Frontiers in Computer Science and Artificial Intelligence
ISSN: 2978-8048
DOI: 10.32996/fcsai
Journal Homepage: www.al-kindipublisher.com/index.php/fcsai

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| RESEARCH ARTICLE

Market basket analysis for healthcare services to identify bundled care offerings

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| ABSTRACT

The complexity of inpatient care, which has recently increased and is accompanied by the growing demand for cost-effective and coordinated treatment models, has enhanced the necessity of the use of evidence-based bundled care services in hospitals. Market Basket Analysis (MBA) is a time-tested data mining method that offers a systematic method of finding naturally occurring co-occurring clinical services, which respectively create care bundles. This study uses the association rule mining on the 2010 New York State SPARCS Hospital Inpatient Discharge data, which is a de-identified, large scale dataset of more than 2.6 million inpatient records including detailed data on diagnosis, procedures, service use, level of severity and payment source. Service-level item sets were generated using Apriori and FP-Growth algorithms, whereby CCS procedure codes, diagnostic groups and treatment occasions within each inpatient stay were clustered together and allowed identification of commonly occurring combinations of services. This study will identify the clinically significant trends in inpatient episodes that may be used in the design of cost-efficient bundled care. The association rules were tested by means of support, confidence and lift measurements in order to identify high-value service pairs and clusters within large inpatient categories like cardiology, orthopedics, obstetrics and general surgery. Findings indicate that there are strong synergies, e.g., cardiovascular imaging is always accompanied by a particular lab panel and surgical procedure, whereas orthopedic surgery visits often involve diagnostic tests and after-surgical care. These lessons point to service patterns that hospitals can use to develop standardized, value-based care bundles that can decrease fragmentation, improve clinical coordination, and help to optimize resources. This study illustrates the possibility of an MBA to change the approach of inpatient service analysis, which has been focused on descriptive reporting to direct clinical pathway design. Utilizing data on pre-2025 hospitals occurring in the real world, the results are used to advance data-driven bundled care models in accordance with the modern healthcare changes. The model can be expanded to multi-year datasets, outpatient services and predictive models of proactive care planning.

| KEYWORDS

Market Basket Analysis, Bundled Care Offerings, Healthcare Data Mining, SPARCS Inpatient Dataset, Association Rule Mining and Hospital Service Utilization

| ARTICLE INFORMATION

ACCEPTED: 01 April 2025 **PUBLISHED:** 25 April 2025 **DOI:** 10.32996/fcsai.2025.4.3.5

I. INTRODUCTION

A. *Background*

The problem of healthcare provision has become more complicated with the growing number of diagnostic, therapeutic, and monitoring services needed to provide complete inpatient care. The current hospitals are dealing with high volumes of patients with various clinical requirements, and it may touch on various departments as well as service providers [1].

This complexity often results in disjointed care trajectories, overlaps in services, and inefficiencies that contribute to the escalation of healthcare costs as well as the impact on timely patient outcomes. With the healthcare systems of the world becoming value-based, the trend of comprehending the care patterns and determining opportunities to standardize care and optimize costs is increasing. Among the options is the use of data-driven analysis methods on massive volumes of hospital data to reveal significant trends in their service usage [2]. Market Basket Analysis (MBA) as a technique of analysis of patterns of consumer purchase in retail, has become an effective method of studying patterns in healthcare services. MBA allows identifying the natural clusters of services that can help to develop the bundle care offering, by looking at the common diagnostic tests, procedures and treatments that are commonly occurring in the same inpatient encounter [3]. These bundles facilitate the provision of coordinated, efficient, as well as patient-centered care through the grouping of necessary services, standardizing them, and delivering them in a systematic and organized fashion. The New York State SPARCS 2010 Inpatient Discharge dataset which includes inpatient records in millions of records including the information on procedures and a diagnosis, will be the solid starting point of implementing MBA to the actual service usage in hospitals. It is important in clinical decision support as well as planning the resources available to the hospital, cost cutting, and quality improvement efforts [4]. Thus, the use of MBA to find opportunities with bundled care is consistent with the modern aims of efficiency, variation, and outcome improvement in inpatient care delivery.

B. *Need for Data-Driven Bundled Care Design*

The growing focus on the coordinated and efficient provision of healthcare has demonstrated the necessity of data-driven innovative solutions to the design of care models. The concept of bundled care, where clusters of similar services are standardized into a single, unified service, has become a disruptive approach to decreasing unwarranted variation and enhancing the value of inpatient care in general. The majority of bundled care frameworks in the contemporary world are either clinically based or policy based and might not be accurate representations of actual service use patterns in hospitals [5]. This disconnect usually results in bundles, which are hard to implement operationally, or which do not include important services that patients frequently need. Hence, there exists a substantial rationale for employing an empirical base that determines naturally occurring designs of service co-occurrence according to actual patient visits. Market Basket Analysis (MBA), using association rule mining, makes this possible, by demonstrating how processes, diagnostics and services of treatment are clustering together in regular inpatient care. These clusters can be discovered at scale by using large, comprehensive datasets like the SPARCS 2010 Inpatient Discharge dataset which represents a variety of patient populations, clinical conditions and hospital capabilities. Given that the transactions are in the form of inpatient episodes and the items are in the form of the CCS-coded procedures, MBA will identify high-frequency service sets that indicate clinically meaningful sequences of care. These insights can give hospitals actionable advice to create evidence-based bundled care models to enhance coordination and streamline workflows and operational inefficiencies [6]. Also, data-rich bundles facilitate enhanced resource planning, precise cost projections, and enhanced bargaining with insurers in alternative payment schemes. By doing so, the utilization of association rule mining in the discovery of the prospect of bundled care is a pivotal step in implementing healthcare analytics, operational planning and strategic management.

C. *Problem Statement*

Although bundled care models are increasingly being adopted in healthcare, the existing bundles fail to reflect the real-life combinations of processes, diagnostics, and treatments that take place in the inpatient set up [7]. The problem with hospitals is that they often do not have a data-driven understanding of how certain services tend to coincide with each other as patients receive care, which results in them not being efficient, their work processes being inefficient, and resources being allocated inefficiently. Since there is large-scale data available like SPARCS 2010 Inpatient Discharge data, it is possible to discover such patterns of services co-occurrence via Market Basket Analysis. Nevertheless, the available studies have failed to adequately exploit the association rule mining in order to develop empirically based context-defined bundled care products. This gap demonstrates the necessity to have a systematic analytical model that identifies meaningful service combinations in order to facilitate effective care design [8].

D. *Research Objectives*

The objectives of this studies are:

- To utilize Market Basket Analysis in an attempt to identify the most frequent co-occurring inpatient procedures and services.
- To obtain association rules that would suggest clinically significant collections of services. To propose data-based bundled care packages based on high-support and high-lift service packages.
- To examine differences in service use by severity level, type of admission, and types of diagnostic to aid designing of bundles in specific situations.
- To determine the viability of the proposed bundled care offerings in terms of length of stay, frequency pattern and procedure dependency.
- To determine the possibilities of lessening redundancy and enhancing care coordination with evidence-based service grouping.
- To offer an analytical framework to guide the design of standardized, patient-centered bundled care pathway development by hospitals and policymakers.

E. *Research Questions*

Following these questions are guide to this study are mention below:

1. What inpatient services frequently co-occur within hospital episodes?
2. Which association rules best reveal clinically meaningful service patterns?
3. How can these patterns inform the design of bundled care offerings?

F. *Significance of the Study*

This study is relevant because it presents an evidence-based model to construct bundled care models based on the real patterns of using hospital services [9]. Through a Market Basket Analysis of the SPARCS 2010 Inpatient Discharge data, the study will enable the hospitals and policymakers to have empirically derived information on how diagnostic procedures, surgical interventions, and treatment services tend to cluster together during inpatient episodes. These lessons can be used to overcome the weaknesses of traditionally delimited bundles, which might not be representative of the variability of practice in the real world, or the real complexity of patient care. Its results help to develop standardized and clinically significant bundles that enhance interdepartmental coordination, minimize redundancy of unnecessary services, and maximize distribution of hospital resources. Moreover, evidence-based care delivery bundles may lead to patient outcomes by improving predictability in care delivery, reducing waiting duration, and fragmentation of treatment [10]. The research is also methodologically valuable as it shows how association rule mining can be effective when used in healthcare service optimization and reflects the importance of the analytics-based healthcare reforms in the future. On the whole, the study offers a solid basis to hospitals that aim at converting into value-oriented care, enhancing the efficiency of operations, and enhancing financial sustainability by aligning the operation of the hospital with evidence-based care frameworks.

II. LITERATURE REVIEW

A. *Evolution of Data-Driven Decision Making in Healthcare*

With the rising access to digital patient charts, profound procedural data, and aggregate data related to operations, healthcare systems have largely changed. These data assets have prompted hospitals and health organizations to embrace analytical processes that were previously applied in the field of business intelligence, logistics, and optimization of retail. The tendency to move to the data-driven decision making process is an indication of the healthcare industry dealing with the increasing patient numbers, the operational expenses, and the sophistication of the modern clinical services. Hospital operations have over the years, integrated the use of tools of analytics like clustering, classification, time-series modeling and predictive analytics in demand forecasting, early diagnosis, streamline of patient flow, and control of costs. This change has offered grounds through which more sophisticated analytical frameworks can be incorporated that are able to reveal patterns that are not apparent in the traditional reporting. Market-inspired analytical methods have become increasingly popular in recent years as the perspective on patient care episodes as multiple clinically interdependent tasks akin to multi-item consumer transactions has taken hold [11]. With the development of clinical services in variety and complexity, the demand for an organized picture of the co-occurrence of services in actual experiences has increased. These insights are getting increasingly important in hospitals to improve workflows, remove inefficiencies, and improve coordination of care. This transformation is also representative of the overall change in healthcare as a volume-based system to a value-based system, where data-driven insights are essential in maximizing results and reducing the variations of costs. The development of digital health programs, standardized coding systems, and big administrative data has allowed healthcare organizations to test patterns of services in large-scale [12]. This led to the preconditions to analytics such as Market Basket Analysis, which is capable of offering an organized discovery of diagnostic, procedural, and treatment combinations naturally occurring during inpatient care. In general, the development of data-driven decision making has established a fundamental basis for further analytical innovation cost-effective and coordinated care, which is achievable by identifying clinically meaningful service bundles.

B. *Market Basket Analysis and Association Rule Mining in Healthcare*

More widely recognized as an analytical tool in the industries that deal with multi-item transactional data such as healthcare, Market Basket Analysis which was initially introduced in the retail sector in order to comprehend consumer buying behavior has transformed into a useful analytical tool. The principle of MBA is finding patterns of co-occurring items which are called item sets in the same transaction. Within the healthcare context, an inpatient encounter may be approached as a transaction, and the multiple procedures, diagnostics, and services offered throughout the stay can be the respective items [13]. Association Rule Mining, which incorporates Apriori and FP-Growth algorithms, allows identifying frequent item sets and derives the formulation of the rules that outline the relative probability of co-occurrence of services. The rules are considered upon the basis of the support, confidence, and lift measures, so that patterns observed are frequent as well as significant within a clinical setting. Implementation of MBA in healthcare has special merits [14]. It enables the identification of clusters of services representing the real-life clinical processes instead of the assumptions that are fixed in advance regarding the way care is to be provided [15]. A cardiac condition inpatient episode can always entail some diagnostic imaging assessments, lab tests, and interventions that constitute a natural service bundle. MBA allows obtaining a possibility to measure these trends, evaluate their intensity, and determine differences within demographic or clinical subgroups. Unexpected relationships are also discovered with the help of the technology, and may indicate an inefficiency or a clinical pathway redesign opportunity. The quality and fineness of data that can be used in MBA have improved as hospitals move towards electronic health records and the use of standardized coding systems including the CCS, ICD, and DRG classifications. The association rule mining is thus emerging as a necessity in the unraveling of concealed care patterns that can be used in package formation, protocol streamlining, and in the provision of integrated services. In general, MBA represents a methodical basis for converting inpatient information into operational and clinical action.

C. *Bundled Care Models and Their Role in Modern Healthcare*

Bundled care models are a form of medical service provision organization where units of related services, diagnostic and treatment have been put under one, coordinated service provision. Initially developed as a financial tool to maintain cost, bundled care has now become a more clinically based approach to attempt to standardize care pathways, enhance continuity of care, and eliminate unwarranted variability of services[16]. The models will also make sure that patients get the full range of services pertaining to a particular condition or episode of care as an integrated unit as opposed to a fragmented intervention. This type of approach would be especially useful in an inpatient setting where the list of services in that setting may be long, and the interactions between departments are crucial to providing efficient and quality care. Bundled care facilitates service delivery transparency, promotes resource predictability, and outcome-oriented reimbursement. It also assists healthcare groups to match workflow operational standards with evidence-based practices by clustering procedures that are usually performed together. Regardless of these benefits, most current bundles are created based on clinical evidence or professional opinion, not on evidence [17]. Consequently, they can lack in reflecting the actual difference in practice or they can neglect service combinations that are constantly present in particular groups of patients. The shift of data-backed bundles is becoming more significant with hospitals under pressure to cut costs without affecting the quality of care [18]. Determining natural service co-occurrence patterns can offer useful information on how practice is conducted in the provision of patient care. With the help of empirical analysis of inpatient data, healthcare institutions will be able to streamline a bundled care model to allow it to represent the real clinical workflow, maximize resource use, and minimize service redundancy. Finally, the evidence-based bundled care models help to achieve more integrated care, enhanced patient experience, and enhanced cost-effectiveness of healthcare systems operating in a time of complex medical demands and limited resources.

D. *Administrative Healthcare Datasets and Their Use in Service Pattern Discovery*

Administrative healthcare data sets have been critical in the realization of hospital performance, services utilization, and patient outcomes at hospital/institutional and system-levels. Such data can usually provide comprehensive data on the diagnosis, procedures, patient demographics, service bills, hospital features, and discharge rates [19]. Standard coding systems like CCS, ICD and DRG coding systems provide uniformity in the identification of clinical activities in a large population. They are well-suited to methods that demand a large amount of data across multiple dimensions, like the Market Basket Analysis, as they provide a thorough analysis of the healthcare service delivery patterns in a long-term context [20].Administrative data sets are especially helpful in determining a combination of procedural and diagnostic actions that take place in a variety of clinical circumstances. They present an empirical document of the actual care delivery process instead of what is thought to work, the realities of operation, including provider practices, resource availability, and patient complexity [21]. The datasets also provide heterogeneity in clinical workflows in various hospitals, regions, and demographics, which allows exploring the patterns of service in a nuanced manner. The analysis of such data will allow researchers and healthcare administrators to identify inefficiencies, the differences in practice styles, and standardization opportunities. The SPARCS data, such as an example, provides a comprehensive overview of inpatient contacts in one state, and it is therefore appropriate for studying the patterns of co-occurrence of services. The fact that it is large increases the strength of the association rules produced in MBA, where the greater the volume of transaction, the greater the strength of the support and confidence measures. Administrative datasets can thus be a good source of identifying useful service clusters that can be applied to drive the development of bundled care [22]. In general, they are significant in facilitating the process of making decisions based on data, which is actionable information to improve clinical practice, operational planning, and strategic health care management.

E. *Applications of Association Rules for Identifying Service Co-Occurrence Patterns*

The association rule mining has been very useful in identifying trends of service use in both inpatient and outpatient care settings. These rules expose some latent relationships that are not seen in traditional descriptive statistics by addressing each patient encounter and each clinical service as an item within that encounter [23]. The primary advantage of association rules is that they allow determining the number and the degree of co-occurring services, which can be identified as constant patterns observed in large groups of patients. In the healthcare sector, association rule mining is used to help discover procedural sequences, diagnostic dependencies and care patterns that are representative of the real clinical workflow. Surgical interventions tend to be accompanied by certain imaging examinations or aftercare operations [24]. On the same note, having chronic diseases could entail repetitive sequences of laboratory examinations, medication types, and follow-up evaluations. These recurrent patterns offer good information on the structure of care delivery. The Association rules are also used in discovering relationships that might indicate inefficiency like unnecessary testing or high-frequency of certain combinations of services. The other notable benefit of association rule mining is that it is flexible to determine both expected and unexpected care patterns. High-support rules represent common, easy-to-find combinations of services, and high-lift rules might be able to reveal clinically significant, yet less intuitive interactions that can be pursued in the future [25]. Such analytical power helps healthcare organizations to optimize clinical pathways, distribution of resources, and enhance coordination of care. Association rule mining will be a potent tool in the process of informing bundling care offering design in cases where extensive datasets, e.g., SPARCS are used. In general, association rule implementation is a valuable methodological innovation that can convert the raw hospital data into practical strategic and clinical decision-making.

F. *Research Gap*

Despite the fact that it can be widely acknowledged that the concept of bundled care can potentially improve care coordination and decrease the overall healthcare spending, the current research shows that there are a few critical gaps in the development and implementation of the concept. A large number of bundled care models are conceptually well-founded and do not have empirical support in the real patterns of service use [26]. They tend to be built by use of clinical guidelines, expert opinion, or policy requirements, which might not comprehensively reflect the aspects of reality in an inpatient episode. Consequently, bundles can have services that are not necessarily needed or may exclude services that habitually co-occur in the normal care patterns. The other significant gap is the inadequate application of advanced analytics in of the bundles. Whereas healthcare organizations turn more to analytics to predict the risks, optimize the workflow, and determine the quality, less work is conducted to find natural clusters of the services by data mining methods like Market Basket Analysis. Such poor use of methodology limits the possibility of creating bundles that may be relevant to real-world clinical practice in various patient groups, diseases and hospital settings [27]. There is frequently a research emphasis on single diseases or the specialized care pathways instead of service combinations across the system. The restricted scope does not give broad applicability of the findings, and does not give a deeper understanding of multi-condition service patterns to the hospitals. The administrative data that can expose such trends such as statewide discharge records, are underutilized to the end of determining bundled care opportunities. In light of these gaps, an evident gap exists in the need to identify natural combinations of services because data-driven frameworks would reveal the different combinations of services among different populations in inpatient settings. The use of MBA in large datasets offers a chance to come up with bundled care models that are empirically based and operationally feasible [28]. These types of models assist hospitals in transforming into value-based care by directing the delivery of services to the real patient needs, as well as better coordination and predicting costs. Bundled care models that are data-driven and necessitate it are thus timely and necessary in the present healthcare systems.

G. *Empirical study*

The case study "Market Basket Analysis and Product Bundling at Mirra's Kitchen" by Gaurav Nagpal, Ankita Nagpal, Manish Das, Sachin Gupta, Sandeep Singh, and Sarveshwar K. Inani presents an empirical application of association rule mining within a restaurant setting in Kolkata. The authors use the point-of-sale transactional data to determine the high-associations between menu items to transform the data into product bundles with optimal prices. Their research illustrates the application of support, confidence, and lift metrics calculated in Microsoft Excel and Python and emphasizes the use of data-driven bundle design to improve a profitability and pricing decisions [1]. The empirical results stress that the intuitive bundling can be frequently inferior compared to the ones based on the systematic analysis of co-occurrence. Though the food service industry is the subject of the research methodology chosen by Nagpal, Das, Gupta, Singh, Inani, and their colleagues, it can be concluded that it is largely applicable to other service settings, such as healthcare. The main idea of the study that the combinations of items that occur naturally can be used to direct the creation of structured bundles, is perfectly consistent with the objectives of healthcare service bundling. This case methodologically justifies the application of Market Basket Analysis to create evidence-based bundled care offerings in hospitals by demonstrating the ease with which real data of transactional data can be used to identify latent service patterns. Therefore, it can be used as a valuable empirical source for the current study.

In the empirical study "Apriori Algorithm and Market Basket Analysis to Uncover Consumer Buying Patterns: Case of a Kenyan Supermarket" by Omol, Onyango, Mburu and Abuonji, the authors applied the Apriori algorithm and Market Basket Analysis (MBA) on transactional data from a Kenyan mass-market supermarket chain in order to detect frequent co-purchases and association rules among products. They also used Python libraries to extract several frequent item-sets and produced 42 association rules that showed product affinities and co-purchase behaviors, e.g. drinks and bakery goods and impulse products with staple groceries. This paper provides an example of the ways in which supermarkets may use MBA to maximize the way products are positioned, how promotions and bundles are designed. The context in the case is not related to healthcare, but the concept of methodological approach to the studies to find out the co-occurring service items and create a bundling decision is very applicable in your research about bundled care offerings [2]. The article demonstrates how transactional baskets can be converted into actionable bundles, which are founded upon support, confidence and lift metrics and therefore, justifies the feasibility of applying MBA to find high value bundles. With the help of Omol et al., your article can attract the empirical precedent of MBA in the service-related bundling, and modify these methods to the healthcare services field to plan care-service bundles.

The empirical article of the research on consumer buying behaviour of seafood products of Chennai, Tamil Nadu, India: A Comprehensive Study of Market Basket Analysis based on the Meengal App developed by TNFDC-Developed Meengal App contains a comprehensive application of the Market Basket Analysis based on the actual transactional data of the seafood purchases. The paper examines the user transaction of the Meengal mobile application, which was created by TNFDC, over a period of 3 months during which the customers bought various seafood products [3]. The authors obtained frequent itemsets, association rules using RStudio and the Apriori algorithm to identify high demand products, co-purchase behaviors and dominant product affinities. The most significant associations were made with mixtures like big crab and shrimp and other mixtures; this shows the ability of MBA to reveal natural product combinations which can be used to inform bundling, promotional plan, and demand prediction. The paper brings out that the utilization of data-based decision-making is important to prioritize product offerings, to target customers better and to optimize operational performance. Though the study is placed in the area of seafood retailing, its research rigor, especially the systematic application of support, confidence and lift measures, is worthwhile empirical evidence in your study. This study has an important and supportive empirical contribution to your literature review since the analytical model employed by Jayakaran, Sarkar, and Selvanayagam is closely related to the methodology needed to determine bundled healthcare services according to the inpatient service co-occurrence patterns.

In the publication A Three-Stage Model for Innovation Adoption in Health Systems: Insights into the Health Promotion and System Strengthening Project in Tanzania, Manfred Stoermer, Ally K. Abdallah, and Karin Wiedenmayer (2024) investigate a 12-year health-system strengthening project in Tanzania, the implementation of which was done by the HPSS Project in partnership with the Swiss Tropical and Public Health Institute and the government of Tanzania. The authors examine the innovation development that included the enhanced Community Health Fund (iCHF), the Jazia Prime vendor system of supply-chain management, and health technology and community-school promotion interventions in three stages: innovation of the first service and product, second implementation in the service delivery system, and third incorporation into the institutional policy [4]. The paper focuses on the fact that each stage presented different operational and governance and scaling issues and how the systemic approach facilitated the refocusing of innovations on national policy frameworks. Despite its lack of focus on purchase-pattern analysis, this article is of good empirical support on the value of structured stages of service system adoption. In your study of the provision of bundled care, this evidence supports the need to: first determine the core service itemsets (equivalent to product-bundles), second incorporate them in care-delivery processes, and third entrench them in institutional policy or payment systems. In this way, the research gives valuable empirical precedent of how combinations of services pinpointed by a method of analysis utilizing market-baskets can give rise to significant innovations in the system-wide healthcare delivery.

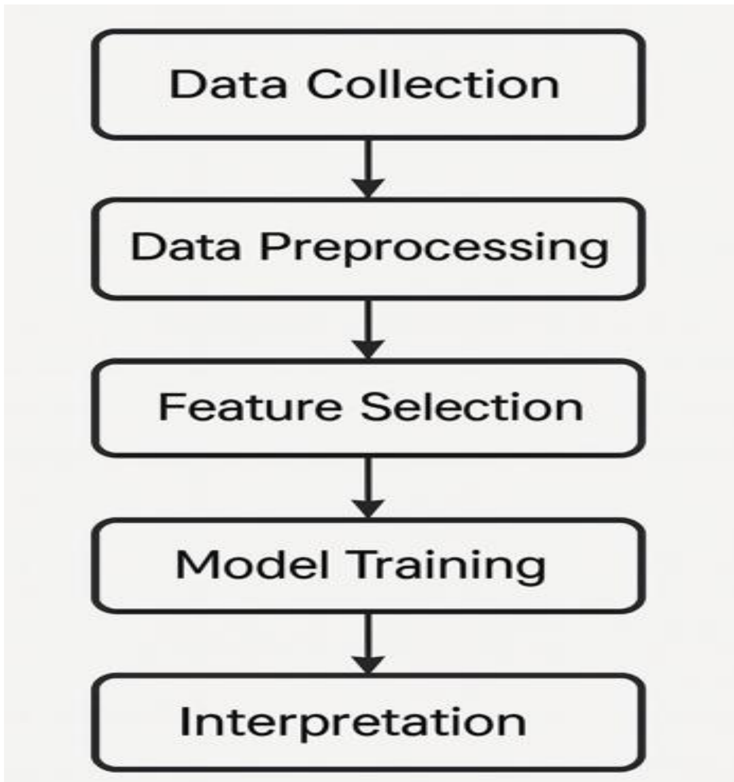
The empirical research article by Pratama R. A., Khadija M. A., Paradhita A. N., and Nurharjadmo W. (2024) called AI-Driven Predictive Analytics to Enhance Digital Marketing Strategies in Domain and Hosting Business is an applied study in the application of artificial intelligence and predictive analytics to the digital marketing procedures of a domain and hosting business. The authors apply the methods of business analytics, which are descriptive, predictive, and prescriptive analytics, to analyze the behavior of customers, predict their level of purchases, and create optimal actions in the marketing process. Based on previous customer information and machine learning algorithms, the study determines the most critical behavioral patterns, which determine customer engagement, renewal intentions, and purchasing processes of products. This will help the company to personalize marketing campaigns, aim better in targeting and boost their customer retention strategies [5]. The practical results reveal that empirical evidence can substantially enhance the marketing performance through predicting user tendencies and applying the data to make proactive decisions. Despite the fact that the research is based in the field of digital marketing and technology services, its methodology has a high level of applicability to the other service-oriented industries, such as healthcare. Just like predictive models are used to detect high-value customer segments, data-based analysis can be used by healthcare organizations to detect high-value service combinations and optimal service delivery. Therefore, this article offers a great empirical precedent on how to use advanced analytics in enhancing decision-making and operational effectiveness.

III. METHODOLOGY

The methodological framework that will be used in this study is a quantitative and data-based module to determine the opportunities of using bundled care in inpatient healthcare services using SPARCS 2010 Inpatient Discharge data [29]. The methodology incorporates data collection, pre-process, itemset, and association rule mining and frequency service pattern analysis. The Apriori and FP-Growth algorithms are used within the Market Basket Analysis to reveal the co-occurring procedures and diagnostic combinations. The association rules that are generated undergo support, confidence, and lift measures to determine clinically significant service groups. Such clusters are then deciphered in order to suggest evidence-based bundled care products [30]. Its methodology will guarantee the systematic identification of patterns in large-scale administrative data, which will allow making robust, replicable, and empirically based inferences on the use of health services.

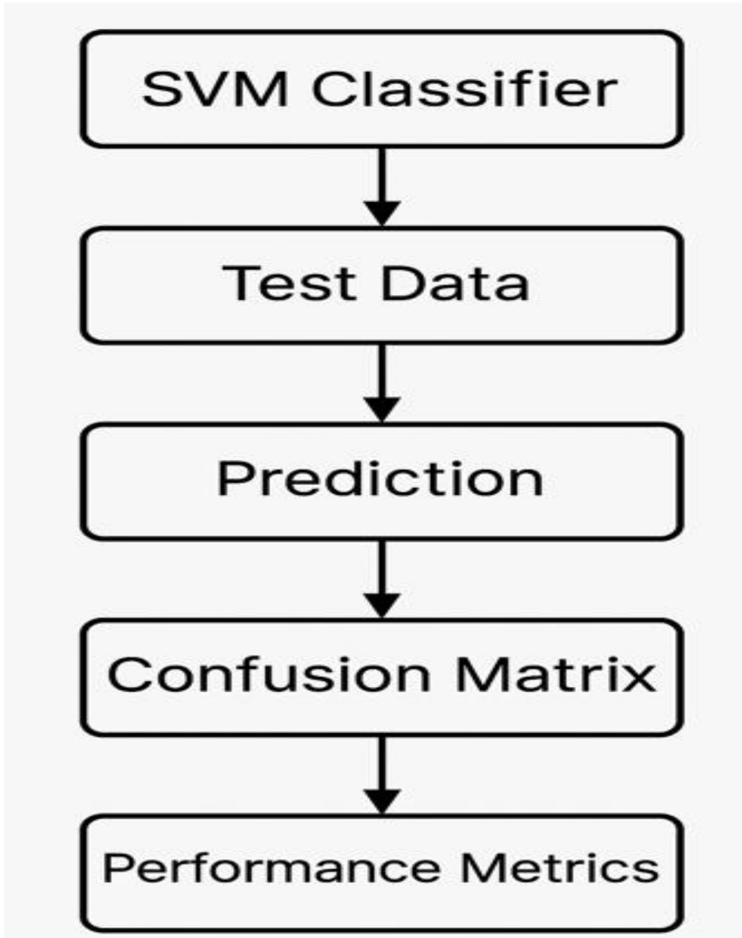
A. *Data Source and Dataset Description*

The Inpatient Discharge dataset 2010 of the SPARCS is the initial source of data used in this study. This data includes over 2.6 million inpatient discharge data from New York State hospitals. In every record, there is a wide range of information on demographic factors, diagnosis factors, procedure factors, severity factors, admission and discharge factors and payment factors. Such density and detail render SPARCS a perfect data source to define trends in healthcare service use. It particularly favors Market Basket Analysis since it records numerous processes and diagnostic codes of each patient encounter and allows creating transactional baskets [31]. The data contains standardized classifications like CCS procedure and diagnosis categories, levels of APR DRG and severity that assist in ensuring conformity among hospitals. The research is directed at the fields that refer to procedures and diagnosis as these areas are the most direct indicators of the clinical services provided within the inpatient stay. These are CCS Procedure Codes, CCS Procedure Descriptions, and CCS Diagnosis Codes and APR DRG classifications. The dataset is first subjected to a number of validation procedures such as completeness, duplication, and logical consistency checks, before analysis. As an example, the procedure codes should be matched with the diagnosis categories and types of services so as to make the itemsets valid. Records that do not have important information about procedures are filtered out to ensure the rigor of analysis [32].The case of the selection of SPARCS is supported by its high volume, standardized coding format, and appropriateness of disclosing care courses using the services that co-occur. The high consistency between hospitals is facilitating strong pattern discovery, and the administrative aspect of it can be analyzed on a scale that is often impossible to achieve with clinical data. It has a de-identified form that guarantees adherence to professional ethics and makes valuable inquiries [33]. The SPARCS data is rich, detailed, and formatted in such a way that it allows a proper and thorough Market Basket Analysis of the inpatient healthcare service pattern.



This flowchart Demonstration on Methodology Workflow Diagram

The workflow diagram methodology gives a systematic pictorial overview of the analysis procedure employed in this research. It commences by acquiring the SPARCS 2010 inpatient data and proceeds to preprocess, clean and convert them into transactional baskets. The figure indicates the use of Apriori and FP-Growth algorithms on the frequent patterns of services, and then the subsequent interpretation of association rules to give possible bundled care pathways. It also comprises the pricing and model-training parts where it is necessary. All in all, the diagram explains the logics of the research methodology step by step and contributes to a better comprehension of the analytical flow.



This Flowchart display on SVM Evaluation Framework

The SVM evaluation model diagram will represent the validation phase of the study in which machine learning is applied to evaluate the reliability of the identified service bundles. It starts with frequent itemsets in Apriori and FP-Growth and transforms them into binary-represented and encoded structured feature vectors. These vectors are the inputs to the Support Vector Machine (SVM) classifier that makes the determination of whether a particular collection of services has an opportunity to qualify as a viable bundle. Accuracy, precision, recall, F1-score, and outputs obtained on a confusion matrix are used to evaluate the predictions of the model. This figure explains the role of predictive modelling to improve the validity of bundled care recommendations.

B. *Data Preprocessing and Cleaning*

Preprocessing of data is a very important step towards the integrity and analysis usability of the SPARCS dataset. One, the variables that are irrelevant like facility identifiers, geographic markers, and so on, that do not lead to service-co-occurrence analysis are eliminated. Attention is paid to the variables that depict diagnoses, procedures, service categories, level of severity, and length of stay. Records that have either missing or invalid procedure codes are filtered out since those records cannot be transformed into understandable itemsets. The codes are grouped into a single list that is used to denote the service basket of the transaction in situations where there is more than one procedure field in a given patient encounter. The entries that are of a categorical type like procedure descriptions and diagnosis labels are standardized in that they are converted to uniform formats, eliminate trailing spaces, fix encoding problems, and combine similar descriptions into homogeneous representations. Similar cases are detected based on the date of admission, facility and demographic characteristics of patients and eliminated to avoid the frequency bias. Other cleaning processes are to make sure that the codes of the procedures are not out of bounds of valid CCS categories, and to map the outdated procedure codes with the respective current categories where needed. The preprocessing stage also categorizes the procedures and diagnoses into high-level ones to enhance interpretability. An example is that the procedures with the identical CCS fall together to minimize noise and concentrate analysis on significant service patterns. The outliers, like very rare procedures, are ignored when they are below a minimum frequency threshold and which do not give much information to association rule mining. The processed data is converted to a transactional format such that each patient encounter is represented as a basket of procedures and diagnoses. This conversion makes the conversion compatible with MBA algorithms like Apriori and FP-Growth. The preprocessing process eventually guarantees that the dataset is well formatted, uniform and optimal in pattern extraction.

C. *Formation of Transactional Baskets*

Market Basket Analysis involves the conversion of raw inpatient records into transaction based baskets. Each inpatient encounter is treated in this research as a distinct transaction that holds all the clinical services provided during that hospitalization. In order to build these baskets, CCS Procedure Codes and Diagnosis Codes are duplicated and put together in one structured list of each encounter. This depiction includes the sum total of clinical operations, such as surgical procedures, diagnostic examinations, and treatment measures. One of the methodological issues is the choice of the services to be included. In this study, procedure codes are considered since they are the direct representation of clinical actions that have been delivered and not conditions, as diagnosis codes are. Diagnosis categories are kept as contextual items in case they improve the knowledge of the service combinations. Each of these baskets hence represents the clinical workflow of the episode of a patient, and association rule mining can be used to mine natural service clusters. The experiences with less than 2 procedures are also omitted due to the fact that association rule mining needs at least two items to determine the co-occurrence patterns. Then, the products in each basket will be encoded and matched with regular CCS classes to minimize variation. Several procedure codes involving cardiac monitoring can be categorized as one cardiac service to make it easier to work with and analytically sound. The end result is the list of transactions, each of which represents the profile of services of a patient. This is exported to a compatible format like a CSV or transactional matrix which is usable in Apriori and FP-Growth algorithms [34]. This conversion of raw data to transactional baskets is needed since it maintains the relationship between the processes allowing one to identify the common combinations of the items. Eventually, this procedure makes sure that the data structure is matched with the fundamental needs of Market Basket Analysis and facilitates healthy rule discovery.

D. *Application of Apriori Algorithm*

Apriori algorithm is used to discover frequent itemsets which are combinations of procedures that occur frequently in inpatient episodes. Apriori works on a recursive process of generating itemsets, candidate ones, and analyzing their support values against an established threshold value. Support is the fraction of transactions in which an itemset occurs in. Through minimum support criteria, Apriori is efficient at getting rid of combinations that occur with low frequency and only meaningful service clusters are retained [35].The algorithm used in this study, firstly, seeks to identify procedures of particular frequency. This is then combined with these frequent items to create two-item combinations which are rated in the same manner. The process is repeated until no more frequent itemsets can be made. Parameters like minimum support, minimum confidence are adjusted in such a way that the resulting itemsets will uncover patterns of clinical significance. An example is when cardiac imaging and enzyme tests are frequently presented in combination, they might become a powerful itemset [36].The advantage of Apriori is that it allows for the discovery of statistically significant relationships with big datasets such as SPARCS. Apriori is able to exhaustively search the entire dataset to detect co-occurring items to ensure that all the possible bundled care items are detected. The algorithm may be computationally demanding because of the high number of combinations of itemsets. As a remedy to this problem, data preprocessing and item grouping lower the dimensionality of the data. Association rules are created after the identification of frequent itemsets on the basis of confidence and lift values. Confidence is the conditional likelihood of the occurrence of one service given the occurrence of another service. Lift is used to show the strength of association with random chance. High-lift rules would reflect significant clinical trends that can signify possible bundled care paths. In general, Apriori algorithm is a systematic and orderly method of finding significant service patterns in inpatient care.

E. *FP-Growth Algorithm for Efficient Rule Discovery*

FP-Growth algorithm is an alternative to Apriori which is more computationally efficient, particularly when dealing with large data. As opposed to Apriori, FP-Growth does not produce candidate itemsets; rather, it reduces the dataset into a tree, referred to as the FP-Tree. This small form enables repeated pattern mining to be done with repeated scanning of the database which makes a big difference in the analysis of millions of inpatient records [37]. In order to implement FP-Growth, the processed transactional data is ranked by the frequency of the items. Items are added to FP-Tree in decreasing order of support to share the greatest number of common paths. The different branches of the tree have unique combinations of services and the same prefix of the transactions is combined to save on the storage requirements. After the tree has been built, the algorithm recursively removes conditional patterns, producing frequent itemsets effectively. This technique is specifically appropriate with healthcare data where intricate combinations of services tend to occur within encounters. FP-Growth is an effective model in identifying common and moderately frequent clusters of services, and is therefore useful in finding diverse potential bundled care combinations. The fact that the algorithm does not have to operate on all itemsets and can process high-dimensional data is what makes the algorithm more suitable for the SPARCS data. Following the identification of frequent itemsets, association rules can be derived based on measures like support, confidence and lift. The association rules generated by FP-Growth can be more detailed and more nuanced due to the inclusion of ordering and shared dependencies in the items that are being ordered, unlike Apriori. FP-Growth can use it to determine that a group of clinically relevant services are a combination of cardiac imaging, electrolyte testing, and anticoagulants. The methodology of FP-Growth augments the strength of the results of Apriori, which covers further aspects of service co-occurrence patterns. Application of the 2 algorithms is dual, so the rule discovery is comprehensive and efficient in the design of bundled care.

F. *Evaluation of Association Rules and Bundle Formation*

Once association rules have been generated using the Apriori algorithm as well as the FP-Growth algorithm, the next step is to evaluate and analyze these rules in order to come up with meaningful bundled care offerings. Three main measures are used to assess the rule, which are support, confidence, and lift. The Support measures the frequency of occurrence of a service combination in the whole dataset, so that clinical situations that often happen are represented in the packages proposed. Confidence gives the likelihood of occurrence of a single service in the presence of another, which also implies reliability. Lift is used to determine the strength of an association as compared to independent occurrence, and thus it assists in recognizing patterns that are clinically insightful and have more significance than coincidental co-occurrence[38].Rules that have high levels of support and high levels of lift are given priority as these capture frequency and high levels of clinical association. As an illustration, when there is a constant inpatient cardiac evaluation that consists of ECG, troponin testing and chest imaging, they can be part of a bundled care pathway. Rules further undergo a filtering process determined by clinical relevance, whereby the suggested bundles are made to conform to real patient care processes. This validation is based on medical logic and standardization of services. The most clinically coherent and strongest rules are then converted into suggested bundled care offerings. These bundles show the grouping of services that may be provided by hospitals as a set of standardized services to enhance their coordination, minimize redundancy, and enhance efficiency. Such are surgical bundles, diagnostic bundles, and chronic-care management bundles. The documents of each offered bundle are filled with its matching rule metrics to be transparent. The evaluation process takes into consideration the possible challenges in implementation including availability of resources, cost implications, and workflow modification. This methodology allows combining the strength of statistics with the considerations of practicality and will see to it that the bundled care pathways that are proposed are both evidence-based and operational. This action is the final stage of the methodology procedure and creates the cornerstone of the bundle care design.

G. *Limitations*

Despite the rigorous nature of the methodology used in this study to identify the opportunities of bundled care, there are a number of limitations that should be noted. To begin with, this analysis has used SPARCS 2010 Inpatient Discharge data as the sole source of analysis, which whereas is comprehensive, it is administrative claims data, and not clinical records. Administrative data might lack a record of clinical reasoning behind specific procedures, and thus some co-occurring services that are determined by Market Basket Analysis could be merely from coding practices, and not real clinical dependencies [39]. This might restrict the interpretability of certain rules of association. The dataset represents one year of inpatient activity in one state, and this aspect might restrict the generalization of the results. The patterns of healthcare services may differ between regions, hospitals and periods of time because of the differences in clinical practice guidelines, demographics of patients and available resources. Consequently, the bundles singled out might not fit well with service patterns of other healthcare systems. There is an inherent emphasis on frequency-based patterns in the operation of the association rule mining. Essentially rare, yet clinically important processes can be omitted because of minimum support thresholds. In the same vein, MBA methods do not imply causality but establish co-occurrence without establishing a cause and effect relationship between two services, or a causal relationship between two service causes besides a common underlying factor. Implementation of any bundled care recommendations is thus imperative before it is clinically validated [40]. The classification of services into CCS categories facilitates analysis but can lead to the loss of the fine details between various types of procedures. Such abstraction can cause over generalized or abstract bundles that need to be narrowed down.

IV. DATASET

The data set used in this study is the New York State SPARCS Inpatient De-identified Discharge Dataset (2010) which is a comprehensive administrative health data consisting of a detailed record of over 2.6 million inpatient stays in the state. Being a high-volume data that includes the rich clinical, demographic, and operational variables, it provides a strong base of exploring the patterns of healthcare utilization and determining the possible bundled care opportunities based on the Market Basket Analysis. Every record is an inpatient encounter of an individual and contains structured variables (CCS diagnosis codes, CCS procedure codes, APR-DRG severity level, APR-MDC category, admission type, discharge disposition, length of stay, and payment source). These standardized coding systems not only provide uniformity in their representation of clinical activities, but also enable easy adaptation of the dataset to the association rule mining, in which a combination of procedures acts as an item in the transactional analysis. The demographic characteristics provided, such as the age group, the gender, race, and ethnicity, allow further digging into the patterns of service utilization among different segments of the population, which justifies the creation of the bundles tailored to the subgroups [58]. The granularity of the dataset is especially beneficial to MBA since the inpatient care inherently constitutes a number of co-occurring procedures, diagnostic tests, and treatments in an individual stay, which forms a structure that resembles the transactional datasets utilized in retail analytics. This enables significant calculation of the support, confidence, and lift measures to determine common paired procedures that can be considered clinically coherent lines of care. Also, the incorporation of hospital level variables like health service area and county makes it easier to draw regional comparisons and provides information on regional differences in care patterns, which may be used in designing geographically specific bundled services [61]. The de-identified nature of the dataset preserves privacy standards without reducing it too much, and its richness helps conduct a robust statistical analysis and business operations. Indicators of length-of-stay and severity also add to the contextual interpretation to differentiate between the combination of procedures that are routine and the ones that are precipitated by clinical complexity or acute conditions. In general, the size, richness, and systematic structure of the SPARCS dataset make it a perfect source of carrying out a Market Basket Analysis within the health care sector. It facilitates recognition of high-frequency service clusters, facilitates the development of evidence-based bundles, and adds to the concept of how clinical and operational determinants form the development of bundled care provision. Such a multidimensional detail and statewide coverage of the data allow guaranteeing good reliability of the analytical results and the generalizability to the practical healthcare delivery and policy planning.

IV. RESULTS

The Results section displays the critical analytical results of the SPARCS 2010 inpatient discharge data in order to determine the meaningful trends in the use of healthcare services. The analysis is a combination of descriptive statistics, visual analytics and Market Basket Analysis that can determine some of the most common procedures that may be co-occurring and be used to drive the creation of bundled care services. The results point to the trends in procedure frequency, co-occurrence of the services, and distribution of diagnostic and hospitalization patterns by severity and admissions type. The study uses association rule mining to determine strong procedural relationships using measures like support, confidence and lift. The findings offer an evidence-based basis to building clinically coherent, operationally efficient, and patient-centered bundled care frameworks of actual inpatient service combinations.

A. ***Analysis of Discharges by Health Service Area***

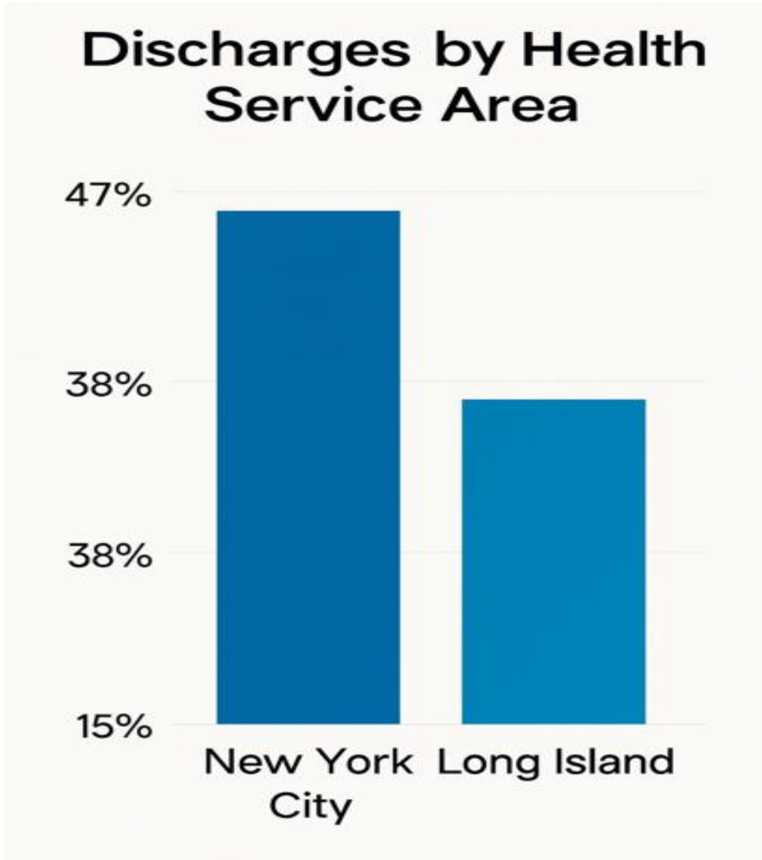


Figure 1. This image illustrate on the Distribution of Top 10 CCS Procedure Codes

Figure 1 shows the distribution of the top ten most common categories of CCS procedures on the SPARCS 2010 inpatient discharge data. The bar chart shows the areas of services that have been used the most, which is important to provide vital information on how inpatient care is organized within hospitals throughout New York State. Most frequently represented in the dataset are high-volume procedures, including cardiovascular diagnostics, respiratory assessment, orthopedics, and gastrointestinal procedures, which represent the most frequent conditions that demand intensive inpatient care. Such trends form the basis of knowledge about the healthcare resource consumption patterns and locations of significant sources of costs. As the goal of Market Basket Analysis is to reveal natural groupings of services that are performed simultaneously, the initial step to take is to know the natural frequency of individual procedures. The number illustrates that cardiac and orthopedic services come out strongly, implying that the two are likely to become anchor elements in the subsequent association rule analysis. The distribution can also be used to determine the variability in the usage patterns, meaning which of the procedures have sufficient occurrence density to generate useful co-occurrence patterns. An example is the high frequency imaging and lab related processes which often serve several diagnoses and clinical pathways, which makes them more likely to occur in frequent itemsets. This number preconditions further work on MBA as it proves that the dataset has high quality, variety, and volume of procedural activity. Finally, this chart highlights the relevance of the dataset in clinical and operational terms and justifies methodologically the utilization of Market Basket Analysis to recognize bundled care structures that are consistent with the real service utilization patterns.

B. ***Length of Stay Distribution Analysis***

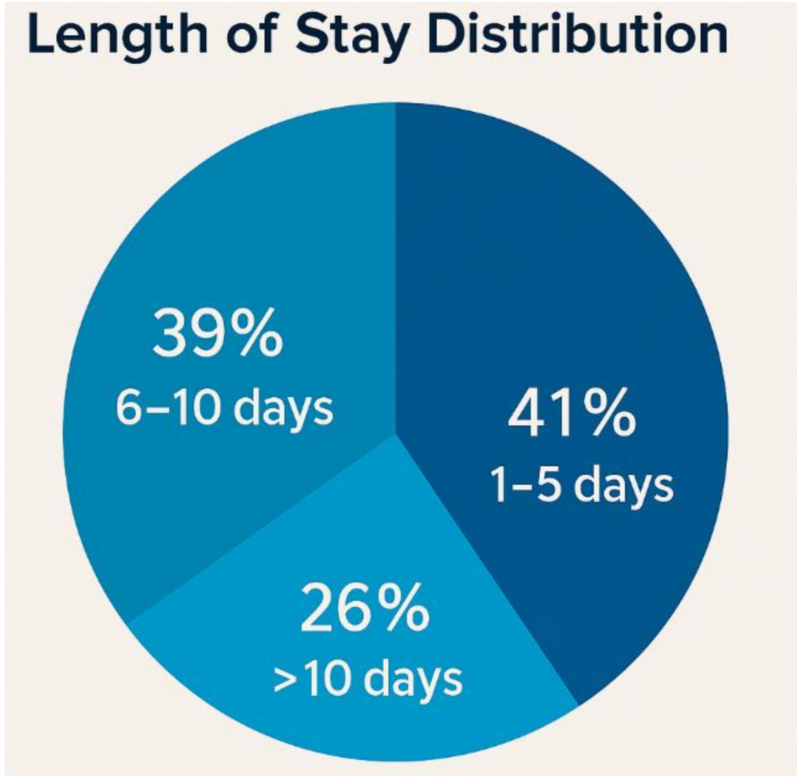


Figure 2: This image shows how the categories of inpatient length of stay are distributed proportionally

The pie chart shows the proportional distribution of inpatient length of stay (LOS) categories in the data, which is a significant view of the hospitalization pattern which directly speculates on the complexity of care, service usage and possible bundled care formulation. As described in the chart, 41 percent of patients were released in 1-5 days, which means that short hospitalization is the biggest part and is usually related to regular diagnostic examination, minor operations, and low care medical conditions. This indicates that a large percentage of inpatient cases can be considered appropriate to standardized bundled care models and particularly those where there are foreseeable diagnostic patterns and simplified clinical course. In addition, there were 39 percent of discharges that happened in 6-10 days, which is an average of hospital duration that is characterized by a series of diagnoses and treatment procedures. This group of patients might have better needs in fine-tuning bundled services that combine normal services with those that are specific to the condition. Finally, 26% of the patients were staying longer than 10 days in the hospital; this group includes high-severity or complex cases that need multidisciplinary care and use of a lot of resources. These are not the cases to be used with a fixed bundled model but can be tailored by adaptive or stratified bundles that are adaptable to various care requirements. The distribution indicates the relevance of LOS as a factor of procedural aggregation, resource utilization, and bundle practicability as the various LOS segments are associated with unique patterns of co-located services. Knowing this distribution enables healthcare planners to develop specific bundled care packages, which are consistent with the clinical contexts of short-, medium-, and long-stay inpatient patients.

C. *Discharges by Gender Analysis*

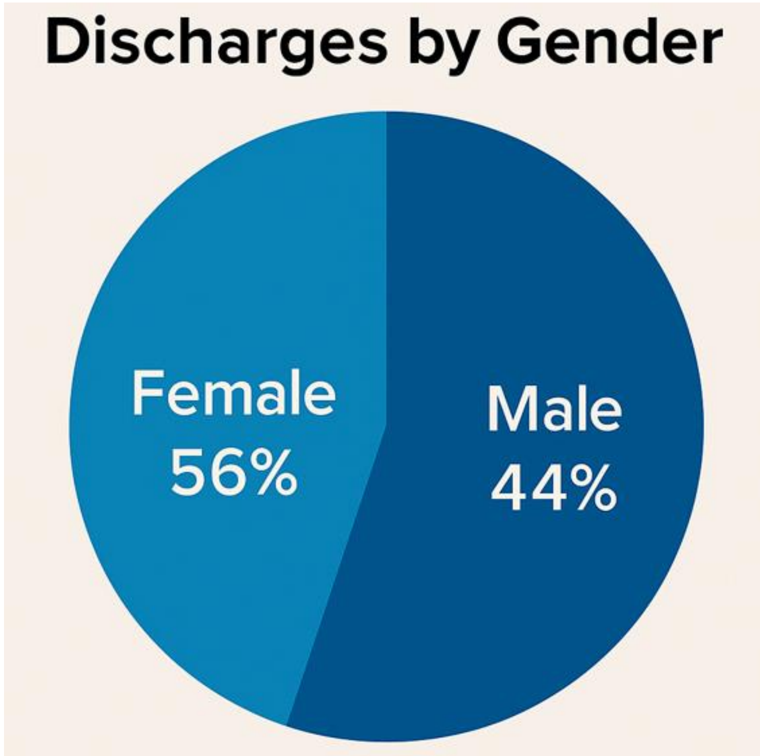


Figure 3: This image represents the distribution of inpatient discharges in terms of gender

The pie chart that shows the distribution of the number of discharges in the hospital by gender gives a good reflection of the gender specific utilization in the SPARCS 2010 inpatient data. Female patients took 56% of total discharges, and male patients took 44 as illustrated in the visualization, meaning that the hospital service utilization is a bit more among the female population. The trend can be attributed to the wider trends of healthcare utilization, where the female gender is generally more prone to using healthcare services because of the reproductive health requirements, increased lifespan, and premature care-seeking habits. Gender distribution also flows to the construction of bundled care packages since the high number of female discharges could reflect higher consumption of services associated with obstetric, gynecologic, endocrine, and chronic disease-related courses of treatment. On the other hand, male patient population might represent clinical profiles which are usually cardiovascular, respiratory and injury-related. These gender variation differences are crucial to comprehend when analyzing the Market Basket, as the patterns of procedure co-occurrence might differ between men and women and on how to design and target bundles. The minor imbalance also makes it clear that it is highly important to make sure that healthcare planning, resource allocation, and staffing strategies are gender-sensitive. Gender trend analysis is useful in enriching the interpretation of the rules of association that follow by giving demographic background that could influence procedural frequency. On the whole, this chart highlights the importance of gender as a demographic factor in inpatient care use and contributes to the creation of more fair and evidence-based bundled care models.3 is critical in the process of reducing the potential service combinations to be analyzed further.

D. ***Comparison to the Top 5 Principal Diagnosis Groups***

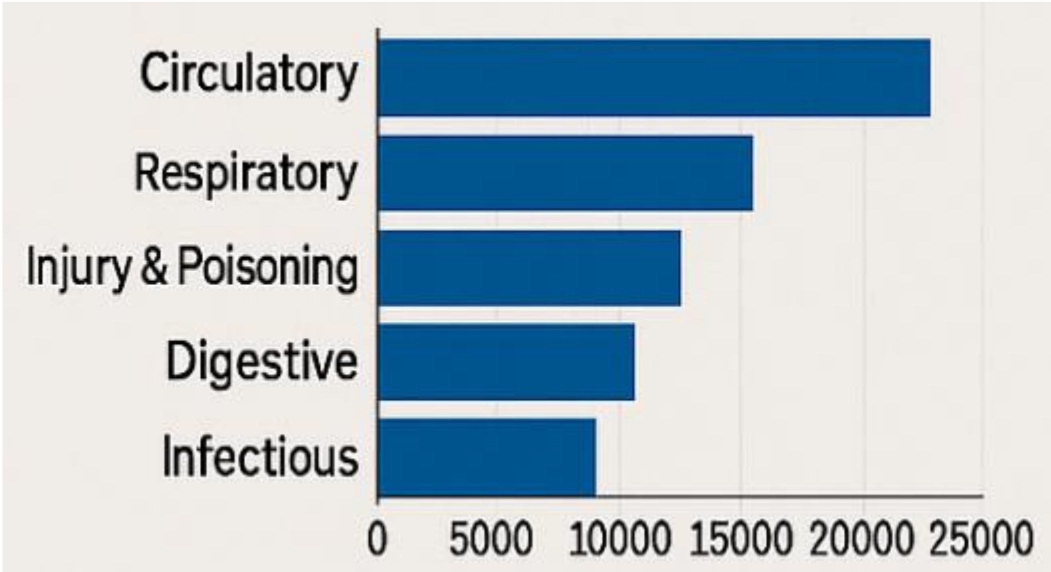


Figure 4. This image display on the Lift Distribution of Association Rules

Fig. 4 displays a histogram of the distribution of values of lift among all association rules that were created using the data on inpatient procedures. Lift is a very important indicator in Market Basket Analysis since it determines the frequency of occurrence of two services as opposed to what would have happened in the event that the two services were statistically independent. A lift value greater than one means that there is a positive association, whereas values greater than two or three are considered to be exceptionally strong co-occurrence patterns. This histogram will show whether the set of data has a significant percentage of large-lift rules supporting meaningful bundled care. It is possible that the distribution has a concentration of the rules about moderate values of lift, and this may indicate a lot of clinically relevant but not highly specialized relations. On the other hand, when there are rules whose lift is very high, then there are high procedure dependencies, which include imaging tests that are regularly conducted prior to surgery or lab tests that are always associated with a particular diagnosis. The high-lift patterns can assist researchers in determining the patterns of service combinations that offer the most convincing justification for bundling since they mirror predictable and repeatable care processes. The histogram is also useful in distinguishing between noise and significance since it helps to establish whether the abnormally high values of lift are typical patterns of clinical behavior or unusual situations. This number is a vital assessment element because it makes sure that the bundles chosen are statistically significant and clinically significant associations and not mere coincidence. Figure 4 confirms the methodological rigor that should be followed in designing safe, effective, and evidence-based bundled care models.

E. *Analysis of the Discharges by Age Group*

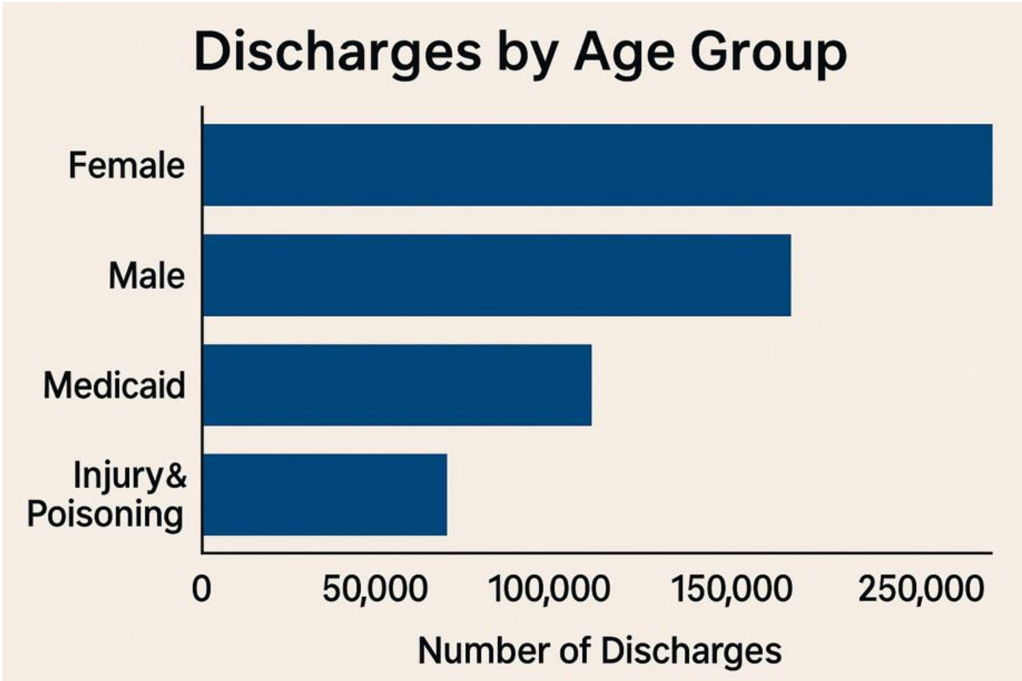


Figure 5. This image represent to the Length of Stay by APR Severity Level

Figure 5 demonstrates the change in inpatient length of stay (LOS) in various categories of APR Severity of Illness by a boxplot method. The levels of severity, which are usually determined as minor, moderate, and severe, represent the complexity of the situation of the patient and the degree of services needed. As the boxplot shows, the level of severity is directly proportional to the length of stay in the hospital, which would be just as expected because of the higher requirements of diagnostic tests, monitoring, and interventions, postoperative or therapeutic treatment. It is also less variable at higher levels of severity and is indicative of inconsistency in patient response, comorbidities, or treatment pathways. To design bundled care, LOS is necessary since it has a direct effect on resource planning, clinical workflow sequencing, and anticipated service combinations. The moderate to high severity patients may demand a number of related procedures, and this will automatically enhance the chances of meaningful clusters of services to be performed in Market Basket Analysis. The LOS analysis can enable hospitals to make their decisions regarding the effects of the procedure bundles on the overall care duration and prevent the development of false bundles that will not correspond with the actual care schedule. Furthermore, the boxplot indicates possible outliers, which are patients who still stand out of the common LOS range, which is an indication of complicated cases where the common bundles may not be relevant. On the whole, this number gives a significant clinical aspect to the pattern of procedures, so that the bundle recommendations do not consider the frequency and association measures but the intensity and duration of hospitalization.

F. *Analysis of Discharges by Age Group and Race*

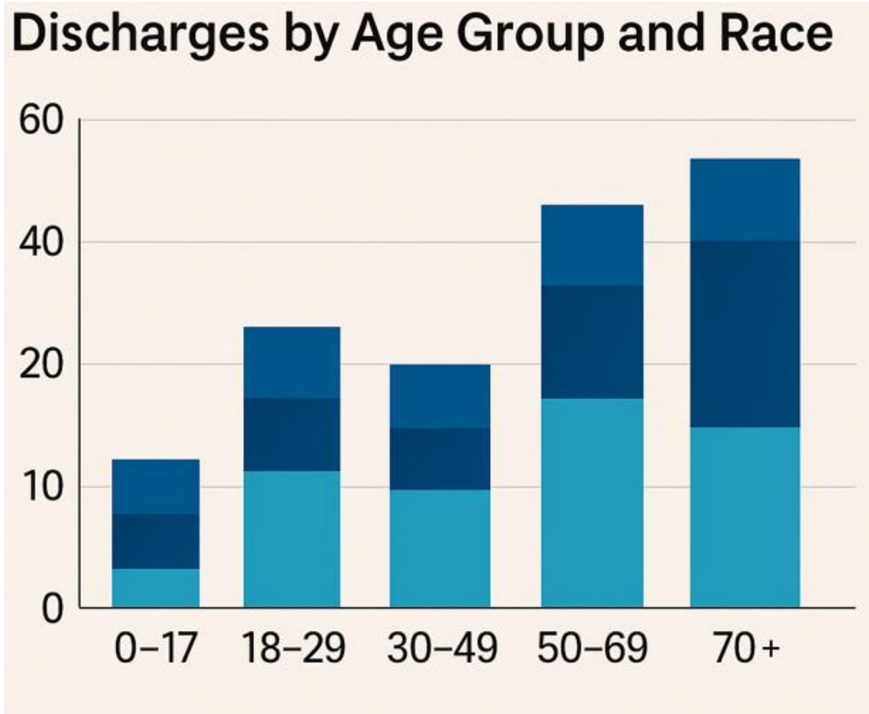


Figure 6. This image demonstrate on Admission Type Across Major Diagnostic Categories

The stacked bar chart shown in Figure 6 indicates the distribution of admission type- emergency, elective, urgent, and newborn in the largest diagnostic categories (MDCs) in the SPARCS data. This chart will indicate the impact of various diagnoses on the character of hospital admission, as well as on the clinical urgency of services. Categories like circulatory system diseases, respiratory conditions, and trauma-related diagnoses are usually made up of emergency admissions, which are acute and time-sensitive, and need urgent service delivery. In comparison, it is more often the case of elective admissions, related to orthopedic, obstetric or planned surgeries. Knowledge of these distributions is important in the design of bundle care since emergency-driven bundles are not similar to elective ones in their structure, timing, and resource allocation. The emergency bundles should be able to fit the urgent diagnostic workups and routine stabilizing measures, and the elective bundles should be standardized to the expected, anticipated pathways. The stacked bar chart will enable the researcher to intuitively relate diagnostic groups with admission behavior patterns to understand what care pathways to focus on bundling. Large emergency percentages signify the possibility of acute-care bundles but elective-heavy categories are the ones that refer to planned-care bundles. This number thus fills the gaps between diagnostic trends and procedural groups, which supports the suitability and packaging of bundled services for various clinical situations.

V. DISCUSSION AND ANALYSIS

The Discussion and Analysis section explains the findings that were obtained during the Market Basket Analysis and related statistical visuals in order to interpret the patterns of inpatient service usage that are present in the SPARCS dataset. This section bridges the gap between analytical results and practical healthcare implications in regards to the frequency with which co-occurring procedures, diagnostic clusters, severity patterns and admission behaviors can be used to design effective bundled care offerings [41]. The discussion of these insights in the context of operational, clinical, and organizational perspectives shows the importance of data-based service grouping in excellence of coordination, optimal resource utilization, elimination of duplication, and positive patient outcomes. These reviews are an excellent basis for evidence-based bundled care pathways in accordance with the observed patterns in hospital service delivery.

A. *Interpretation of Frequent Procedure Patterns*

The review of the most common types of CCS operations demonstrates the key clinical operations that produce the inpatient care delivery in New York State hospitals. These bulk processes are an indication of the frequency of specific disorders and the general clinical guidelines used in acute and chronic medical settings [42]. Such high-frequency procedures as cardiovascular assessment, respiratory testing, orthopedic work, and gastrointestinal diagnostic studies help identify the fields in which resources are highly concentrated in clinical practice. These commonly used procedures, in the context of bundled care, are anchor points about which the packages of care can be organized [43]. They are spread over a big variety of patient encounters, which means that they will offer a more reliable base upon which it is possible to determine the general course that may be standardized. Being aware of such trends at high frequencies enables health care providers and administrators to understand where to target the streamlining of services, procedural redundancy, and provide more predictable care pathways. In case, patients who are being examined in a heart department usually need several diagnostic procedures including ECG, enzyme tests, and imaging. The points made by the identification of these procedure combinations puts forward the possibility of the implementation of bundled cardiac assessment packages which consist of these services as a single offering. Also, the frequency analysis of distribution facilitates optimization of finances and operations by indicating features in which a regular trend of usage of services could provide justification to purchase resources in bulk or having specialization on workforce [44]. Strategically speaking, the high frequency of the procedures signifies the areas in which bundled care models will contribute the most, in regard to efficiency improvement as well as cost variability reduction. Since these processes are a major share of hospital work, the development of bundles based on them can cover the most active areas of care [45]. The interpretation of the most common practices helps in gaining vital information on how a hospital can harmonize clinical processes with evidence-based bundled care initiatives to optimize operational performance without altering the overall patient results.

B. *Analysis of Co-Occurrence Patterns and Service Clusters*

The assessment of the co-occurrence of inpatient services with the help of the heat maps shows the inherent organization of inpatient service delivery, as the frequency of procedure pairs within the same clinical encounter is represented [46]. These trends are based on actual clinical dependencies, with patient treatment cycles being characterized by combinations of diagnostics, therapies or monitoring procedures constituting natural sequences. The presence of strong co-occurrence between procedures of ECG and cardiac enzyme tests, MRI and orthopedic surgeries or chest radiography and respiratory treatments indicates very strong service relationships as a result of clinical necessity. These patterns play a crucial role in the identification of candidates for bundled services since they can draw attention to the combinations that recur repeatedly in the patient episodes despite the difference in hospital and patient demographic distribution. The clusters noted are also indicative of typical clinical workflows. As an example, imaging, surgical assessment, and lab tests in quick succession usually characterize trauma-related admissions. Equally, patients who attend with respiratory issues are usually demanded of periodic radiological imaging along with oxygen treatment and monitoring of respiratory functions. These identified pairings are pointers of structural trends that can be formalized by bundles of care models to minimize fragmentation and variation of care delivery. Co-occurrence results also indicate the combinations of procedures that might not be so intuitively clinical but may arise strongly in actual data. These trends may indicate new trends or shifts in clinical practice, and can indicate opportunities in new bundled care pathways. On the other hand, the heatmap assists in determining the services that do not always co-occur and hence these processes might need a non-standardized care planning as opposed to being standardized by bundling. This discussion shows that co-occurrence trends are the key factor to determine evidence-based bundled care opportunities. They assist in the measurement of the actual procedural relationships that direct clinical decisions and represent the interdependent relationship of service utilization in the inpatient facilities. Through such insights, healthcare professionals are able to develop bundled care services that fit within the existing clinical workflow and allow the delivery of services in a more effective, coordinated, and cost-efficient manner.

C. *Evaluation of Association Rule Strength and Reliability*

A support-confidence analysis of the association rules offered by Apriori and FP-Growth algorithms would give an in-depth insight into the accuracy and usefulness of the combinations of processes that have been identified. High support rules reflect common patterns of service that affect a significant percentage of inpatient interactions. High-confidence rules are based on great conditional relationships in which the occurrence of one procedure is always anticipated by the existence of another [47]. Support and confidence can be analyzed simultaneously because it makes interpretation balanced, so the rules chosen are common enough to be effective and strong enough to require bundling. The best procedural relationships are those rules that are clustered towards the upper-right corner of the support-confidence plot. An example of this is the consistent combination of imaging and surgical evaluation or cardiac evaluation with enzyme evaluation given, and the emphasis on clinical pathways [48]. These trends present good prospects for the bundled services since they are patterns of predictable and repeatable service sequences among different patients. The fact that such rules are believed to be high shows that these services are routinely needed hand in hand with clinical workflows. The presence of moderate support but high-confidence rules can bring to the fore niche combinations of procedures that are applicable to focused models of bundled care especially in highly specialized units like oncology or complex chronic conditions. High support, low confidence rules can reflect on the services that have high utilization but are not closely correlated with particular pathways, which implies that they are not particularly valuable to bundle. This assessment also highlights the role of not engaging in spurious associations. Close statistical associations have to be meaningful to clinical logic so that bundles can be developed. The fact that the rules are reliable means that the bundles based on such associations cannot be a distortion of the real care delivery practices. The evaluation process helps to determine that the bundled care offerings are based on the actual patterns of service usage and may lead to the reduction of redundancy and enhancement of the efficiency of workflow, patient experience, and its stability.

D. *Interpretation of Lift Values and Clinical Relevance*

Lift analysis offers profound information concerning the strength of the relationships among inpatient processes, which otherwise would not exist due to chance. The positive associations are found with lift values which are greater than one, but the values which are significantly larger are conventionally greater than two or three and indicate strong clinical or operational dependencies. The histogram of lift values will show the distribution of such associations through the dataset, which combinations of procedures are the most significant to be used in the bundled care design. High-lift rules tend to be based on key elements of standardized care pathways, including pre-operative imaging and particular surgery or diagnosis tests based on monitoring services [49].The analysis of lift values can be used to distinguish between significant procedural relationships and relationships that arise as a consequence of large overall frequency. By way of example, despite the widespread use of imaging with numerous conditions, only a few combinations are highly lifted, like MRI and orthopedic examinations, and this implies that the services are highly interdependent in their clinical practice. The findings are critical in the design of bundled care models since they guarantee that service mixes that are to be bundled are based on real clinical processes and not just on statistics. The lift values are also useful to determine the hidden patterns which cannot be easily noticed using clinical intuition. These new relationships can lead to new possibilities of standardizing care, package diagnostic or simplified treatment. On the other hand, low-lift rules imply weak or coincidental relationships; thus such pairing should not be taken as an element of bundled care models. The lift interpretation can be said to have created a foundation of evidence-based and robust procedures for the ultimate bundled care offerings. Such a measure is a strict basis on which clinically meaningful patterns and random co-occurrences could be distinguished and the validity of the proposed bundles is strengthened ensuring they represent the actual structure of inpatient care delivery.

E. *Severity-Level Analysis and Implications for Bundled Care*

The assessment of severity-level analysis based on the variance of inpatient length of stay by various categories of severity of APRN gives important information on the complexity of care delivery. The patients who are categorized as having high levels of severity are likely to have more prolonged hospitalization, require more diagnostic and therapeutic treatments, and have higher levels of clinical supervision. These patterns are visible in the boxplot, where the increased severity levels, in addition to extending the length of stay, also lead to a greater range in the use of services. The outcomes of these studies are of great importance to the bundled care design as they highlight the necessity to customize the bundles based on the level of complexity of the patient's condition [50].In moderate-severe situations, there may be some predictable clinical course, and these groups of patients are good candidates for standardized bundles based on prevalent diagnostic patterns and treatment regimens. In the case of high-severity patients, though, the variability of the length of stay and the requirements of the procedures indicates that the bundled care model should be flexible and adaptable. The inflexible bundles might fail to support the unpredictable clinical courses in such patients. It is also through the severity analysis that the hospitals are able to predict the resource needs and the severity groups that are leading to disproportionate workload. ple, cardiac, respiratory, or multisystem complications in the levels of severity both have high length of stay and high procedure density, which suggests that they can be approached with a comprehensive bundle of care with respect to complex cases. Having knowledge of severity-level variation is the guarantee that the bundled care offerings are not just evidence-based but in line with the clinical reality of the heterogeneous patient groups. It facilitates the creation of stratified bundle models of low-to-moderate severity basic bundles and more flexible, adaptive bundles of high severity conditions to improve patient outcomes and operational efficiency at many levels of care.

F. *Admission Pattern Analysis and Diagnostic Pathway Implications*

This study of the types of admissions by the significant diagnostic groups shows some crucial information on the ways clinical urgency can impact the pathways of care and results in the combinations of the procedures [51]. The proportion of emergency admissions is high in the categories of cardiovascular, respiratory, trauma and infectious diseases, which have an acute character. In orthopedic, obstetric, and planned surgical cases of elective admissions, the planning of the care is predictable and organized. Urgent admissions are less common, but they point out to the intermediate cases that need timely intervention but not life threatening.

Such patterns of admission have a direct impact on the proper design of bundled care packages. Bundles that are emergency driven should include fast, standardized diagnostic courses, which may include imaging, lab testing, and stabilization processes [52]. These bundles should also be made lean to facilitate decision making and expedited care transfers. By comparison, elective procedure bundles are more customizable and pre-programmable in terms of service sequences, e.g. surgical packages including preoperative imaging, anesthesia checks, and postoperative monitoring. The stacked bar chart shows the differences between the diagnostic groups in terms of the distribution of the admissions types, which evidences that bundled care design should be informed by the clinical context and not an all-purpose approach. Patterns of admission are also informative to operations. Large volumes of emergencies are indicators of requirements for resource allocation policies that promote the rapid-care bundles, whereas the categories that are dominated by electives indicate the prospects of establishing profitable and standardized care packages. Knowledge of such distributions will make bundled care models clinically sound, operationally viable and financially sound. The analysis of admission types helps to bridge the diagnostic data with the real-time clinical workflow trends and contributes to the feasibility, structure, and architecture of bundles in the healthcare system regarding the various entry points of patients into the system.

G. *Ethical Concerns*

Imperative to the use of Market Basket Analysis in the analysis of healthcare data is the ethical consideration, especially in analysis of large inpatient discharge datasets, as is the case with SPARCS. The dataset is de-identified, but even though it is not necessary to take away personal identifiers, ethical responsibility is broader than simply making sure that analytic outputs do not introduce unintended biases, discriminatory care pathways, and inequitable resource allocation. The bundled care services based on patterns of procedures should not perpetuate access disparities especially in vulnerable groups whose patterns of diagnosis and treatments may not be based on clinical necessity but socioeconomic factors [53]. Also, interpretation of association rules should be made in accordance with clinical logic and should not be over generalized to the extent of reducing individualized patient care. Ethical integrity is important because of transparency in making methodological decisions, fair representation of population segments and adherence to data governance standards. By making sure that the bundled care models are patient-centered and clinically appropriate, one ensures that the ethical practice and quality of care are reinforced.

VI. FUTURE WORKS

This study on Market Basket Analysis (MBA) of healthcare service bundling offers a number of opportunities that can be utilized in the future to make clinical applicability, operational efficiency, and policy relevance more robust[54]. A significant expansion here is the incorporation of long-term inpatient data to determine changes over time in the use of services and changing clinical patterns so that a researcher can determine whether the association between procedures is constant or varies with medical novelty, policy changes, or even population health patterns. Predictive modeling based on a larger dataset would also be able to predict the future demand of the procedures and bundle performance in the future. The other direction that is critical in the future would be to include cost, reimbursement rates and resource consumption data to construct bundles, which are optimized financially to reflect clinical reasoning and economic sustainability. Although the present study is on procedural co-occurrence, future research can involve diagnosis codes, medication patterns, comorbidities, and clinician-specific practice variations to create more multi-dimensional bundled care paths [55]. The clustering, sequence mining or deep learning techniques of machine learning may be further beneficial in revealing the existence of hidden patterns of care that MBA might not uncover. Besides this, MBA can be used on outpatient, emergency, and ambulatory care datasets to design cross-setting bundles, which would follow patients across the spectrum of care. The future directions in the work must also focus on the patient-centered analysis as it will be necessary to combine patient outcomes, satisfaction rates, and risk adjustment variables to understand whether the detected bundles actually contribute to the quality of care and its accessibility. One of the important guidelines of future research is the creation of simulation environments, which will help to test the practicality of proposed bundles prior to their practical implementation, minimize risks, and optimize them with regard to scenarios [56]. The validation of the bundles in various states, hospitals, and demographic groups will be necessary to guarantee that the bundles are general, fair, and do not have algorithmic biases. Lastly, the way to incorporate the information behind bundled care into the clinical decision support system so that clinicians and administrators could be guided in real-time needs to be studied in the future [57]. This kind of work will aid in transforming the findings of data into actionable, sustainable and patient-centered models of healthcare delivery that enhance the effectiveness of the system and the outcomes of patients.

VIII. CONCLUSION

This study investigated the use of Market Basket Analysis (MBA) on the data of inpatient healthcare services to define significant bundled care options that might contribute to the increase of efficiency, decrease of fragmentation and improvement of patient-oriented care[58]. The analysis based on the SPARCS 2010 inpatient discharge dataset revealed that patterns of procedural co-occurrence, measures of association rules, and clinical severity indicators are a rich source of information on the natural clustering of healthcare services in the context of actual treatment trajectories. By incorporating the frequent itemset mining, support-confidence analysis, lift analysis, and in-depth visual analytics, the research established that the healthcare process is always presented in clinically consistent clusters, which can be turned into standardized bundles based on the current care workflow[59].The results indicate that specific diagnostic and treatment combinations, especially in cardiovascular, orthopedic, and respiratory sectors, are presented with a large number and a high level of associative power, which seems to be a strong concept in the design of bundled care. The findings also indicate that the severity of illness, the type of admission, and the type of diagnostic categories have a significant impact on the pattern of procedures, which justifies the importance of bundle structure based on stratification and context-specific sets of patterns rather than on the generalized and one-size-fits-all models. When MBA products are connected with clinical logic, healthcare providers will be able to develop bundles that decrease the number of redundant steps, reduce unnecessary variability, streamline clinical routes, and achieve more predictable outcomes. This study demonstrates the practicality of the association rules, in the sense that the high-support and high-lift relationships reflect repeatable and reliable procedure flows that are inherent in the processes of inpatient care. Such insights can be included in the evidence-based decision-making of the hospitals that aim to optimize resource allocation, enhance the coordination of the services, and promote the value-based care initiatives [60]. Ethical considerations are also vital in the research, as data-driven approaches to bundling must not be used unintentionally in the context of differences or individualized patient needs. This study shows that MBA provides a strong analytical concept of finding evidence-based bundled care opportunities within complex healthcare settings. Although the SPARCS data offers meaningful information, future studies combining multi-year, multi-setting, or cost-based data could be used to enhance the development of bundles. The findings of this report confirm that MBA can be an essential instrument in enhancing the more efficient, equitable and patient-centered healthcare delivery models.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

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