Int. j. adv. multidisc. res. stud. 2026; 6(6):1126-1131

Received: 07-10-2026
Accepted: 17-11-2026

International Journal of Advanced Multidisciplinary Research and Studies

ISSN: 2583-049X

Examining the Effectiveness of Data Mining and Utilization in Human Resource Recruitment Processes in Selected Branches of Zambia National Commercial Bank (ZANACO) in Lusaka, Zambia

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Abstract

The banking sector in Zambia faces increasing pressure to attract, select and retain high-quality talent in a competitive and digitally transforming environment. This study examined the effectiveness of data mining and its utilization in human resource (HR) recruitment processes in selected Zambia National Commercial Bank (ZANACO) branches in Lusaka. A quantitative, descriptive survey design was adopted. Structured questionnaires were administered to 92 respondents, comprising HR officers, data analytics personnel, IT support staff and line managers involved in recruitment decisions, selected through stratified random sampling. Data were analysed using descriptive statistics, cross-tabulation and the Chi-square test of independence. The findings show that data mining is adopted but unevenly utilised. Among respondents who used data mining (n = 68), only 11.8% reported no effect on recruitment, while the remainder reported positive effects on recruitment quality, speed and candidate–job fit. Among non-users (n = 24), 33.3% reported no effect, 25.0% a negative effect and 41.7% found the question not applicable. Two main barriers were identified: inadequate technical skills (59.8%) and continued reliance on manual recruitment processes (44.6% high, 31.5% moderate and 23.9% low reliance). Technical skills were significantly associated with reliance on manual processes, $\chi^2(2, N = 92) = 61.88$, $p < .001$. Among respondents with skill gaps, 74.5% reported high reliance on manual processes and none reported low reliance. The study concludes that data mining is perceived to be effective when properly utilised, but its potential is constrained by skills deficits and manual work practices. It recommends annual appraisal of data mining adoption and continuous capacity building for HR and related staff.

Keywords: Data Mining, Human Resource Management, Recruitment, Banking, Zambia, ZANACO, HR Analytics, Talent Acquisition

1. Introduction

1.1 Background to the Study

In the contemporary digital age, data has emerged as one of the most valuable strategic resources for decision-making, particularly in Human Resource Management (HRM). Organisations, especially in the banking sector, are increasingly leveraging data mining techniques to enhance the effectiveness of recruitment processes. Data mining refers to the process of discovering patterns, correlations and insights from large datasets that can be used to inform decision-making (Han, Pei & Kamber, 2011) [5]. Within HR recruitment, data mining holds considerable potential for improving candidate selection, predicting employee performance, reducing hiring bias and aligning recruitment efforts with organisational goals (Marler & Boudreau, 2017) [8].

Globally, multinational corporations such as Google and IBM have applied predictive analytics to workforce planning, hiring decisions and employee retention (Davenport, Harris & Shapiro, 2010) [3]. These organisations use data points ranging from résumés, social media profiles and psychometric test results to performance records to build predictive models that assess a candidate's likelihood of success.

In Africa, adoption is growing but fragmented. Countries such as South Africa, Nigeria and Kenya have seen increased adoption of talent analytics, especially in large corporations (Nzukuma & Bussin, 2011) [10]. However, adoption is constrained

by infrastructural challenges, limited technical expertise and resistance to change (Muriithi & Wanjiru, 2018) [9].

1.2 Statement of the Problem

In Zambia, and specifically at ZANACO, the uptake and integration of data mining into HR recruitment remains inconsistent and underexplored. Recruitment is no longer viewed as a purely transactional HR function but as a strategic enabler that determines workforce quality (Huselid, 1995) [6]. Yet many recruitment decisions at ZANACO are still made manually, which slows down processes and reduces efficiency. There is limited empirical evidence on how effective data mining is in this setting and on the factors that limit its use.

1.3 Objectives of the Study

The study sought to:

1. To assess the extent of adoption of data mining in HR recruitment at ZANACO.
2. To examine the perceived effectiveness of data mining on recruitment outcomes.
3. To identify challenges affecting the utilisation of data mining in recruitment.
4. To establish the relationship between technical skills and reliance on manual processes.

1.4 Research Questions

The study was guided by the central question: *How effective is data mining and its utilisation in HR recruitment processes at ZANACO in Lusaka, and what factors limit its effectiveness?* This was broken down into the following questions:

1. To what extent has ZANACO adopted data mining in recruitment?
2. How effective is data mining in improving recruitment outcomes?
3. What challenges hinder effective utilisation of data mining?
4. Is there a relationship between technical skills and reliance on manual processes?

1.5 Research Hypothesis

To address the fourth objective, the following hypotheses were tested:

H_0: There is no relationship between technical skills and reliance on manual recruitment processes.

H_1: There is a significant relationship between technical skills and reliance on manual recruitment processes.

1.6 Significance of the Study

The study is significant for ZANACO management, HR practitioners, policymakers and scholars. For ZANACO, it provides evidence to guide investment in HR analytics and training. For HR practitioners, it highlights practical barriers to digital recruitment. For academia, it contributes to the limited literature on HR analytics in developing economies and in the Zambian banking context.

1.7 Scope of the Study

The study was confined to selected ZANACO branches in Lusaka, Zambia. It focused on staff directly involved in recruitment decisions: HR officers, data analytics personnel, IT support staff and line managers. Conceptually, it examined three issues: the extent to which data mining is adopted in recruitment, its perceived effect on recruitment outcomes, and the technical and procedural barriers that limit its use.

1.8 Definition of Key Terms

Data mining refers to the process of discovering patterns and relationships in large datasets to support decisions (Han, Pei & Kamber, 2011) [5]. In this study it covers the use of software tools to screen, rank or profile candidates using recruitment data.

Utilisation refers to the actual, routine use of data mining tools by staff in recruitment tasks, as distinct from the mere availability of such tools.

Recruitment effectiveness refers to respondents' perceived improvement in the speed, quality and candidate–job fit of recruitment, and in the cost of hiring.

Reliance on manual processes refers to the degree to which recruitment tasks such as shortlisting and approval are carried out by hand or on paper rather than through digital systems. It was rated as high, moderate or low.

1.9 Organisation of the Paper

The rest of the paper is organised as follows. Section 2 reviews the relevant theory and literature. Section 3 describes the research methodology. Section 4 presents the results, which are discussed in Section 5. Section 6 concludes the paper and Section 7 gives recommendations.

2. Literature Review

2.1 Theoretical Framework

This study is anchored on two theories: the Resource-Based View (RBV) and the Technology Acceptance Model (TAM).

2.1.1 Resource-Based View (RBV)

Barney (1991) [1] argues that organisations gain competitive advantage from resources that are valuable, rare, inimitable and non-substitutable. Data, analytical capability and skilled HR personnel constitute such strategic resources. ZANACO's ability to mine recruitment data effectively can therefore become a source of sustained advantage.

2.1.2 Technology Acceptance Model (TAM)

Davis (1989) [4] posits that perceived usefulness and perceived ease of use determine technology adoption. If HR staff perceive data mining tools as useful but difficult to use because of skill gaps, adoption will remain low. This helps explain why tools may exist but remain underutilised.

2.2 Data Mining in Human Resource Management

Data mining in HR involves classification, clustering, association and prediction. In recruitment, it is used for CV screening, candidate ranking, predicting turnover and identifying success profiles (Sharma & Sharma, 2017) [13]. LaValle *et al*. (2011) [7] found that organisations using analytics are more likely to outperform competitors in talent decisions. Marler and Boudreau (2017) [8] argue that HR analytics shifts HR from intuition-based to evidence-based decision-making.

2.3 Effectiveness of Data Mining in Recruitment

Recruitment effectiveness is commonly measured by time-to-hire, cost-per-hire, quality-of-hire, candidate–job fit and retention. Research suggests that data mining reduces time-to-hire by automating screening, improves fit by matching skills to job requirements and reduces bias by focusing on

objective criteria (Davenport *et al*., 2010) [3]. However, effectiveness depends on data quality, system integration and user competence. Without proper training, tools may be misinterpreted or ignored.

2.4 Challenges in Developing Contexts

In developing countries, challenges include inadequate ICT infrastructure, limited budgets, data privacy concerns, resistance to change and low digital literacy (Muriithi & Wanjiru, 2018) [9]. In Zambia, many banks still operate hybrid systems in which digital tools coexist with paper-based processes.

2.5 Conceptual Framework

Fig 1 presents the conceptual framework guiding the study. Data mining adoption, technical skills and system availability are the independent variables; utilisation of data mining is the mediating variable; and recruitment effectiveness (speed, quality, fit and cost) is the dependent variable. Organisational culture, expressed as reliance on manual processes, is the moderating factor. The study hypothesises that higher technical skills lead to higher utilisation and lower reliance on manual processes, which in turn leads to more effective recruitment.

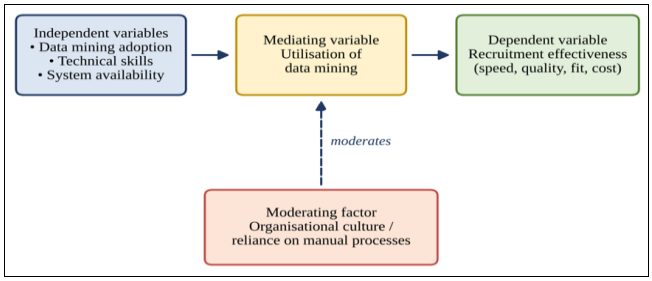

Fig 1: Conceptual framework of the study

2.6 Empirical Review and Research Gap

The literature points to a consistent pattern. First, analytics-based recruitment is widely associated with better talent decisions where organisations have the data, systems and people to use it (LaValle *et al*., 2011; Marler & Boudreau, 2017) [7, 8]. Second, the benefits are not automatic. Davenport *et al*. (2010) [3] stress that analytics creates value only when it is embedded in everyday HR decisions rather than treated as a specialist add-on. Third, evidence from Africa suggests that skills shortages, limited infrastructure and resistance to change slow adoption (Muriithi & Wanjiru, 2018) [9].

The wider HRM literature adds that people-management practices matter for organisational performance (Huselid, 1995) [6], which strengthens the case for treating recruitment as a strategic function. However, most of the studies cited above were conducted in large corporations or in more developed economies. Little empirical work has examined how HR staff in Zambian banks actually use data mining in recruitment, or how their technical skills relate to continued reliance on manual methods. This study addresses that gap by providing survey evidence from selected ZANACO branches in Lusaka.

3. Research Methodology

3.1 Research Design

A quantitative research approach with a descriptive survey design was used. This design is appropriate for gathering factual information and analysing relationships among variables without manipulating them (Saunders, Lewis & Thornhill, 2019; Creswell, 2014) [12, 2].

3.2 Target Population and Sample

The target population comprised employees in HR departments, data analytics teams, IT support units and line managers involved in recruitment decisions across selected ZANACO branches in Lusaka. Although 50 respondents were initially planned, the final sample was expanded to 92 respondents. Stratified random sampling was used to ensure that all key categories of staff were proportionately represented.

3.3 Data Collection Instrument

Data were collected using a structured questionnaire with closed-ended questions, including Likert-scale items. The sections covered demographics, adoption of data mining, perceived effectiveness, technical skills and reliance on manual processes (see Appendix).

Table 1 summarizes how the main variables were measured.

Table 1: Operationalization of the main study variables

Variable	Indicator	Measurement
Adoption of data mining	Use of data mining tools in recruitment	Yes / No
Perceived effectiveness	Effect on recruitment quality, speed and candidate–job fit	Positive, no effect, negative, not applicable
Technical skills	Adequacy of skills to use data mining tools	Adequate / Inadequate
Reliance on manual processes	Extent of manual shortlisting, paper files and manual decisions	High, moderate, low

Source: Study questionnaire.

3.4 Data Analysis

Data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics (frequencies and percentages) were used to summarize responses. Cross-tabulation and the Chi-square test of independence were used to test the relationship between variables, at a 5% level of significance. Qualitative comments from open-ended items were used to support the quantitative findings.

3.5 Data Collection Procedure

After permission had been granted, the questionnaire was distributed to the sampled respondents in the selected branches. Respondents completed the closed-ended items and, where they wished, added comments in the open-ended spaces. Completed questionnaires were checked for completeness, coded and entered into SPSS for analysis.

3.6 Ethical Considerations

Participation was voluntary and confidentiality was assured. Permission was obtained from ZANACO management and from the University. No respondent names were recorded.

3.7 Limitations of the Study

The study was limited to selected Lusaka branches and relied on self-reported perceptions. It did not measure actual hiring data such as time-to-hire or staff turnover over time. The findings should therefore be generalized to other settings with caution.

4. Results

4.1 Demographic Profile

Respondents were drawn from HR (the majority), IT, data analytics and management. Most had between two and ten years' experience at ZANACO and were directly involved in shortlisting, interviewing or approving hires.

4.2 Adoption and Perceived Effectiveness of Data Mining

Of the 92 respondents, 68 (73.9%) reported using data mining in recruitment, while 24 (26.1%) did not. The results on perceived effectiveness present a mixed picture (Table 2 and Fig 2). Among users, 8 respondents (11.8%) reported no effect on recruitment, while the remaining 60 (88.2%) reported positive effects. In contrast, among the 24 non-users, 8 (33.3%) reported no effect, 6 (25.0%) reported a negative effect and 10 (41.7%) indicated that the question was not applicable to them.

Table 2: Perceived effect of data mining on recruitment, by use of data mining

Perceived effect	Users (n = 68)	Non-users (n = 24)	Total (N = 92)
Positive effect	60 (88.2%)	0 (0.0%)	60 (65.2%)
No effect	8 (11.8%)	8 (33.3%)	16 (17.4%)
Negative effect	0 (0.0%)	6 (25.0%)	6 (6.5%)
Not applicable	0 (0.0%)	10 (41.7%)	10 (10.9%)

Source: Field data.

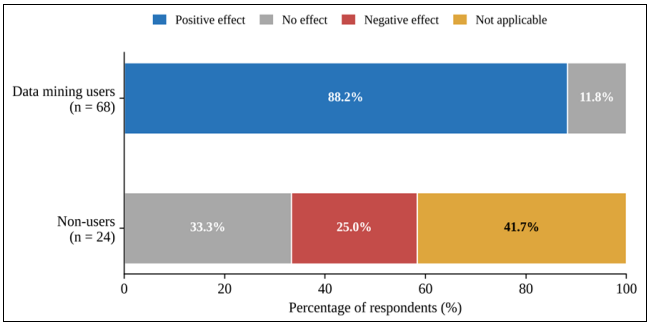

Fig 2: Perceived effect of data mining on recruitment by usage group

Users of data mining were more likely to report improved candidate quality, faster shortlisting and better candidate–job fit. The absence of data-driven procedures appears to be associated with less predictable recruitment outcomes. One HR officer noted: "We have the tools, but not everyone knows how to fully leverage them to identify the best candidates." This is consistent with the Technology Acceptance Model: the tools exist, but perceived ease of use is low.

4.3 Inadequate Technical Skills as a Barrier

A major finding was inadequate technical skills (Fig 3a). Of the 92 respondents, 55 (59.8%) reported that they lacked sufficient technical proficiency to use data mining tools effectively, while 37 (40.2%) indicated that their technical skills were adequate. Respondents highlighted that the absence of advanced skills hinders accurate interpretation of recruitment data. A data analytics officer observed: "Without proper technical training, the potential of these systems is underutilized, which can delay or compromise recruitment decisions." This supports Muriithi and Wanjiru (2018) [9], who identify skill gaps as a primary constraint in African HR analytics adoption.

4.4 Reliance on Manual Recruitment Processes

The findings reveal continued reliance on manual processes (Fig 3b): 41 respondents (44.6%) reported high reliance on manual methods, 29 (31.5%) moderate reliance and 22 (23.9%) low reliance. One HR manager stated: "Even with advanced tools available, many recruitment decisions are still made manually, which slows down the process and reduces efficiency." A branch supervisor added: "Manual intervention often overrides insights from data mining, making it hard to fully realize the benefits of automation." This indicates a hybrid system in which digital tools are available but human judgement, paper files and manual shortlisting still dominate.

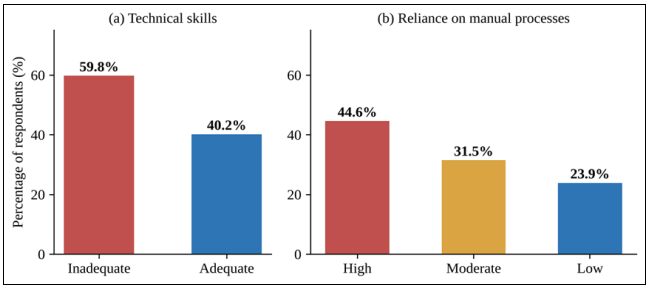

Fig 3: Technical skills (a) and reliance on manual recruitment processes (b)

4.5 Relationship between Technical Skills and Manual Reliance

Cross-tabulation (Table 3 and Fig 4) revealed a highly significant relationship between technical skills and reliance on manual processes, $\chi^2(2, N = 92) = 61.88$, $p < .001$. The effect size was large (Cramér's V = 0.82). All expected cell counts exceeded 5, so the assumptions of the test were met. The null hypothesis was therefore rejected.

Table 3: Reliance on manual processes by level of technical skills

Technical skills	High reliance	Moderate reliance	Low reliance	Total
Inadequate	41 (74.5%)	14 (25.5%)	0 (0.0%)	55 (100%)
Adequate	0 (0.0%)	15 (40.5%)	22 (59.5%)	37 (100%)
Total	41 (44.6%)	29 (31.5%)	22 (23.9%)	92 (100%)

Note: $\chi^2(2, N = 92) = 61.88$, $p < .001$; Cramér's V = 0.82. Percentages are row percentages.

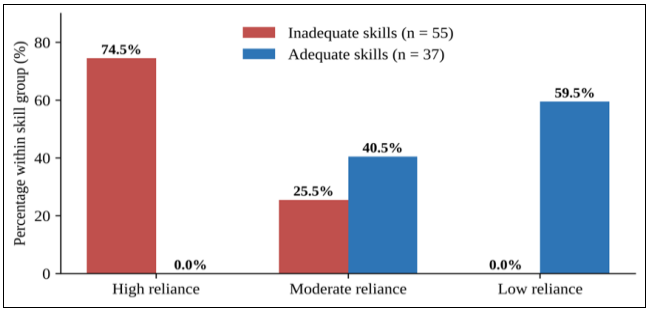

Fig 4: Reliance on manual processes by level of technical skills

Among respondents who reported inadequate technical skills (n = 55), 74.5% (41) indicated high reliance on manual processes, 25.5% (14) moderate reliance and none low reliance. Among respondents without skill gaps (n = 37), 59.5% (22) indicated low reliance, 40.5% (15) moderate reliance and none high reliance. Lack of technical competence is therefore strongly associated with a fallback

to traditional methods. One HR manager explained: "Many of our staff are not fully trained to use analytics software, so we fall back on traditional paper-based processes." An IT officer added: "Even with automated systems available, inadequate skills mean we cannot exploit their full potential, leading to manual interventions."

5. Discussion

5.1 Interpretation of the Findings

The study indicates that data mining is perceived to be effective in recruitment, but that this effectiveness is conditional. It is not the availability of tools that matters most, but the capability to use them.

From the RBV perspective, ZANACO has invested in a valuable resource (data mining tools) but has not yet developed the complementary human capability (skills) needed to turn it into a rare and hard-to-imitate source of advantage. From the TAM perspective, low perceived ease of use, arising from skill gaps, is blocking fuller adoption.

Because the Chi-square test establishes association rather than causation, the relationship between skills and manual reliance should be interpreted with care. Nevertheless, together with the qualitative comments, the results suggest a self-reinforcing cycle (Fig 5): low skills lead to low confidence, which leads to high manual reliance, low utilisation and low perceived value, which in turn discourages investment in training and keeps skills low. Breaking this cycle requires deliberate capacity building, not simply the purchase of software.

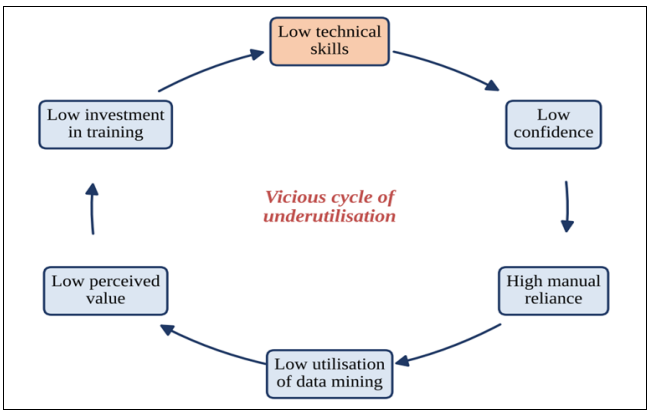

Fig 5: Proposed cycle of underutilization of data mining at ZANACO

5.2 Summary of Findings by Objective

Table 4 links the main findings to the four objectives of the study.

Table 4: Summary of findings by objective

S. No	Objective	Key finding
1	Adoption	68 of 92 respondents (73.9%) used data mining in recruitment; 24 (26.1%) did not.
2	Perceived effectiveness	Only 11.8% of users reported no effect, compared with 33.3% of non-users, 25.0% of whom reported a negative effect.
3	Challenges	Inadequate technical skills (59.8%) and high reliance on manual processes (44.6%).
4	Skills and manual reliance	Significant association, $\chi^2(2, N = 92) = 61.88$, $p < .001$; Cramér's V = 0.82.

Source: Field data.

5.3 Implications

For theory, the findings support the view that technology investments translate into advantage only when matched by human capability (Barney, 1991) [1], and that perceived ease of use shapes whether available tools are actually used (Davis, 1989) [4]. For practice, they suggest that the next gains at ZANACO are more likely to come from training and process redesign than from additional software. For policy, they reinforce the need for data governance arrangements that protect candidate data as analytics use grows.

6. Conclusion

Data mining is perceived to improve HR recruitment at ZANACO when it is utilised, particularly in terms of speed, candidate quality and predictability of outcomes. However, its effectiveness is currently limited by two main factors:

1. Inadequate technical skills (59.8% of respondents); and
2. High reliance on manual processes (44.6% of respondents).

The statistically significant relationship between skills and manual reliance ($p < .001$) provides strong evidence that addressing skills is a key lever for digital transformation in HR recruitment.

6.1 Contribution of the Study

The study contributes survey-based evidence from the Zambian banking sector, where little published work on HR analytics exists. It shows that the main constraint on data mining in recruitment is human capability and working culture rather than the availability of tools, and it demonstrates a strong statistical link between skills and manual reliance that can guide training priorities.

6.2 Limitations and Areas for Further Research

Because the study relied on self-reported perceptions from selected Lusaka branches, the results describe how staff experience data mining and should not be treated as direct measures of hiring performance. Future studies could combine survey data with records of time-to-hire, cost-per-hire and retention, and could compare banks across several provinces.

7. Recommendations

7.1 For ZANACO Management

1. **Conduct annual appraisals of data mining adoption:** Evaluate each year how well data mining tools are being used, what return on investment is achieved and where gaps remain.
2. **Provide continuous capacity building:** Introduce mandatory quarterly training on HR analytics, data interpretation and software use for all HR, IT and line management staff.
3. **Integrate systems:** Fully integrate Applicant Tracking Systems (ATS), HR Information Systems (HRIS) and analytics dashboards to reduce manual duplication.
4. **Designate HR analytics champions:** Appoint two to three staff per region as super-users to mentor others.
5. **Develop a data governance policy:** Ensure data quality, privacy and ethical use in line with the Data Protection Act of Zambia (Republic of Zambia, 2021) [11].

7.2 For HR Practitioners

- Embrace evidence-based recruitment and reduce subjective bias.
- Document recruitment decisions to build a data base for future mining.

7.3 For Future Researchers

- Conduct longitudinal studies linking data mining use to actual retention and performance data.
- Extend the study to other commercial banks in Zambia (for example Stanbic, Absa and First National Bank) for comparison.
- Use mixed methods to explore organisational resistance to change in greater depth.

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