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OPTIMIZING MOBILE OPERATOR SERVICES: UNCOVERING CUSTOMER PREFERENCES WITH MARKET BASKET ANALYSIS

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ABSTRACT

This study leveraged the Apriori algorithm for Market Basket Analysis to unveil hidden patterns in customer transaction data, specifically exploring combinations of mobile operator services frequently used together. Using transaction data from eight universities, the analysis revealed compelling associative rules. Notably, a significant rule indicates a strong association between effective problem-solving and fulfilled service promises, with 58.6% of customers expressing satisfaction in both areas. These insights empower mobile operators to optimize service offerings, provide personalized recommendations, and drive strategic marketing initiatives. By harnessing these data-driven insights, operators can anticipate customer needs, enhance service bundles, and ultimately boost customer engagement and revenue growth. This study underscored the untapped potential of Market Basket Analysis in the mobile telecommunications sector, paving the way for further exploration of data-driven strategies to optimize operations and enhance the customer experience.

Keywords: *Association rule mining, Confidence, Lift, Market Basket Analysis, Support*

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INTRODUCTION

Understanding customer's purchasing behavior and the associations between items is crucial for improving profits and minimizing losses in the mobile telecommunications sector (Sinha, 2021). This study focuses on Market Basket Analysis (MBA) data using the Apriori algorithm to identify frequently co-occurring mobile operator services. Past efforts have explored similar analyses (Darmaastawan *et al.*, 2020; Ghous *et al.*, 2023; Kayalvily *et al.*, 2020; Pathan *et al.*, 2019; Qisman *et al.*, 2021; Sinha, 2021) demonstrating the potential for promotions in one category to influence the sales of complementary services.

Association rule mining, a key technique in market basket analysis, establishes relationships between items in a dataset. The process involves two main phases: 'Frequent Item Generation,' which identifies item sets satisfying a minimum support threshold, and 'Rule Generation,' which extracts high-confidence rules from the frequent item sets (Arcos & Hernandez, 2019; Darmaastawan et al., 2020; Sinha, 2021). Additionally, the strength of relationships is assessed using lift, indicating whether associations are positive or negative (Abdulsalam *et al.*, 2014; Darmaastawan *et al.*, 2020).

Mathematically, the association rule mining process is represented as:

$$\text{Support, } s\ (X \Rightarrow Y) = P(X \cap Y)/N \quad (1)$$

$$\text{Confidence, } c\ (X \Rightarrow Y) = P(X \cap Y)/P(X) \quad (2)$$

$$\text{Lift} = \text{Confidence, } c\ (X \Rightarrow Y)/\ \text{Support}\ (Y) \quad (3)$$

Where; N represents total number of transactions in a database over a given period; $P(X \cap Y)$ represents number of transactions where X and Y are transitioned together; P(X) represents total number of transactions where item X is involved (Ghous *et al.*, 2023; Kayalvily *et al.,* 2020; Sinha, 2021; Pathan *et al.*, 2019; Qisman *et al.*, 2021).

This study employs MBA to determine the frequencies of questionnaire items that customers respond together, aiming to identify patterns that can be used by operators to improve services.

EMPIRICAL REVIEW

MBA served as a fundamental tool in this study, aimed at uncovering interrelated responses within customer questionnaires. As a methodological framework, MBA plays a pivotal role in determining the co-occurrence frequencies of distinct survey items, highlighting instances where one response may trigger others beyond a predefined threshold. The primary objective is to engage service operators by identifying significant response patterns, indicating potential areas of improvement in service provision.

Expanding upon this methodology, a confluence of diverse studies underscores the versatility and practicality of MBA across various domains. For instance, (Qisman *et al*., 2021) conducted a study to discern purchasing patterns at the Cirebon Computer Mizan Retail Store. Their findings revealed a confidence level of 100% for associations such as Joystick, Laptop => Mouse, and Laptop Charger => Keyboard, with lift ratio values of 2.17 and 3.39, respectively. This suggests that if a consumer purchases a Laptop Charger, they are highly likely to also purchase a keyboard, and similarly, if a consumer buys a Joystick and a laptop, they are highly likely to purchase a mouse.

In a similar vein, (Darmaastawan *et al*., 2020) employed MBA to investigate consumer behavior, finding that customers who purchased Tigers Base Grey had a 100% likelihood of buying Tribal Green, with Tribal Green emerging as the most frequently purchased item.

(Putra *et al*., 2018) conducted a study involving fifty transactions to identify frequent item sets in a minimarket, utilizing the Apriori algorithm. Their analysis revealed that Bread and Jam exhibited the best support and confidence combination, with 10% and 100%, respectively, closely followed by Soy Sauce and ABC Tomato Sauce, with support and confidence values of 10% and 71%, respectively. Rice Flour and Wheat Flour also demonstrated significant support and confidence at 6% and 100%, respectively.

Furthermore, (Ruswati *et al.*, 2018) utilized association analysis and Apriori algorithms in a study involving a small-medium enterprise in the building materials sector. Analyzing 1.302 transaction records, their research unveiled several association rules, such as the likelihood of customers purchasing "sand" alongside "faucets" and "cement," or "cement" alongside "glue isarplas."

These findings shed light on potential purchasing behaviors within the building materials market, informing strategic decision-making for businesses in this sector.

These studies collectively underscore the utility of MBA in uncovering hidden patterns and associations within transaction data across various industries, offering valuable insights for optimizing operations and enhancing customer experiences.

METHODOLOGY

Area of Study

This study focused on mobile telecommunication services in Tanzania. The decision to select Tanzania as the study area was based on its vibrant mobile telecommunications market and diverse range of services offered by operators in the country. The choice of Tanzania ensures access to ample data for comprehensive analysis and insights into customer behavior and service usage patterns within the mobile telecommunications sector.

Study Population

University students were selected as the study population due to their:

- High mobile phone usage: The demographic characterized by high mobile phone usage represents a population segment that heavily relies on mobile services. Consequently, their perceptions and preferences hold substantial importance in the context of service optimization within the mobile telecommunications industry (Jones *et al.*, 2010).
- Understudied demographic: Compared to other customer segments, university students mobile service experiences have received less attention (Jaradat, 2010).
- Accessibility: Access to university students through existing networks facilitated recruitment and data collection.

Sample of the Study

A convenience sampling method was employed to select 500 university students from eight universities across Tanzania. The sample size determination was based on statistical considerations to ensure adequate power for the analysis.

Justification of Sample Size: To determine the sample size, a power analysis was conducted using a priori calculations. Considering the anticipated effect size and variability based on similar studies in the literature, a sample size of 500 was deemed necessary to provide sufficient statistical power at a confidence level of 95% and a margin of error of 5%.

The formula for sample size calculation for proportions $n= Z^2p(1−p)/E^2$, was utilized, where:

n = required sample size

Z = Z-score corresponding to the desired confidence level

p = anticipated proportion of the population with the characteristic of interest

E = margin of error

Considering a conservative estimate of 50% for the proportion of the population with the characteristic of interest and a Z-score of 1.96 for a 95% confidence level, the calculated sample size was 384. To account for potential non-response or incomplete surveys, the sample size was increased to 500 to ensure robustness and reliability of the findings.

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This scientifically determined sample size provides adequate power to detect meaningful associations between mobile service aspects, enhancing the validity and generalizability of the study's results.

Data Collection

The data collection process was meticulously designed to capture a comprehensive understanding of respondent's perceptions and experiences with mobile operator services in Tanzania. A self-administered questionnaire served as the primary instrument, carefully constructed to address key aspects relevant to the study's objectives.

Questionnaire Composition

1. **Likers -scale Questions:**
   - The questionnaire incorporated Likers-scale questions, strategically formulated to assess respondents' perceptions across critical dimensions of mobile operator services. Each question aimed to solicit specific feedback on various aspects such as complaint resolution, service reliability, network coverage, problem-solving efficiency, service experience, and switching costs.
   - For instance, respondents were asked to indicate their level of agreement with statements such as "The mobile operator promptly addresses my complaints" and "I perceive the network coverage provided by the operator as reliable."
2. **Open-ended Prompts:**
   - In addition to Likers-scale questions, the questionnaire included open-ended prompts designed to capture qualitative insights and nuanced perspectives from respondents. These prompts encouraged participants to elaborate on their experiences, articulate specific challenges or satisfactions, and offer suggestions for service enhancement.
   - Examples of open-ended prompts included inquiries such as "Please describe any difficulties you have encountered with the mobile operator's services," "What aspects of the mobile operator's services do you find most commendable?" and "How do you envision the operator could improve its service offerings?"

Intention of the Questionnaire: The questionnaire was meticulously crafted with the overarching aim of gaining a holistic understanding of respondent's perceptions, preferences, and encounters with mobile operator services. By combining quantitative ratings through Likers-scale questions with qualitative insights from open-ended prompts, the questionnaire sought to uncover multifaceted insights into various service dimensions. Ultimately, these insights aimed to inform strategic recommendations for optimizing mobile operator services and enhancing the overall customer experience.

Data Analysis

MBA with Apriori Algorithm

We employed the Apriori algorithm, a well-established technique in MBA, to uncover frequent service sets within the collected data. This involved the following steps:

Data Preparation: The questionnaire responses were converted into (csv) a suitable format for analysis, ensuring consistent data representation and handling missing values appropriately.

Minimum Support Threshold: We defined a minimum support threshold (0.35) based on empirical considerations and the research objective. This threshold determined the minimum frequency of service co-occurrence for a set to be considered frequent.

Frequent Item set Generation: The Apriori algorithm iteratively identified service sets that met the minimum support threshold. This process involved generating candidate sets and pruning infrequent ones based on their support values.

Association Rule Mining: For each frequent item set, association rules were generated, expressing the relationship between the set and individual services within it. These rules were evaluated based on support, confidence, and lift, which provided insights into the strength and direction of associations between service aspects.

Analysis of Open-ended Responses:
Thematic analysis was conducted on the collected open-ended responses to identify recurring themes and patterns. This involved:

Coding: Responses were carefully coded based on emerging themes and relevant categories aligned with the study's objectives.

Theme Identification: Through an iterative process, key themes and sub-themes were identified, reflecting the main areas of concern, satisfaction, and suggestions expressed by respondents.

Integration with Quantitative Findings: The qualitative insights from the thematic analysis were triangulated with the quantitative findings from the MBA to provide a more comprehensive understanding of customer perceptions and service interdependencies.

This combined approach, utilizing both MBA with the Apriori algorithm and thematic analysis of open-ended responses, allowed us to capture both the quantitative patterns of service co-occurrence and the qualitative experiences and perspectives of mobile operator customers. This triangulation of quantitative and qualitative data provided a richer and more nuanced understanding of the research problem, enabling us to move beyond simply identifying frequent service combinations to uncovering the underlying reasons behind these associations and their implications for mobile operator service optimization.

FINDINGS

Tables that follow shows the top ten support values obtained for service for provider with minimum support set at 0.35.

Table 1: Support for service sets under operator

SUPPORT	SERVICESET
0.654	(FREE_COMPLAINTS)
0.586	(DO_WHAT_THEY_SAY)
0.504	(WIDE_COVERAGE)
0.476	(GET_THROUGH)
0.468	(PROBLEM_SOLVING)
0.448	(DO_WHAT_THEY_SAY, FREE_COMPLAINTS)
0.442	(TIMELY_EFFECTIVE_COMPLAINTS)
0.392	(EXCEPTIONAL_SERVICE_EXPERIENCE)
0.364	(HIGH_SWITCHING_COST)
0.360	(GET_THROUGH, FREE_COMPLAINNTS)

FREE_COMPLAINTS achieved the highest support above 65%. This implies that more than 65% of all the responses involve a customer response of ‘A’ or ‘SA’. Likewise other services achieving high support were DO_WHAT_THEY_SAY, WIDE_COVERAGE and GET_THROUGH.

Tables that follow shows the top support, confidence and lift values obtained for each service in ascending lift order with minimum threshold set at 0.30.

Table 2: Support, confidence and lift values

ANTECEDENTS	CONSEQUENTS	CONSEQUENTS SUPPORT	CONFIDENCE	LIFT
(Problem_solving)	(Do_what_they_say)	0.586	0.765	1.31
(Do_what_they_say)	(Free_complaints)	0.654	0.765	1.17
(Get_through)	(Free_complaints)	0.654	0.756	1.16
(Wide_coverage)	(Free_complaints)	0.654	0.718	1.10

Association Rule 1: (Problem_solving) and (Do_what_they_say)

Support: 58.6%

Confidence: 76.5%

Lift: 1.31

Interpretation:

This rule means that 58.6% of customers who agree that their problems are solved by their service providers (Problem_solving) also agree that their service provider do what they promise to do (Do_what_they_say) and that 76.5% of customers who agree to (Do_what_they_say) are also likely to agree on (Problem_solving) with strong association of 1.31.

Association Rule 2: (Do_what_they_say) and (Free_complaints)

Support: 65.4%

Confidence: 76.5%

Lift: 1.17

Interpretation:

This rule means that 65.4% of customers who agree that their service providers do what they promise to do (Do_what_they_say) also agree that they receive free complaints (Free_complaints) and that 76.5% of customers who agree to receive free complaints (Free_complaints) are also likely to agree on (Do_what_they_say) with strong association of 1.17.

Association Rule 3: (Get_through) and (Free_complaints)

Support: 65.4%

Confidence: 75.6%

Lift: 1.16

Interpretation:

This rule means that 65.4% of customers who agree that they are able to get through on time whenever they contact their providers (Get_through) also agreed that they receive free complaints from their providers (Free_complaints) and that 75.6% of customers who agree to (Free_complaints) are also likely to agree to (Get_through)with strong association of 1.16.

Association Rule 4: (Wide_coverage) and (Free_complaints)

Support: 65.4%

Confidence: 71.8%

Lift: 1.10

Interpretation:

This rule means that 65.4% of customers who agree to receive wide coverage from their operator (Wide_coverage) also agreed to receive free complaints from their providers (Free_complaints) and that 71.8% of customers who agreed on (Free_complaints) are also likely to agree on (Wide_coverage)with strong association of 1.10.

The Frequent service sets revealed strong associations between several service aspects, including:

- Free complaints and reliability (Do-what-they-say, Get-through): Customers who perceive their complaints being handled effectively also value timely call connection and service reliability.
- Problem-solving and service delivery: Customers who experience effective problem resolution tend to associate it with reliable service delivery (Do-what-they-say)

By considering Customer Feedback, An Open-ended responses highlighted several areas for service improvement:

- Lack of awareness regarding free complaint channels: Many respondents were unaware of available free complaint options, suggesting a need for increased customer education.
- Difficulties accessing specific services: Some services, like PIN number requests or suspension reactivations, were perceived as inconvenient or not entirely free, requiring operator to clarify service terms and conditions.

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DISCUSSION AND RECOMMENDATIONS

This study illuminated the interconnectedness of various mobile service aspects in shaping customer perceptions and experiences. By leveraging data analysis techniques such as the Apriori algorithm, operators can derive actionable insights to enhance service delivery and customer satisfaction.

Prioritizing Service Improvements: The identification of frequent service sets through the Apriori algorithm enables operators to prioritize improvements in key service aspects such as complaint handling, reliability, and problem-solving. These aspects often co-occur in customer responses, suggesting a significant opportunity for enhancing overall satisfaction.

Strengthening Service Bundling and Marketing: Understanding the associations between different service features allows operators to develop targeted service bundles and promotional campaigns that align with specific customer needs and preferences. Operators can tailor their offerings more effectively, thereby enhancing customer engagement and loyalty.

Enhancing Customer Education: By improving awareness of free complaint channels and service terms, operators can enhance customer understanding and reduce frustration, leading to improved overall satisfaction and retention rates.

Limitations and Future Research

Data Limitations: Privacy concerns may have restricted access to certain customer data, necessitating reliance on self-reported data. Future research could explore ways to overcome these limitations, such as implementing more robust data collection methods or leveraging advanced privacy-preserving techniques in data analysis.

Generalizability: While this study focused on a specific operator and geographic location, the findings may not be directly generalizable to other operators or regions. Future research could involve multi-operator studies across diverse geographic locations to enhance the generalizability of findings and uncover broader industry trends.

Sample Size and Diversity: Expanding the sample size and including diverse customer segments could provide deeper insights into mobile service preferences and behaviors. By incorporating more diverse demographic groups, future research can strengthen the robustness and applicability of findings, thereby contributing to a more comprehensive understanding of customer needs in the mobile telecommunications sector.

CONCLUSION

In conclusion, the use of Apriori algorithm in ML holds promise for optimizing mobile operator services and enhancing the overall customer experience. By leveraging these techniques to uncover hidden patterns and associations in customer data, operators can make informed decisions that drive customer satisfaction, loyalty, and business success.

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DECLARATIONS

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

Availability of data and materials

The dataset analyzed during the current study is available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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