical benefits into strategic advantages by connecting unit KPI improvements (churn, AHT, NPS) and strategic performance measures as well as decision-making processes. Otherwise, the benefits would remain local.

4.5.3 Limitations of effective use

The major issues here are the lack of integration of systems (billing, customer relationship management, network), bad quality of the data used (missing/inconsistent records), lack of defined governance, as well as the presentation formats of the data used. Trust is not present: 38% follow analytics when it contradicts the judgment of management; 36% are neutral and 26% don't agree with analytics. The problems mentioned are present across departments, unlike in some companies where concerns are separated.

5. Conclusion and Recommendations

MTN Zambia has established operational analytics capacity that improves customer management, network monitoring and campaign targeting. However, analytics influence at the strategic/executive level remains limited. Persistent barriers, data quality, system fragmentation, weak governance and skill gaps, reduce trust and prevent company-wide leverage of analytics. Analytics has produced positive, localised competitive effects, but these will only become sustainable if unit successes are linked to formal strategy processes, backed by governance, integration and executive sponsorship. Technical capacity exists; institutional embedding is the remaining task.

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