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Apriori and FP-Growth Comparative Analysis of MPL Indonesia Season 13 Hero Drafts

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ABSTRACT *– Hero combination selection or drafting is a crucial factor in determining victory in Mobile Legends: Bang Bang (MLBB) games at the professional level such as MPL Indonesia Season 13. However, counter-pick strategies are often based solely on the subjective intuition of players or coaches. This study aims to provide an objective basis for determining winning hero combination patterns by applying the Association Rule Mining (ARM) technique. Two main algorithms, namely Apriori and Frequent Pattern Growth (FP-Growth), are compared to evaluate the performance efficiency and accuracy of the resulting rules. The research data includes 183 winning transactions during the regular season of MPL ID Season 13, with parameters of minimum support 0.05 (5%), minimum confidence 0.40 (40%), and minimum lift 1.2. The results show that the strongest association rules are found in the combinations {Lapu-lapu} → {Fredrinn} (confidence 0.71) and {Cici} → {Fredrinn} (confidence 0.59). In terms of technical performance, the Apriori algorithm recorded a faster execution time than FP-Growth on this dataset. This study concluded that both algorithms produce identical association rule outputs, while Apriori demonstrated faster execution on this small-scale dataset, a finding attributed to the limited transaction volume rather than a universal superiority of Apriori over FP-Growth. The resulting rules can serve as a data-driven strategic recommendation system for professional esports teams in the pick and ban phase.*

Keywords *- Association Rule Mining, Apriori, FP-Growth, MPL Indonesia, Winning Patterns.*

Analisis Perbandingan Apriori dan FP-Growth terhadap Pilihan Hero di MPL Indonesia Musim ke-13

ABSTRAK *– Pemilihan kombinasi hero atau drafting merupakan faktor krusial dalam menentukan kemenangan pada pertandingan Mobile Legends: Bang Bang (MLBB) di level profesional seperti MPL Indonesia Musim ke-13. Namun, strategi counter-pick seringkali hanya didasarkan pada intuisi subjektif para pemain atau pelatih. Penelitian ini bertujuan untuk memberikan landasan objektif dalam menentukan pola kombinasi hero pemenang dengan menerapkan teknik Association Rule Mining (ARM). Dua algoritma utama, yaitu Apriori dan Frequent Pattern Growth (FP-Growth), dibandingkan untuk mengevaluasi efisiensi kinerja dan akurasi aturan yang dihasilkan. Data penelitian mencakup 183 transaksi kemenangan selama musim reguler MPL ID Season 13, dengan parameter minimum support 0,05 (5%), minimum confidence 0,40 (40%), dan minimum lift 1,2. Hasil menunjukkan bahwa aturan asosiasi terkuat ditemukan pada kombinasi {Lapu-lapu} → {Fredrinn} (confident 0,71) dan {Cici} → {Fredrinn} (confident 0,59). Dari segi kinerja teknis, algoritma Apriori mencatatkan waktu eksekusi yang lebih cepat dibandingkan FP-Growth pada dataset ini. Studi ini menyimpulkan bahwa kedua algoritma menghasilkan output aturan asosiasi yang identik, sementara Apriori menunjukkan eksekusi yang lebih cepat pada dataset berskala kecil ini, temuan yang bersifat spesifik terhadap skala dataset dan tidak dapat digeneralisasi sebagai keunggulan universal Apriori atas FP-Growth. Aturan yang dihasilkan dapat berfungsi sebagai sistem rekomendasi strategis berbasis data bagi tim esports profesional pada fase pemilihan dan larangan hero.*

Kata Kunci *– Association Rule Mining, Apriori, FP-Growth, MPL Indonesia, Pola Kemenangan.*

1. INTRODUCTION

Mobile Online Battle Arena (MOBA) games are one of the most popular genres globally, particularly in Southeast Asia. Mobile Legends: Bang Bang (MLBB), developed by Moonton Technology since 2016, has become one of the most popular mobile MOBA games with over 100 million monthly active users [1]. In Indonesia, the popularity of MLBB has led to the creation of the MPL (Mobile Legends Professional League) Indonesia, which entered its 13th season in 2024 [2].

The hero draft phase, which includes the ban and pick process, is considered one of the most strategic aspects that determine victory before the match even begins. The right hero selection, including the ability to counter-pick, provides a distinct competitive advantage for professional teams [3]. However, draft decisions have largely relied on subjective intuition rather than empirical data analysis.

Association Rule Mining (ARM) is a data mining technique aimed at discovering interesting relationships or recurring patterns within a dataset [4]. ARM has been applied across various domains, ranging from shopping basket analysis to recommendation systems [5]. The two most widely used ARM algorithms are Apriori [6] and FP-Growth [7].

ARM is particularly well-suited for hero drafting analysis compared to other machine learning approaches for several key reasons. First, ARM produces explicit, interpretable if-then rules (e.g., “if Lapu-Lapu is picked, then Fredrinn is likely”) that can be directly communicated to coaches and players without requiring specialized machine learning expertise, unlike black-box models such as deep neural networks [8]. Second, the hero draft context is inherently transactional in nature — each winning game constitutes a transaction and each selected hero constitutes an item — making ARM a semantically natural fit for this domain [4]. Third, classification and deep learning approaches are typically optimized for predictive accuracy on large labeled datasets, whereas ARM is specifically designed to discover co-occurrence patterns in transactional datasets of the scale typical of a single professional league season [5]. Fourth, unlike recommendation systems built on collaborative filtering or supervised learning, ARM derives synergy recommendations directly from observable match outcomes without requiring user profiling or historical preference data, making it robust to the frequent roster and hero pool changes that characterize professional esports [9]. These properties collectively justify ARM as the most appropriate analytical methodology for extracting actionable draft intelligence from MPL Indonesia Season 13 match records [18] [19].

Several previous studies have explored data mining in the context of MOBA games. Alcan et al. [10] compared Apriori and FP-Growth for market basket analysis. Yang et al. [11] developed a real-time victory prediction system for the game Honor of Kings. Shen et al. [8] proposed a deep learning mechanism for the ban-pick phase in MOBA games. However, no study has yet integrated ARM with actual win data from the MPL Indonesia competition [20] .

The novelty of this study lies in: (1) the use of actual win data from 183 MPL ID Season 13 games; (2) a systematic comparison of Apriori and FP-Growth in the context of MOBA esports; and (3) the integration of ARM results into actionable counter-pick recommendations for professional teams.

This study aims to: (1) identify hero association patterns in winning matches from MPL Indonesia Season 13; (2) generate hero counter-pick recommendations based on association rules with a lift value > 1.2; and (3) compare the efficiency and effectiveness of the Apriori and FP-Growth algorithms.

2. LITERATURE REVIEW

2.1 Data Mining and Knowledge Discovery

Data mining is the process of discovering hidden, previously unknown, and potentially useful patterns from large datasets [4]. As a core component of the Knowledge Discovery in Databases (KDD) process, data mining encompasses techniques including classification, clustering, regression, and pattern discovery. The foundational work by Agrawal, Imieliński, and Swami [4] in 1993 established the conceptual basis for mining association rules from large transactional databases. While classification and regression techniques require labeled training data and are oriented toward prediction, pattern mining techniques such as ARM operate on unlabeled transactional data and are oriented toward discovery — a distinction that makes ARM particularly appropriate for exploratory analysis of competitive match records where ground-truth labels beyond win/loss are unavailable. This study leverages data mining principles to transform raw competitive match records from MPL Indonesia Season 13 into actionable strategic intelligence for professional esports teams.

2.2 Association Rule Mining (ARM)

Association Rule Mining (ARM) is a rule-based method for discovering co-occurrence relationships among variables in large datasets [4]. Given a set of transactions T, ARM seeks to identify rules of the form X → Y that satisfy user-specified thresholds of support, confidence, and lift. Support quantifies the proportion of transactions containing both X and Y. Confidence measures the conditional probability that a transaction containing X also contains Y. Lift evaluates whether the co-occurrence of X and Y exceeds what would be expected by chance; a lift value greater than 1.0 confirms a genuine positive association [12]. Kotsiantis and Kanellopoulos [13] highlighted that threshold selection directly governs the quantity and quality of generated rules — a finding that informs the parameter calibration in the present study, where minimum support was set to 0.05 to yield 43 informative itemsets without generating spurious rules. Compared to supervised learning approaches such as classification or deep learning, ARM offers a key advantage in this context: it requires no prior labeling of hero combinations as "good" or "bad," instead deriving synergy patterns directly from observed outcomes. This makes ARM more appropriate than predictive models when the goal is to surface interpretable strategic patterns rather than to maximize classification accuracy.

2.3 The Apriori Algorithm

The Apriori algorithm [6] operates on the anti-monotonicity property: if an itemset is infrequent, all its supersets must also be infrequent. This enables a breadth-first, level-wise search that prunes candidate itemsets early, reducing unnecessary computation. Association rules are subsequently derived from frequent itemsets by testing all antecedent/consequent splits against the minimum confidence threshold. The primary computational bottleneck of Apriori is its repeated full scans of the transaction database — once per level — and the potential generation of a large candidate itemset volume, both of which scale poorly with dataset size and dimensionality [14]. Despite these limitations, Apriori remains widely used as a benchmark due to its conceptual clarity, ease of implementation, and interpretability. Critically, on small-scale datasets such as the 183-transaction MPL Season 13 corpus used in this study, Apriori's linear scanning approach can outperform more complex algorithms due to lower initialization overhead — a point directly validated by the experimental findings in Section 4.5.

2.4 The FP-Growth Algorithm

The FP-Growth algorithm [7] was designed to overcome Apriori's inefficiencies through two key innovations: compressing the transaction database into a compact prefix-tree structure (FP-Tree) in just two database scans, and mining frequent itemsets directly from this tree through a divide-and-conquer strategy, eliminating candidate generation entirely. Zaki [14] demonstrated FP-Growth's superior scalability on high-dimensional datasets with large transaction volumes. Alcan et al. [10] and Srinadh [5] empirically confirmed shorter execution times for FP-Growth on large datasets. However, these performance advantages are contingent on dataset scale: as demonstrated in this study, the memory overhead required to construct the FP-Tree on a small dataset (183 transactions, 75 items) can make FP-Growth slower than Apriori — a nuance underreported in prior comparative literature. This contextual dependency on dataset scale is a central empirical contribution of the present work.

2.5 Mobile Legends: Bang Bang and the MOBA Genre

MOBA games feature two teams of five players who control heroes to destroy the opposing team's base, with a pre-match drafting phase in which teams alternately ban and pick heroes. This drafting phase is widely recognized as a decisive factor in match outcomes [3]. MLBB, developed by Moonton Technology since 2016, is the dominant MOBA title in Southeast Asia and is supported by the MPL Indonesia professional league — the highest level of competitive MLBB play in Indonesia [1]. Unlike PC-based MOBAs such as Dota 2 and League of Legends, which have received considerably more attention in the sports analytics literature, MLBB's mobile platform and distinct hero roster present a unique and underexplored dataset for data mining research. This gap further motivates the present study's focus on MPL Indonesia Season 13.

2.6 Data-Driven Analysis in Esports and MOBA Research

Prior work in MOBA analytics falls broadly into two categories: in-game performance prediction and pre-game strategic analysis. Yang et al. [11] developed a real-time win prediction system for Honor of Kings using interpretable deep learning on in-game telemetry data. Shen et al. [8] proposed a deep learning-based sequential recommendation mechanism for the MOBA ban-pick phase, framing each draft decision as a sequential prediction task. Liu et al. [2] developed BPCoach, a visual analytics system for assisting coaches in hero drafting through interactive visualization of historical draft patterns. Delalleau et al. [15] proposed patch-agnostic analytics frameworks to maintain model validity across game patch cycles — a limitation directly relevant to this study, where all transactions were drawn from a single season's patch cycle. While the deep learning approaches of Yang et al. and Shen et al. achieve strong predictive performance, they require large training corpora, operate as black-box models, and produce outputs that are difficult to communicate directly to coaches without machine learning expertise. In contrast, ARM produces explicit, human-readable rules that are immediately actionable in the drafting context — a practical advantage that distinguishes the present study from prior work and justifies the choice of ARM over deep learning-based approaches.

2.7 Comparative Studies of Apriori and FP-Growth

Alcan et al. [10] confirmed that FP-Growth requires less computation time than Apriori on larger retail transaction datasets, attributing the gap to FP-Growth's avoidance of explicit candidate generation. Srinadh [5] extended this comparison to include Eclat, finding that FP-Growth consistently outperforms Apriori on large datasets but that the advantage diminishes on smaller datasets. Zaki [14] provided theoretical scalability bounds showing that FP-Tree-based structures achieve superior performance at scale due to reduced I/O overhead. Cheung et al. [16] introduced incremental ARM techniques (FUP) relevant to future extensions of this work, where new MPL season data could be incorporated without full reprocessing. Collectively, these studies establish that FP-Growth is the preferred algorithm for large-scale datasets, while Apriori remains competitive on smaller ones. The present study contributes to this body of evidence by providing empirical comparison in a previously untested context, professional esports data characterized by small transaction volume (183 games) but moderate item dimensionality (75 heroes), yielding findings that challenge the assumption of FP-Growth's universal superiority.

2.8 ARM for Recommendation Systems in Online Gaming

Araujo, Rios, and Parra [9] applied data mining techniques to build an item recommendation system for MOBA games, demonstrating that patterns derived from ranked match purchase histories of experienced players could produce contextually relevant recommendations with up to 80% mean average precision. Their work validates the practical viability of data-driven recommendation in the MOBA gaming context and establishes a direct precedent for the present study's application of ARM to hero draft patterns. More broadly, ARM has been adopted as a backbone for collaborative filtering recommendation systems in scenarios where transaction logs are naturally sparse [4]. Putri and Kuswinarno [17] further noted the increasing demand for evidence-based coaching strategies in the Indonesian professional esports ecosystem. The present study directly addresses this gap by applying ARM not merely as an analytical tool, but as the basis for a transparent, reproducible, and coach-interpretable hero draft recommendation system — an application that extends prior MOBA data mining work from in-game item purchasing to the pre-match strategically critical domain of competitive hero drafting.

3. METHOD

This study employs a quantitative experimental approach using the ARM algorithm comparison methodology. The research workflow comprises six main stages: (1) data collection, (2) data exploration and preprocessing (EDA & preprocessing), (3) data transformation into transaction format, (4) implementation of the Apriori algorithm, (5) implementation of the FP-Growth algorithm, and (6) integration and comparative analysis of results. The entire implementation was carried out using the Python 3.10 programming language within the Jupyter Notebook environment, divided into four structured notebooks: 01_EDA_Preprocessing.ipynb, 02_Apriori.ipynb, 03_FPGrowth.ipynb, and 04_Comparison.ipynb.

3.1 Data Sources and Collection

The dataset is sourced from official MPL Indonesia Season 13 match records held from February to April 2024, obtained from the Kaggle platform. The data includes hero draft information (picks and bans), match results (win/loss), team names, dates, and match stages. Each row represents one player in a single game, so each game has 10 rows (2 teams × 5 heroes).

3.2 Data Exploration and Preprocessing

The EDA and preprocessing stages were conducted comprehensively. The cleaning process included: (1) stripping whitespace from all string columns, (2) standardizing the Win column to 'Win'/'Lose', (3) filling missing values in the Emblem/Talent column with 'Unknown' and the Gold/Buff column with the median value per Win class.

Each game is assigned a unique identifier using the formula. The review identified an anomaly consisting of 30 orphan rows (rows without a valid game pair) in the data from 3/24/2024, which were discarded, resulting in 184 valid games. Of these, 183 games produced valid win transactions with exactly 5 heroes per winning team. Validation ensures that every valid game_id has exactly 10 rows (2 teams × 5 heroes).

Descriptive statistical analysis reveals: the total number of unique heroes ever picked reached 87, but in the win records there were 75 active unique heroes. The hero Fredrinn was recorded as the most frequently picked hero (~60% pick rate) [2].

3.3 Data Transformation into Transaction Format

To prepare the data for the ARM algorithm, it was transformed from a relational table format into a binary transaction format. Each transaction represents a single game won, with items consisting of the heroes picked by the winning team. This process yields 183 winning transactions represented in a 183 × 75 binary matrix (183 winning games × 75 unique heroes). A value of '1' in a matrix cell indicates that the hero was picked by the winning team in the relevant game, while '0' indicates it was not picked.

3.4 Association Rule Mining: Basic Concepts

Association Rule Mining aims to discover rules X → Y where X and Y are disjoint itemsets [4]. In the context of this study, the rule {HeroA, HeroB} → {HeroC} is interpreted as: teams that win a match while selecting HeroA and HeroB tend to also select HeroC. The quality of each rule is measured using the following three metrics [12]:

Support measures the frequency of an item set's occurrence across all transactions. The support formula for item set X is:

$$support(X) = \frac{|\{t \in T : X \subseteq t\}|}{|T|}$$

where T is the set of all transactions and |T| is the total number of transactions. The minimum support value (min_support) set in this study is 0.05, meaning that only itemsets appearing in at least 5% of all winning transactions (±9 games out of 183 games) are considered frequent itemsets. This value was chosen because it yields 43 informative frequent itemsets without generating too many meaningless rules.

Confidence measures the reliability of an association rule, specifically the proportion of transactions containing X that also contain Y:

$$confidence(X \rightarrow Y) = \frac{support(X \cup Y)}{support(X)}$$

The minimum confidence level set is 0.40, meaning that only rules with a confidence level of at least 40% are included in the analysis results.

Lift measures the strength of the association between X and Y compared to what it would be if the two were statistically independent:

$$lift(X \rightarrow Y) = \frac{confidence(X \rightarrow Y)}{support(Y)}$$

A lift value greater than 1 indicates that the occurrence of X increases the probability of Y occurring (positive association). The minimum lift threshold is set at 1.2 to ensure that the resulting rules have practical relevance and are not merely statistical coincidences [14].

3.5 The Apriori Algorithm

The Apriori algorithm, introduced by Agrawal and Srikant [6], operates based on the anti-monotonicity property: if an itemset does not meet the minimum support threshold, none of its supersets do either. The algorithm operates iteratively, generating candidate itemsets from 1-itemsets to k-itemsets, pruning candidates that do not meet the threshold at each iteration. The implementation uses the apriori() function from the mlxtend 0.23 library with the parameter max_len=None to avoid limiting the length of the itemset. The Apriori algorithm's strength lies in its ease of implementation and interpretation; however, it has a weakness with high-dimensional datasets because it requires many database scan iterations [14].

3.6 The FP-Growth Algorithm

The FP-Growth algorithm introduced by Han et al. [7] overcomes the limitations of Apriori by compressing the dataset into a tree structure (FP-Tree) that requires only two database scans. FP-Growth does not generate candidate itemsets; instead, it directly mines frequent patterns from the FP-Tree using a recursive technique based on a conditional pattern base. The implementation uses the fpgrowth() function from the mlxtend 0.23 library with parameters identical to those of Apriori to ensure a fair comparison. The efficiency of FP-Growth has been shown to be significantly greater on high-dimensional datasets [10].

3.7 Experimental Parameter

To ensure consistency and comparability of results between the two algorithms, the experimental parameters were set uniformly based on a combination of established practices from prior ARM literature and the characteristics of the dataset used in this study. Table 1 summarizes the parameters and their literature-grounded justifications.

Minimum Support (0.05 / 5%). The selection of a minimum support threshold of 0.05 follows the approach of Alcan et al. [10], who demonstrated that low support thresholds in the range of 0.03–0.10 are appropriate for sparse transactional datasets where item co-occurrence is naturally infrequent — a condition directly applicable to professional esports drafting, where hero pool diversity limits the repeat frequency of any specific combination. Srinadh [5] similarly employed support thresholds in this range when evaluating ARM algorithms on datasets with high item dimensionality. A threshold of 0.05 in this study yields 43 informative frequent itemsets, consistent with the practical guideline proposed by Kotsiantis and Kanellopoulos [13] that threshold selection should balance rule informativeness against the risk of generating trivially rare or ubiquitously common patterns.

Minimum Confidence (0.40 / 40%). A minimum confidence of 0.40 was selected in alignment with the threshold range validated by Araujo, Rios, and Parra [9] in their data mining framework for MOBA game item recommendation, where moderate confidence thresholds were shown to produce rules of sufficient reliability for recommendation purposes without over-constraining the rule set. Kotsiantis and Kanellopoulos [13] further noted that confidence thresholds below 0.50 are appropriate when the primary objective is pattern discovery rather than high-precision prediction, which is consistent with the exploratory nature of this study.

Minimum Lift (1.2). The minimum lift threshold of 1.2 was established based on the recommendation of Zaki [14] and Kotsiantis and Kanellopoulos [13] that a lift value strictly greater than 1.0 is required to confirm a genuine positive association between antecedent and consequent beyond statistical independence. This threshold is consistent with the practice in prior esports and gaming ARM studies, where lift thresholds in the range of 1.1–1.5 are commonly used to ensure that discovered rules reflect meaningful co-occurrence rather than coincidental correlation [5], [10].

Table 1. ARM Experiment Parameters

Parameters	Value	Literature-Based Justification
Minimum Support	0.05 (5%)	Suitable for sparse datasets with high item diversity [5], [10], [13]
Minimum Confidence	0.40 (40%)	Appropriate for exploratory pattern discovery [9], [13]
Minimum Lift	1.2	Ensures genuine positive association beyond chance [5], [10], [14]
Number of Transactions	183	Games won out of 184 valid MPL S13 games
Number of Items	75	Unique heroes appearing in winning transactions
Library	mlxtend 0.23	Standard Python library for Apriori and FP-Growth
Strong Rules Filter	Conf ≥0,5 & Lift ≥1,5	Secondary filter for high-quality rules

3.8 Evaluation and Comparison

A comparison between the Apriori and FP-Growth algorithms was conducted across two main dimensions [10]. First, the computational efficiency dimension was measured in terms of execution time using the Python time.time() function and memory usage via the memory_profiler library. Second, the result quality dimension was evaluated through the number of frequent itemsets, the total number of rules, and the identification of strong rules with a confidence threshold of ≥ 0.5 and a lift of ≥ 1.5. An overlap analysis was performed to identify rules discovered by both algorithms, which were then semantically validated using domain knowledge from experienced MLBB players to ensure their practical significance [2]. The integration of all results is performed in the 04_Komparasi.ipynb notebook, which combines the output from both JSON files to generate comprehensive and actionable hero counter-pick recommendations, complete with support, confidence, and lift values as indicators of recommendation quality.

4. RESULTS AND DISCUSSION

4.1 Data Exploration Results

The EDA process yielded several important findings. Of the 184 valid games, there were 183 valid win transactions with exactly 5 heroes per winning team. The EDA dashboard displays the win/loss distribution, hero pick frequency, win rate, and scatter plot of pick frequency vs win rate. The frequency distribution of hero picks shows the dominance of certain heroes in the MPL Indonesia Season 13 meta [2]. Fredrinn was recorded as the most frequently picked hero in all transactions.

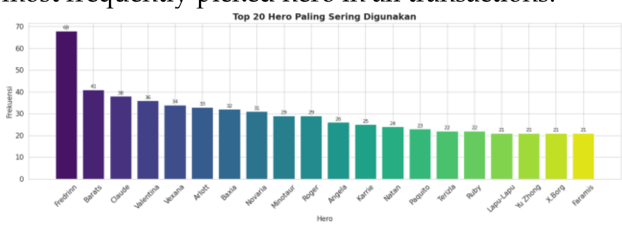

Figure 1. Top 20 most frequently used heroes

The analysis of the confidence heatmap for the top 15 heroes shows an initial indication of the correlation between pairs of heroes, such as Lapu-Lapu–Fredrinn and Cici–Fredrinn, which was then validated mathematically through ARM [4].

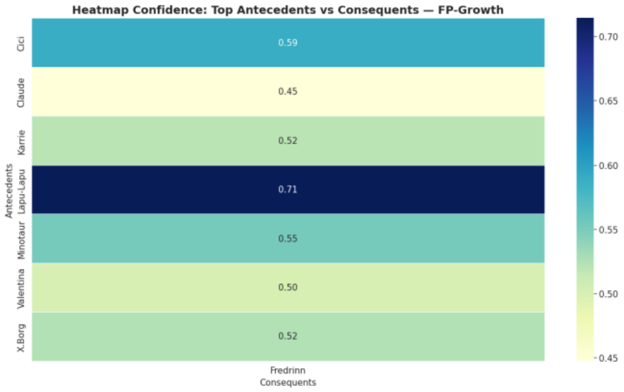

Figure 2. Heatmap Confidence

4.2 Results of frequent itemset mining

The two algorithms with identical parameters produce the same number of frequent itemsets mathematically, in line with the deterministic nature of the two algorithms when run on the dataset and with identical parameters using the same library [13]. Table 2 shows the distribution of frequent itemsets based on the length of the itemset.

Table 2. Distribution of Frequent Itemsets by Length

Itemset Length (k)	Number of Frequent Itemsets	Description
K = 1	31	Individual heroes frequently picked
K = 2	12	Hero pairs frequently picked together
Total	**43**	**Total Frequent Itemsets**

From a computational perspective, the natural termination at k=2 has a direct implication on algorithm behavior: both Apriori and FP-Growth were effectively operating on a very shallow search space. For Apriori, this means only two levels of candidate generation and database scanning were required. For FP-Growth, the FP-Tree constructed from this data was correspondingly compact, with limited branching depth. This shallow search space is an important contextual factor when interpreting the efficiency comparison in Section 4.5, as it reduces the performance gap between the two algorithms relative to what would be observed on deeper, more complex itemset structures.

The frequent itemset mining process was performed without limiting the maximum combination length (max_len = None). However, the mining results naturally stopped at itemsets with a maximum length of two heroes (k=2). Based on the anti-monotonic property of the ARM algorithm, the halting of the search at k=2 indicates that no combination of three heroes (k=3) succeeded in exceeding the minimum support threshold of 0.05 (5%) in winning matches.

Tactically, within the context of MPL Indonesia Season 13, the termination at k=2 indicates that professional teams' drafting styles are highly dynamic and adaptive. Coaches tend to secure only a core hero pair (duo), while the remaining three slots are flexibly varied in response to the opponent's picks, preventing overly rigid and predictable team compositions.

4.3 Association Rule Mining Results

From the resulting frequent itemsets, association rules were generated with a minimum confidence of 0.40. After filtering for a lift of ≥ 1.2, a set of rules was obtained, from which strong rules were identified (confidence ≥ 0.5 and lift ≥ 1.5). Table 3 presents the association rules sorted by highest lift values.

Table 3. Strong Association Rules for Winning Hero Combinations

Antecedents	Consequents	Support	Confidence
{Lapu-lapu}	{Fredrinn}	0,08	0,71
{Cici}	{Fredrinn}	0,05	0,59
{Minotaur}	{Fredrinn}	0,09	0,55
{X-Borg}	{Fredrinn}	0,06	0,52
{Karrie}	{Fredrinn}	0,07	0,52
{Valentina}	{Fredrinn}	0,10	0,50
{Claude}	{Fredrinn}	0,09	0,45

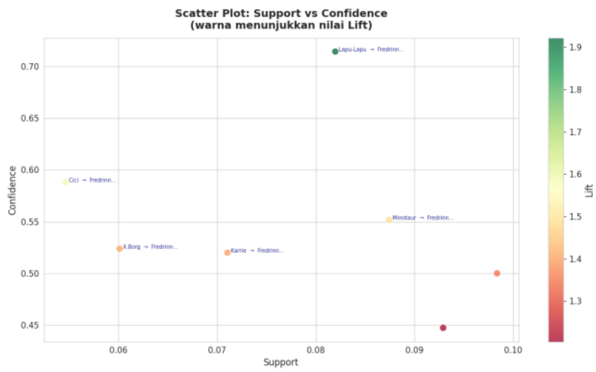

Figure 3. Scatter plot: Support vs. Confidence

A lift value > 1.2 across all rules indicates a significant positive association [12]. Tactically, Fredrinn's dominance as the consequent in all top-tier rules underscores his status as a crucial core/jungler in the MPL Indonesia Season 13 meta. The strategic implications of these association rules can be categorized based on role synergy as follows:

- **Defensive Frontline Synergy (Double Sustain Frontline):** The strongest associations are found between EXP Laner heroes such as Lapu-Lapu (confidence 0.71; lift 1.92), Cici, and X-Borg and Fredrinn. A 71% confidence level for Lapu-Lapu makes this the most certain rule. This tactic relies on a double frontline formation, where Fredrinn (Jungler) acts as the primary damage absorber and provides crowd control initiation, while EXP Laners like Lapu-Lapu or X-Borg deliver area burst damage or dive into the enemy backline.

- **Area Crowd Control (CC) Chain Synergy:** The combination of Minotaur and Fredrinn has a confidence level of 0.55 and a lift of 1.48. The synergy between this Tank-type Roamer and Jungler creates a massive CC chain in teamfights. The airborne effect from Minotaur's ultimate provides crucial momentum for Fredrinn to safely build up combo points and unleash his ultimate without interruption.
- **Backline and Space Creation Synergy:** The presence of sustained damage dealers like Karrie, Valentina, and Claude pairs well with Fredrinn. These Marksman and Mage heroes require safe space to deal optimal DPS. Fredrinn provides layered protection (peel-off) and holds back enemy movements, allowing these heroes to land hits from a safe distance.

It should be noted that all seven rules share Fredrinn as the consequent. While this strongly reflects Fredrinn's dominance in the Season 13 meta, it also indicates a limitation of the dataset scope: the rules discovered are specific to this season's patch cycle and hero balance state, and may not generalize to other seasons or patches [15].

4.4 ARM-Based Counter-Pick Recommendations

The results of the ARM rules can be directly implemented as a data-driven counter-pick recommendation and draft-building system [9]. The drafting phase in esports competitions accounts for a significant portion of the probability of victory before the match begins [3]. Unlike approaches that rely solely on a coach's intuition, ARM provides mathematically validated recommendations with transparent and auditable confidence and lift metrics [4]. As an example of synergy drafting: if a team has secured Lapu-Lapu during the early pick phase, the system strongly recommends immediately securing Fredrinn, supported by the highest confidence value of 71%. For defensive strategies (counter-drafting): when the opponent has secured Minotaur as a Roamer, the system flags the probability of a CC chain combination forming if the enemy successfully obtains Fredrinn (55% confidence). Based on this data, the team can decide to ban or deny-pick Fredrinn in the next rotation phase to disrupt the opponent's synergy plans [9].

Compared to deep learning-based draft recommendation systems such as that proposed by Shen et al. [8], the ARM-based approach offers a meaningful practical advantage: each recommendation is directly traceable to its support, confidence, and lift metrics, allowing coaches to weigh recommendations against their own contextual judgment rather than accepting model outputs without explanation. This transparency is particularly valuable in high-stakes competitive settings where decision accountability matters.

4.5 A Comparative Analysis of Apriori vs. FP-Growth

A comprehensive comparison was conducted in the 04_Komparasi.ipynb notebook, integrating the JSON output from both algorithms. Since both algorithms use identical parameters and the same library, they produce a mathematically identical number of frequent itemsets and association rules [13]. The main difference lies in computational efficiency. Table 4 presents the comparison results.

Table 4. Comparison of the Performance of the Apriori Algorithm vs. the FP-Growth Algorithm

Evaluation Metrics	Apriori	FP-Growth
Execution Time (seconds)	0.0069	0.0210
Number of Frequent Itemsets	43	43
Total Association Rules	7	7
Strong Rules (Conf ≥0,5 & Lift ≥1,5)	2	2
Rules for Lifts ≥1.5	2	2
Rules for Confidence ≥0,5	6	6
Overlap Rules	7	7

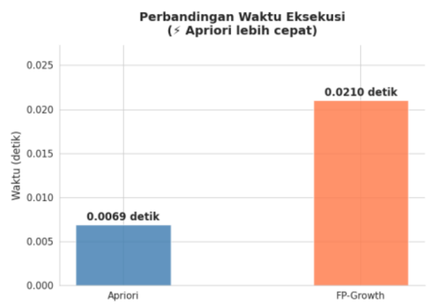

Figure 4. Comparison of execution times

The results reveal an empirically interesting finding: Apriori recorded a faster execution time (0.0069 seconds) compared to FP-Growth (0.0210 seconds), a result that superficially contradicts the general theoretical assumption that FP-Growth is the more efficient algorithm. However, this finding is consistent with prior literature when dataset scale is properly considered. Srinadh [5] and Alcan et al. [10] both noted that FP-Growth's performance advantage diminishes on smaller datasets, and Zaki [14] established that the scalability benefits of FP-Tree structures become significant only when transaction volume and item dimensionality are sufficiently large. On the 183-transaction, 75-item MPL Season 13 dataset, the overhead required to construct the FP-Tree in memory outweighs the cost of Apriori's linear iterative scanning, particularly given that the search space terminates naturally at k=2 itemsets.

It is important to interpret this efficiency finding with appropriate caution. The observed execution times (0.0069 vs. 0.0210 seconds) are both in the millisecond range, and the absolute difference — approximately 15 milliseconds — has no practical significance for real-world deployment. On datasets with thousands of transactions and hundreds of items, FP-Growth's avoidance of candidate generation would be expected to produce substantially faster execution times than Apriori [10], [14]. The present finding is therefore best understood as dataset-scale-specific evidence, rather than a universal endorsement of Apriori over FP-Growth.

The overlap analysis confirms that both algorithms exhibit fully deterministic and consistent computational behavior: the 7 association rules discovered are 100% identical across both algorithms, with exactly matching support, confidence, and lift values. This absolute overlap validates that algorithm choice in this context affects only computational time, not the accuracy or completeness of the extracted patterns [5].

5. CONCLUSION AND SUGGESTION

5.1 Conclusion

This study successfully applied the Association Rule Mining method to 183 winning matches from MPL Indonesia Season 13 to identify hero draft patterns used by winning teams. Using a minimum support of 5%, minimum confidence of 40%, and minimum lift of 1.2, the ARM framework extracted statistically significant hero combination patterns from the dataset. The frequent itemset discovery process naturally terminated at two-hero combinations ($k=2$), indicating that winning teams' synergy was formed primarily through core hero pairs rather than through combinations of three or more heroes appearing with consistent frequency. This finding reflects the highly adaptive and dynamic nature of professional MLBB drafting, where only a small number of hero pairings recur with sufficient regularity to exceed the minimum support threshold across an entire season.The association rules with the highest strength were found in the relationships {Lapu-Lapu} $\rightarrow$ {Fredrinn} with a confidence of 0.71 and a lift of 1.92, and {Cici} $\rightarrow$ {Fredrinn} with a confidence of 0.59 and a lift of 1.58. These findings indicate the presence of strong hero synergy patterns that can serve as the basis for a more objective hero draft recommendation system to support decision-making during the pick and ban phase. It should be noted, however, that all discovered rules are specific to the Season 13 patch cycle and hero balance state, and their applicability may diminish in subsequent seasons where the meta shifts due to game updates.Regarding computational efficiency, Apriori recorded a faster execution time (0.0069 seconds) compared to FP-Growth (0.0210 seconds) on the dataset used in this study. This result is strictly attributable to the specific characteristics of the dataset — namely the small transaction volume (183 games), moderate item dimensionality (75 heroes), and a shallow search space terminating at $k=2$. On a dataset of this limited scale, the computational overhead required to construct the FP-Tree structures inherently outweighs the cost savings generated from avoiding candidate generation. Therefore, this efficiency finding represents dataset-scale-specific evidence and should not be generalized as a universal performance advantage of Apriori over FP-Growth in larger data environments. Regardless of the execution time difference, both algorithms produced fully identical outputs — 43 frequent itemsets and 7 association rules with matching metric values — confirming that algorithm choice in this context affects only computational time, not the quality or completeness of the extracted patterns.

5.2 Suggestion

This study has several limitations that present opportunities for further research. The analysis did not account for hero tier shifts caused by periodic game patch updates, which alter hero balance and directly reshape the dominant meta, nor did it account for individual players' mechanical skills, all of which can influence match outcomes. Future research is encouraged to incorporate patch version as an additional variable so that the resulting draft patterns more accurately represent the current in-game meta.

To address the dataset scale limitation identified in this study, future work should consider expanding the dataset by utilizing data from multiple seasons or international tournaments, which would simultaneously increase transaction volume, enhance the generalizability of findings, and provide a more suitable context for evaluating FP-Growth's scalability advantages over Apriori. Further algorithmic comparisons can also be pursued by including Eclat or other frequent itemset mining algorithms, or through incremental mining approaches that update association rules as new match data becomes available without reprocessing the entire dataset. Finally, the results of Association Rule Mining can be integrated with machine learning classification algorithms to build a real-time victory prediction system capable of providing more adaptive decision support in the hero draft process for professional esports competitions.

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