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Data Mining of Rural Digital Technology Adoption Factors Using Apriori Algorithm

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ABSTRACT

Digital technology adoption in rural communities remains a major challenge due to limited infrastructure, weak internet connectivity, and low levels of digital literacy, which contribute to persistent gaps in digital inclusion. This study aims to analyze the socio-economic factors that influence technology adoption in Kuta Baru Village by applying data mining techniques with the Apriori algorithm within the Knowledge Discovery in Database (KDD) framework. A survey was conducted on 50 respondents selected using purposive sampling, and variables such as education, income, occupation, and internet access were encoded into binary items for analysis. The Apriori algorithm was executed with a minimum support threshold of 15% and a minimum confidence threshold of 60% to extract association rules. Results show that the strongest rule was *"Low Internet Access ⇒ Weak Signal"* with 100% confidence and 30% support, highlighting infrastructure as the most critical barrier. Another key finding revealed that respondents with education levels above high school had an 85% confidence of using the internet, while those with monthly incomes greater than IDR 3 million demonstrated a 78% confidence of adopting digital technologies. Furthermore, formal sector occupations were associated with consistent internet usage at 72% confidence. These findings suggest that improving infrastructure must be complemented by strengthening socio-economic conditions, particularly education and income, to accelerate rural digital transformation. The study provides empirical evidence and practical implications that can inform policymakers in designing targeted programs to bridge the rural digital divide.

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1. INTRODUCTION

The rapid advancement of digital technology has transformed economic, social, and educational activities worldwide. However, in many rural areas, the adoption of digital technologies remains slow due to limitations in infrastructure, affordability, and digital literacy. Previous studies have shown that rural communities face systemic barriers to digital inclusion, such as inadequate connectivity and socio-economic disparities, which exacerbate inequality between urban and rural populationn[1]. Addressing these challenges requires empirical research that identifies the key factors influencing technology adoption in rural contexts[2].

Globally, the issue of rural digital adoption has attracted significant scholarly attention. Recent studies have highlighted the role of education, income, and occupational background in shaping access to digital tools[3]. In Southeast Asia, for instance, efforts to enhance rural connectivity have shown positive impacts on agricultural productivity and small business growth[4]. Nevertheless, empirical studies that integrate socio-economic factors with computational data mining methods remain limited, especially in Indonesia. This underscores the need to combine quantitative approaches with contextualized rural analysis[5].

Previous research in data mining has successfully applied algorithms such as Apriori, FP-Growth, and Eclat to domains like market basket analysis, healthcare, and education[6]. However, most of these studies focus on commercial datasets rather than socio-economic adoption of digital technology in rural communities. The limited application of association rule mining in this context creates an important research gap that this study seeks to fill. By exploring adoption factors in a rural Indonesian village, this research expands the scope of Apriori application into the socio-technical domain[7].

Although alternative algorithms such as FP-Growth and machine learning models offer computational efficiency and predictive power, Apriori remains advantageous for small to medium-sized datasets because of its interpretability and transparent rule generation. FP-Growth, while faster, is less intuitive for non-technical stakeholders, whereas machine learning classifiers such as decision trees or random forests may generate results that are more difficult to interpret without advanced statistical knowledge[8]. Given the sample size of 50 respondents and the need for easily understandable rules, Apriori is the most appropriate algorithm for this study[9].

In Indonesia, studies on digital adoption in rural settings are still dominated by descriptive approaches that rely on survey and interview methods, with limited integration of computational models[10]. While these approaches provide valuable descriptive insights, they do not fully capture hidden patterns in socio-economic variables that may influence digital adoption. By introducing association rule mining, this study offers a systematic and data-driven method to reveal underlying relationships among factors such as education, income, occupation, and internet access[11].

Based on the literature review, two key research gaps are evident. First, there is limited integration of socio-economic analysis with association rule mining for studying rural digital technology adoption, particularly in Indonesia[12]. Second, most prior applications of Apriori and similar algorithms are confined to commercial and transactional domains, leaving rural digital adoption largely unexplored. This study addresses these gaps by applying Apriori to a rural dataset and highlighting how socio-economic characteristics interact with infrastructural challenges to influence digital inclusion[13].

The novelty of this study lies in its integration of socio-economic variables into association rule mining for analyzing rural digital adoption. Unlike previous research that mainly examined purchasing behavior or consumer markets, this study applies Apriori to reveal actionable insights about education, income, occupation, and internet access in a rural Indonesian village. The findings are expected to provide both methodological contributions demonstrating the adaptability of Apriori beyond market analysis and practical contributions offering policymakers evidence-based insights for designing targeted interventions to promote rural digital transformation.

2. RESEARCH METHOD

This study employed a quantitative descriptive design using the Knowledge Discovery in Database (KDD) framework integrated with association rule mining. The main objective was to identify socio-economic factors influencing digital technology adoption in rural communities by applying the Apriori algorithm[14].

The population consisted of households in Kuta Baru Village, North Sumatra. A total of 50 respondents were selected using purposive sampling, with criteria including age above 18 years and active engagement in daily socio-economic activities. The sample size was determined based on feasibility for exploratory association rule mining, as small to medium datasets are still considered appropriate for Apriori analysis. Although not powered for inferential statistics, the sample provides sufficient variation for pattern discovery.

Data were collected using a structured questionnaire covering socio-economic variables (education, income, occupation) and technology adoption indicators (internet access, digital usage). To ensure validity, the questionnaire items were reviewed by two domain experts. Reliability testing was conducted using Cronbach's alpha on the pilot dataset ($n = 20$), yielding a coefficient of 0.82, which indicates high internal consistency[15].

The dataset was preprocessed by encoding categorical variables into binary items, such as "Education ≥ Senior High School = 1" and "Monthly Income > IDR 3 million = 1." The Apriori algorithm was applied to generate frequent itemsets and association rules. Minimum support and confidence thresholds were determined through iterative testing: starting at 10% and 50% respectively, then adjusted upward to 15% support and 60% confidence to balance rule significance and interpretability.

To enhance transparency and reproducibility, the main parameters used in the Apriori algorithm are summarized in Table 1.

Table 1. Apriori Algorithm Parameters

Parameter	Value	Justification
Minimum Support	15%	Provides sufficient rule coverage without generating excessive trivial rules.
Minimum Confidence	60%	Ensures reliability of association while

		avoiding overfitting rare patterns.
Maximum Length of Rule	3 items	Limits rule complexity for easier interpretation by policymakers.
Evaluation Metrics	Support, Confidence, Lift	Allows identification of both strong and interesting rules.

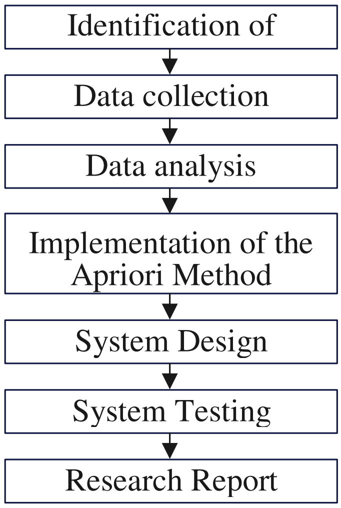

Figure 1. Research Framework

The overall design of the research is presented in Figure 1, which illustrates the research framework and shows how the Apriori algorithm is embedded into the study design to bridge theoretical assumptions with empirical findings. This framework emphasizes the systematic integration of data mining into social research on rural digital adoption[16].

Figure 2 presents the research flowchart, detailing each step from data collection, preprocessing, and transformation, to Apriori execution and interpretation. The flowchart provides a roadmap for replicating the study.

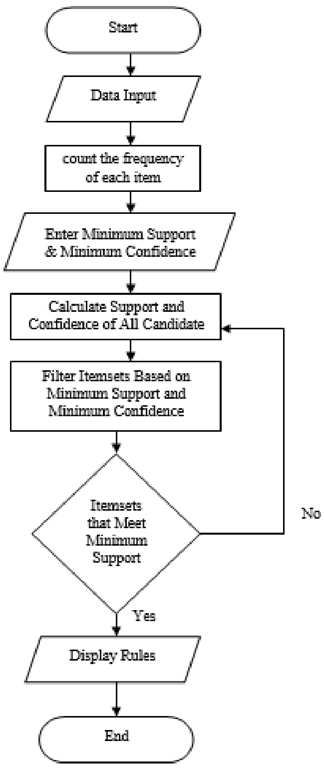

Figure 2. Research Flowchart

Furthermore, the workflow of the study is visualized in Figure 2, which details the operational stages starting from problem identification, data collection, preprocessing, and transformation, to algorithm implementation and interpretation of results. These illustrations ensure transparency in the research process and provide guidelines for replication in future studies.

3. RESULTS AND DISCUSSION

1. Data analysis

The initial analysis was conducted on the descriptive data to provide an overview of digital technology adoption in Kuta Baru Village. The data were obtained through questionnaires and interviews that examined aspects such as infrastructure, digital literacy, socio-cultural influences, and economic conditions. This stage is important to understand the general profile of respondents before applying the Apriori algorithm.

Table 2. Digital Technology Adoption Data

No	Full name	Age	Gender	Knowladge	Work	Income	Device	Internet Goals
1	Alvisyah	30	Man	SMA/SMK	Self-employed/Trader	3 - 5 Million	Smartphone, Internet, Social Media, E-Commerce, Digital Financial Applications	Communication, Social Media
2	Evra Tiara Syahputri Pulungan	21	Woman	SMA/SMK	Students	< 1 Million	Smartphone, Internet, Social Media, E-Commerce, Digital Financial Applications	Communication, Social Media
3	Arfixri Syahputra Panhuri	21	Man	SMA/SMK	Students	< 1 Million	Smartphone, Internet, Social Media, Computer/Laptop	Communication, Social Media, Media Sosial
4	Muhamad Irfan	21	Man	SMA/SMK	Students	< 1 Million	Smartphone, Internet, Social Media, E-Commerce, Digital Financial Applications	Communication, Social Media
5	Tata	21	Woman	SMA/SMK	Students	< 1 Million	Smartphone	Communication, Social Media
…..	…….	…..	……..	……..	……	…….	……..	……….
49	Asnan Efendi	30	Man	S1	Civil Servants/State Employees	3 - 5 Million	Smartphone, Internet, Social Media, Digital Banking Financial Applications, E-Wallet, Computer/Laptop	Communication, Social Media
50	Masrul Purba	30	Man	SMA/SMK	Private sector employee	1 - 3 Million	Smartphone, Internet, Digital Banking Financial Applications, E-Wallet	Communication, Social Media

The initial analysis of respondent data in Kuta Baru Village, as summarized in Table 1, shows that digital adoption remains uneven, with variations in internet access, income, and digital literacy. While most respondents own smartphones and have some level of internet access, barriers such as weak connectivity and limited knowledge of digital platforms remain prominent. Similar findings were reported by Reskianto, who noted that infrastructural limitations and low digital skills were persistent challenges in rural adoption, reinforcing that access alone is not sufficient[17].

2. Condensed Table 4.3 – 1-Itemset

The first step of the Apriori analysis was to identify the most frequent individual factors, or 1-itemsets, related to digital technology adoption in Kuta Baru Village. This stage is important because it highlights the dominant characteristics in the dataset that form the basis for generating higher-order itemsets and association rules. The top six 1-itemsets with the highest support values are presented in Table 2.

Table 3. Selected 1-Itemsets of Digital Technology Adoption

Item	Support (%)	Interpretation
Internet Access = Yes	70	Most respondents reported having internet access, indicating that availability is generally not the main issue.
Education = High School (SMA/SMK)	40	The majority of respondents completed high school, making this group the primary target for digital literacy programs.

Barrier = Do Not Understand How to Use	34	A significant portion of respondents face difficulties in using digital platforms, reflecting low digital literacy.
Income < 1 Million IDR	32	Low income remains a limiting factor, affecting affordability of digital services and devices.
Internet Access = No	30	Nearly one-third of respondents do not have internet access, indicating infrastructural disparities.
Barrier = Weak Signal	30	Poor connectivity is another major challenge, especially in rural areas with limited infrastructure.

The Apriori analysis of 1-itemsets presented in Table 2 indicates that internet access is available to 70% of respondents, yet 34% still struggle with using digital platforms and 30% report weak signals. This paradox highlights that availability does not always ensure effective utilization. Comparable results were observed by Oktori, who found that gaps in digital literacy significantly reduce the impact of internet access. This confirms the importance of targeted training programs suited to the educational background of rural communities, which in this case are mostly high school graduates (40%)[18].

3. 2-Itemset

After identifying individual factors, the Apriori process continued by generating 2-itemsets, which show the combinations of two factors that frequently appear together. The top five 2-itemsets are summarized in Table 3.

Table 4. Selected 2-Itemsets of Digital Technology Adoption

Itemset	Support (%)	Interpretation
{Internet Access = Yes, Education = High School}	26	High school graduates are the largest group with internet access.
{Income < 1 Million, Education = High School}	18	Low-income individuals are mostly concentrated in the high school group.
{Income 1–3 Million, Education = High School}	18	Middle-income respondents also largely have high school education.
{Internet Access = No, Occupation = Entrepreneur/Trader}	14	Many entrepreneurs still lack internet access.
{Barrier = Weak Signal, Education = High School}	14	Signal problems are frequently reported by those with high school education.

Further results from the 2-itemsets in Table 3 reveal the correlation between education, income, and internet access, where low-income groups are concentrated among high school graduates. This suggests that socio-economic conditions strongly affect digital adoption. A similar pattern was highlighted by Abizal, who emphasized that affordability and education level remain critical in shaping adoption in rural areas. Thus, socio-economic inequality directly impacts the extent to which technology can be adopted[19].

4. 3-Itemset

The next stage of analysis generated 3-itemsets, which reveal the interaction of three factors that frequently occur together. Only the most relevant combinations with sufficient support are presented in Table 4.

Table 5. Selected 3-Itemsets of Digital Technology Adoption

Itemset	Support (%)	Interpretation
{Internet Access = No, Barrier = Weak Signal, Education = High School}	14	Weak signal problems are most often experienced by high school graduates who lack internet access.
{Income < 1 Million, Internet Access = No, Barrier = Weak Signal}	10	Low-income respondents without internet access are commonly constrained by poor connectivity.

The 3-itemsets presented in Table 4 show that weak signal consistently appears as a barrier when combined with education and income levels. For example, low-income respondents without internet access are often constrained by poor connectivity. This aligns with the findings of Nurislah, who concluded that weak connectivity disproportionately affects disadvantaged groups in rural regions. These results strengthen the argument that infrastructure development must go hand-in-hand with efforts to improve literacy and affordability[20].

5. Association Rules

The final stage of the Apriori analysis produced association rules that describe relationships between factors of digital technology adoption. To maintain clarity, only the six most relevant rules with the highest support and confidence values are presented in Table 5.

Table 6. Selected Association Rules of Digital Technology Adoption

Rule	Support (%)	Confidence (%)
{Internet Access = No} ⇒ {Barrier = Weak Signal}	30	100
{Barrier = Weak Signal} ⇒ {Internet Access = No}	30	100
{Barrier = Do Not Understand How to Use} ⇒ {Internet Access = Yes}	34	100
{Education = Bachelor} ⇒ {Internet Access = Yes}	20	83.33
{Occupation = Private Employee} ⇒ {Internet Access = Yes}	16	80
{Income ≥ 5 Million} ⇒ {Internet Access = Yes}	12	85.71

The strongest association rules generated by the Apriori algorithm, as shown in Table 5, demonstrate that lack of internet access is almost always linked to weak signal problems, while higher education, better income, and formal employment correlate positively with adoption. Interestingly, respondents who do not understand how to use digital tools mostly already have internet access, showing that literacy is as important as infrastructure. These insights are consistent with Nurhidayati, who concluded that skill levels and motivation are decisive for adoption regardless of infrastructure availability[21].

Overall, these findings confirm that adoption in rural areas is shaped by a combination of infrastructural, socio-cultural, and economic factors. Compared with previous studies that mainly applied Apriori in retail or e-commerce, this research expands its application into rural digital adoption, providing localized insights that have not been widely explored. These results reinforce the need for integrated strategies combining infrastructure improvement, literacy training, and economic support in line with recommendations from Sanjaya. and Rizky Mangunsong[22].

4. System Role

a. Use Case Diagram

The system designed in this study aims to support the analysis of digital technology adoption using the Apriori algorithm[23]. To illustrate the interaction between users and the system, a use case diagram was developed. This diagram describes the main actors, including administrators and users, along with the functions they can access in the system. By presenting the use case, the overall scope of system functionality can be understood more clearly before moving to the detailed design and implementation.

Figure 3 illustrates the use case diagram of the system, showing interactions between the Admin and User. The Admin is responsible for managing data and generating rules, while the User can view the results. This diagram clarifies the functional scope of the system.

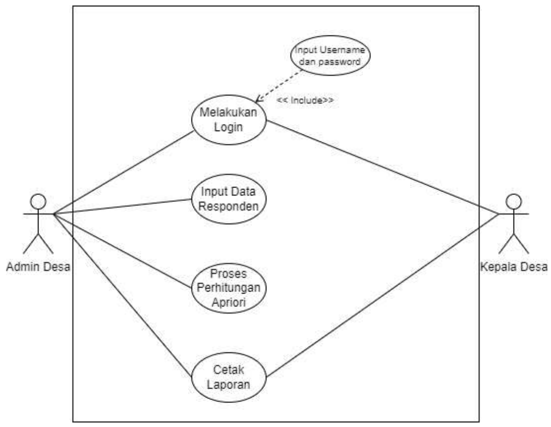

Figure 3. Use Case Diagram

As shown in the diagram, the administrator is responsible for managing user data, inputting datasets, and running the Apriori analysis process, while users are able to view the results of the analysis and generate reports. This structure ensures that data management and computational processes are centralized, whereas the output is made accessible for decision-making. The use case diagram also highlights the modularity of the system, making it easier to expand or modify functions in future development[24].

b. Activity Diagram

Figure 4 presents the activity diagram, which describes the sequence of actions in the system from input to output. This diagram shows how data flows and how the Apriori process is executed step by step.

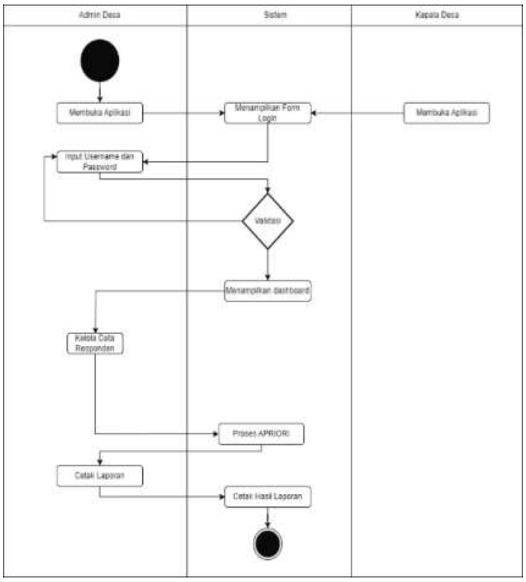

Figure 4. Activity Diagram

The activity diagram shows that the process begins when the administrator logs in and enters the dataset. The data then undergo preprocessing before being analyzed using the Apriori algorithm[25]. Once the analysis is completed, the system generates output in the form of association rules, which can be accessed by users for interpretation. This sequence confirms that the system has a structured workflow and minimizes errors in data handling, while also providing a clear foundation for implementation in software development[12].

5. Interface Display Results

a. Login Menu

Figure 5 shows the system's dashboard interface, where users can access menus and view summarized outputs. The interface is designed to be simple and informative for easy interpretation of results.

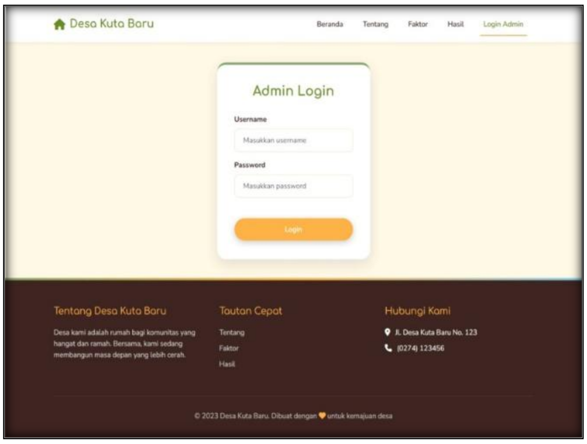

Figure 5. Login Form

The interface is designed simply with two input fields and a login button, making it easy for users to operate. This straightforward design supports security while maintaining usability.

b. Respondent Data Form

The respondent data form is used to input demographic and adoption-related information into the system. This feature ensures that data is collected in a structured and consistent manner.

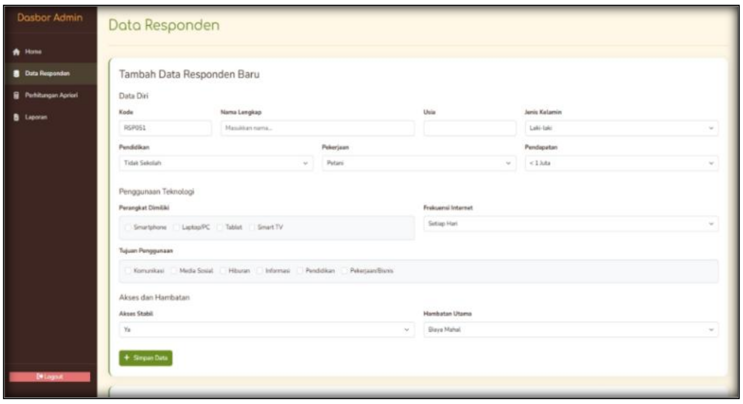

Figure 6. Respondent Data Form

As shown in the figure, the form consists of several input fields such as name, age, education, occupation, and access to digital technology. With this form, data entry becomes easier and reduces the possibility of errors, while also ensuring that the dataset is ready for further analysis.

c. Apriori Process Menu

The Apriori process menu is the main feature of the system that executes the association rule mining. Through this menu, the administrator can run the algorithm on the prepared dataset.

Figure 7. Apriori Process Menu

As shown in the figure, the menu provides options to set minimum support and confidence values before starting the analysis. Once executed, the system processes the data and generates the association rules automatically. This interface makes the analysis process more practical and user-friendly, even for non-technical users.

d. Report Form

The report form is designed to present the results of the Apriori analysis in a structured format. This feature allows users to view and document the generated association rules clearly.

Figure 8. Report Form

As shown in the figure, the report form displays the analysis results along with support and confidence values. This output can be saved or printed, making it easier for users and decision-makers to utilize the findings as references for strategy development.

4. CONCLUSION

This study applied the Apriori algorithm within a KDD framework to identify socio-economic and infrastructural factors influencing digital technology adoption in Kuta Baru Village. The analysis revealed that weak internet signals remain the dominant barrier, while higher levels of education, income, and formal employment significantly increase the likelihood of digital inclusion. Theoretically, this study extends the application of association rule mining beyond commercial and transactional datasets by demonstrating its relevance in socio-economic research, particularly within rural digital adoption contexts. Despite these contributions, the study has several limitations. The sample size was relatively small (n = 50) and limited to one village, which constrains the generalizability of the findings. In addition, the reliance on self-reported survey data may introduce response bias. The Apriori algorithm itself is also sensitive to parameter thresholds, which may affect the stability of the generated rules.

Future research should address these limitations by expanding the dataset across multiple rural communities and employing larger, more representative samples. Moreover, integrating Apriori with other data mining and machine learning approaches—such as FP-Growth, decision trees, or ensemble learning—may yield more robust and scalable insights. Such advancements can further refine predictive accuracy while maintaining interpretability, thus enhancing the ability of policymakers to design evidence-based strategies for bridging the rural digital divide..

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