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An Integrated Approach for an Academic Advising System Using Association Rule

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ABSTRACT: Academic advising plays a crucial role in guiding students towards successful educational trajectories; however, the manual and resource-intensive nature of traditional advising methods can lead to inefficiencies and inconsistent outcomes. To tackle this issue, the research introduces a system that leverages association rule mining, a data mining technique, to offer personalized course recommendations to students.Several prior researchers have explored the use of technology in academic advising, focusing on various aspects such as predictive analytics, decision support systems, and artificial intelligence. While these initiatives have contributed to improving advising practices, a noticeable gap exists in harnessing association rule mining specifically for course recommendations. This gap prompts the need to explore how association rule mining can enhance the precision and relevance of course suggestions based on students' academic histories and preferences.The core objective of this research is to bridge the aforementioned gap by implementing a student advising system that employs association rule mining techniques. The research strives to enhance the accuracy and customization of course recommendations, thereby facilitating more informed decision-making for students. This solution also benefits advisors by providing data-driven insights that facilitate tailored guidance during advising sessions.The research utilizes a robust combination php as the programming language and MySQL database, technologies to build and implement the student advising system. This toolswas used to create an end-to-end solution that effectively mines association rules and translates them into actionable recommendations. The findings of this research offer significant contributions to the realm of academic advising and educational technology. The student advising system demonstrates the potential to revolutionize advising practices, enhancing student satisfaction and academic outcomes. By harnessing association rule mining, the system generates tailored course suggestions that align with students' academic profiles and aspirations. These findings underscore the transformative impact of data-driven approaches in the realm of educational guidance and decision-making. This research addresses the gap in utilizing association rule mining for personalized course recommendations in academic advising. By implementing a student advising system, this research contributes to improving the efficacy and quality of advising interactions, fostering better-informed academic choices for students. The findings hold implications for educational institutions aiming to enhance their advising processes by harnessing advanced data mining techniques.

I. INTRODUCTION

In today's rapidly evolving educational landscape, effective academic advising is paramount to guide students towards their educational goals and ensure a successful learning experience (Villalobos &Kallarakal, 2018). Traditionally, academic advising relied on face-to-face interactions, which posed limitations in terms of time, location, and accessibility. With the advancements in technology and the increasing demands of a digitally connected generation, there is a pressing need for innovative solutions to enhance the efficiency, effectiveness, and accessibility of the advising process. This thesis aims to design and implement a web-based student academic advising system that harnesses the power of technology to revolutionize the advising experience. By leveraging web-based technologies, the proposed system seeks to provide a comprehensive and user-friendly platform for students and advisors to interact, access relevant information, and streamline the advising process. Through the utilization of online platforms, the system aims to overcome the limitations posed by traditional advising methods, allowing for greater flexibility and convenience in accessing advising services.

Effective academic advising has been recognized as a critical factor in student success and retention in higher education (Drake, Jordan, & Miller, 2017). Academic advising systems have evolved over the years, transitioning from manual paper-based processes to technology-driven platforms. These systems aim to provide personalized guidance to students, assist in course selection, facilitate degree planning, and monitor academic progress. However, many existing systems still face challenges such as limited functionality, outdated interfaces, and difficulties in integration with other university systems (Villalobos &Kallarakal, 2018). These limitations can impede the seamless flow of information, communication, and collaboration between students and advisors. The role of technology in academic advising has been transformative, offering new possibilities for enhancing the advising process. Technology-driven solutions have the potential to streamline advising tasks, improve communication channels, and provide students with self-service options (Mastrodicasa&Metzner, 2019). The integration of technology enables advisors to access student records, track progress, and provide timely support. Additionally, it empowers students by providing them with convenient access to advising resources, degree audits, and course registration tools (Morrison, 2018). Web-based systems have emerged as a popular solution for student academic advising, leveraging the power of the internet and web technologies to deliver advising services remotely (Campbell, 2017). These systems provide a flexible and accessible platform for students and advisors, overcoming geographical barriers and time constraints. They offer features such as online appointment scheduling, degree tracking, course registration, and communication tools, facilitating efficient and effective advising interactions. Despite the advancements in technology, many existing academic advising systems face challenges that hinder their effectiveness. Outdated interfaces, complex navigation, and limited functionality can impede user adoption and satisfaction (Hawk, 2019). Moreover, difficulties in integrating advising systems with other university systems, such as student information systems and learning management systems, can result in data inconsistencies and inefficient workflows. Privacy and security concerns related to handling sensitive student data also pose significant challenges that need to be addressed (DeWitt, 2020). To overcome the challenges faced by existing systems and ensure the successful implementation of a web-based student academic advising system, several best practices and recommendations have been identified. User-centered design principles should guide the development process to ensure intuitive interfaces and positive user experiences (Pasquini & Steele, 2018). Seamless integration with existing university systems, such as real-time data synchronization, can enhance the accuracy and efficiency of the advising process (Wang et al., 2020). Regular system updates, user training, and ongoing technical support are essential to ensure system.

II. ASSOCIATION RULE MINING WITH FORMULAR

Association rule mining is a data mining technique that can be applied to the field of student academic advising to discover interesting relationships and patterns within large datasets. Association rule mining aims to uncover associations or relationships among a set of items in a transactional database. It identifies frequent itemsets, which are combinations of items that occur together frequently, and generates association rules based on these itemsets. Association rules consist of an antecedent (or left-hand side) and a consequent (or right-hand side), indicating the presence of certain items leading to the occurrence of other items.

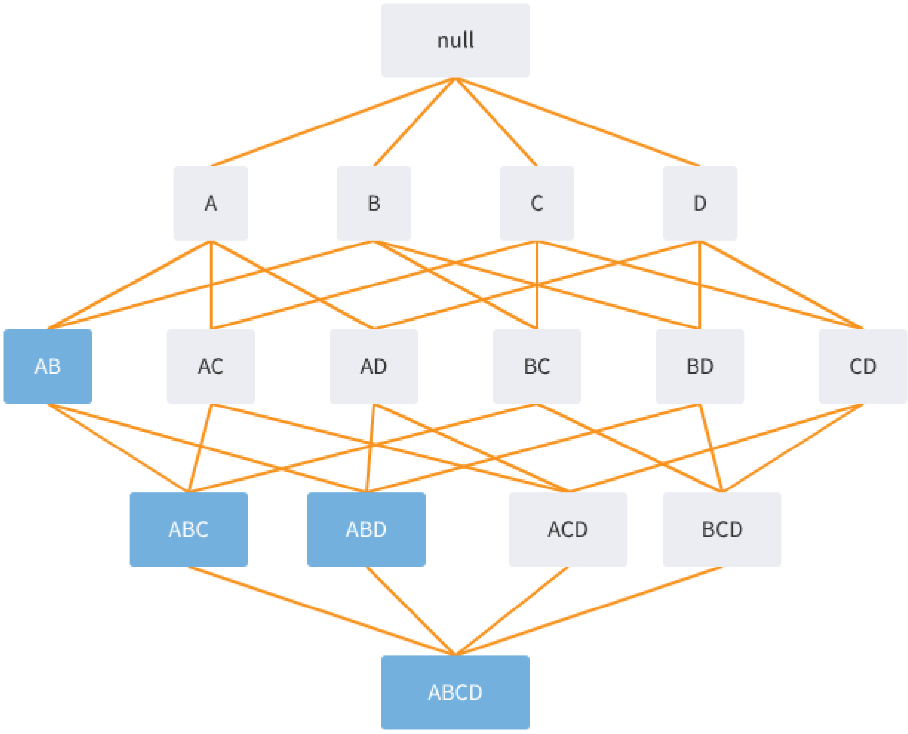

Figure 1.1Apriori algorithm for association rule learning (Source: Agrawal et. al. 2019)

The mathematical formula for association rule mining is as follows:
A → B (support, confidence)

The formula represents an association rule, where A and B are itemsets, support measures the frequency of occurrence of the rule in the dataset, and confidence measures the conditional probability of the occurrence of the consequent given the antecedent. In the context of the web-based student academic advising system, association rule mining can provide valuable insights into the relationships between various academic factors and student outcomes. For example, it can help identify patterns such as "If a student enrolls in a specific course, they are more likely to succeed in related courses" or "If a student receives regular advising, they are more likely to graduate on time." By mining association rules from historical student data, the advising system can provide personalized recommendations and interventions to students based on their individual profiles. These recommendations can include suggested courses, study strategies, or additional support services tailored to the student's needs and goals. Furthermore, association rule mining can contribute to the continuous improvement of the advising system by identifying patterns of success or challenges faced by students. It can help academic advisors and administrators gain insights into factors that positively or negatively impact student performance and make data-driven decisions to enhance the effectiveness of the advising process.

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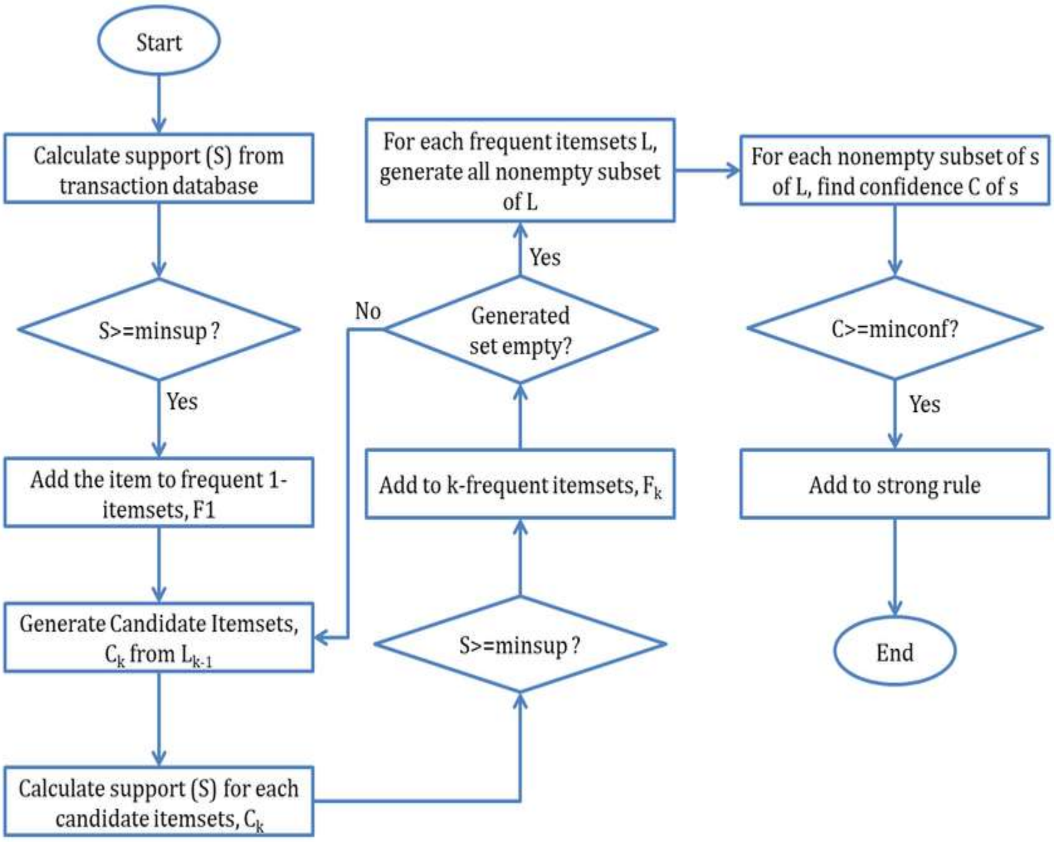

Figure 2.3 Steps of association rule mining technique (apriori algorithm) (Source:Drake, 2011)

Association rule mining is a data mining technique that aims to discover interesting relationships or associations between items in large datasets. It is commonly used in various fields, including retail, marketing, and recommendation systems. The steps involved in association rule mining include:

Data Preparation:Collect and preprocess the dataset: Gather transactional data where items are associated with unique identifiers (e.g., product IDs, course codes). Remove duplicates and irrelevant data.

Support and Confidence Definitions:Set minimum support and confidence thresholds: These thresholds determine the significance of the associations. Support refers to the proportion of transactions containing a specific itemset, while confidence measures the likelihood of an item **B** being purchased when item **A** is purchased.

Frequent Itemset Generation:Generate frequent itemsets: Identify itemsets that meet the minimum support threshold. This involves finding all combinations of items that appear frequently in transactions.

Rule Generation:Create association rules: From the frequent itemsets, generate rules by dividing itemsets into antecedents (left-hand side) and consequents (right-hand side). The antecedent implies the presence of the consequent with a certain confidence.

Pruning and Filtering:Prune rules: Remove rules that do not meet the minimum confidence threshold. Eliminate redundant rules that convey similar information.

Rule Evaluation and Selection:Evaluate rule interestingness: Assess rules based on various metrics such as lift (measuring the dependency between antecedent and consequent), conviction (measuring the strength of implication), and leverage (measuring the difference between observed and expected support).

Results Interpretation:Interpret and analyze results: Examine the generated rules to identify meaningful and actionable associations. Understand the implications of the discovered relationships in the context of the problem domain.

Validation and Testing:Validate and test rules: Apply the generated rules to new data to confirm their effectiveness and practical applicability. Analyze how well the rules generalize to unseen transactions.

Visualization and Reporting :Visualize and report findings: Represent the discovered rules through visualizations like graphs, charts, and diagrams. Prepare comprehensive reports explaining the relationships and their implications.

Iteration and Refinement:Iterate and refine the process: Adjust the support and confidence thresholds, try different evaluation metrics, and experiment with preprocessing techniques to refine the quality and relevance of the generated rules.

Association rule mining provides valuable insights into patterns and correlations within large datasets. While these steps outline the general process, specific algorithms like Apriori and FP-Growth implement these steps differently. The choice of algorithm depends on factors like dataset size, memory usage, and computational efficiency.

III. ANALYSIS OF THE SYSTEM

The analysis of the proposed system is a critical phase in the development process, where the envisioned improvements and changes are meticulously evaluated. This process involves a thorough examination of the proposed system's features, functionalities, and potential benefits compared to the existing system. By conducting a comprehensive analysis, organizations can validate the viability of the proposed changes and ensure that they align with their objectives and requirements. During the analysis of the proposed system, several key aspects are typically considered. Firstly, a detailed comparison is made between the proposed system and the existing system. This involves assessing how the proposed changes address the constraints, limitations, and shortcomings identified in the existing system analysis. If the proposed system fails to adequately resolve these issues, it might not provide the desired benefits. Furthermore, the analysis delves into the potential impacts of implementing the proposed system. This includes evaluating how the changes will affect various stakeholders, such as end-users, administrators, and other relevant parties. Understanding these impacts is crucial for anticipating challenges, managing expectations, and ensuring a smooth transition to the new system. Another critical aspect of the analysis is the alignment of the proposed system with the organization's goals, strategies, and long-term vision. Organizations must assess whether the proposed changes are in line with their strategic priorities and whether they contribute to enhancing efficiency, productivity, or competitiveness. In addition, the analysis considers the feasibility of implementing the proposed system. This includes assessing technical feasibility, where the organization evaluates whether the required technology is available and can be effectively implemented. Financial feasibility is also crucial, as organizations need to ascertain whether the proposed changes are financially viable and justifiable within their budget constraints. Moreover, user acceptance and satisfaction are integral components of the analysis. The proposed system's user interface, functionality, and usability are evaluated to ensure that they meet user needs and expectations. Resistance to change is a common challenge during system implementation, so addressing user concerns and incorporating their feedback is paramount for successful adoption. Ultimately, the analysis of the proposed system aims to provide a well-rounded assessment of its potential benefits, risks, and alignment with organizational goals. It serves as the basis for making informed decisions about whether to proceed with the proposed changes, refine the system further, or explore alternative solutions. The analysis of the proposed system is a pivotal step in the development process, ensuring that the envisioned changes are thoroughly examined and evaluated. By comparing the proposed system with the existing system, considering its impacts, alignment with organizational goals, feasibility, and user acceptance, organizations can make informed decisions that contribute to the success of the project.

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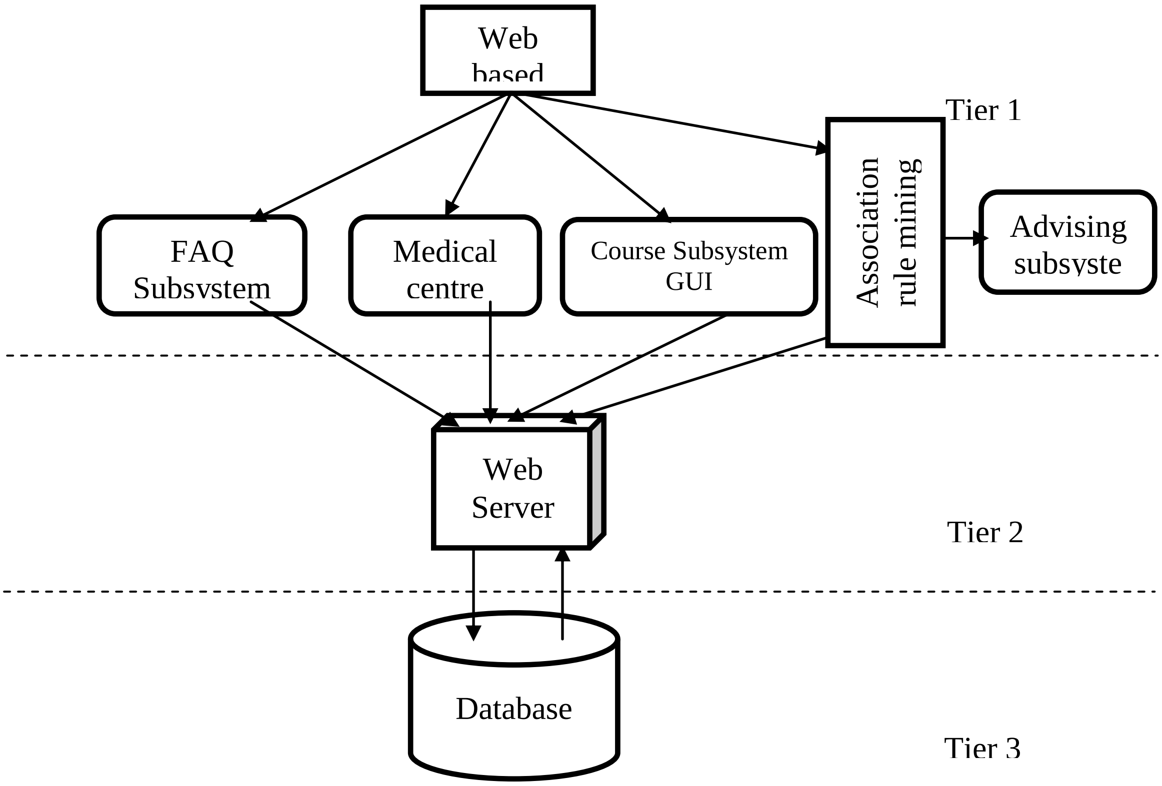

IV. METHOD ADOPTED IN THE STUDY

The study adopts an association rule mining method to analyze the relationships and patterns within a dataset. Association rule mining is a data mining technique that identifies interesting associations or correlations among variables in a large dataset (Agrawal, Imielinski, & Swami, 1993). This method is particularly well-suited for uncovering hidden patterns in data, making it useful in various fields, including retail, market basket analysis, recommendation systems, and more. Association rule mining involves two main measures: support and confidence. Support indicates the frequency of occurrence of a specific combination of items in the dataset. Confidence, on the other hand, measures the likelihood that an item (or a set of items) will be present in the dataset given the presence of another item (or set of items) (Han, Pei, & Yin, 2000). These measures help identify strong associations between items and can provide insights into customer behavior, preferences, or trends. The Apriori algorithm is a widely used approach for association rule mining (Agrawal, Imielinski, & Swami, 1993). It works by iteratively generating candidate itemsets and pruning those that do not meet the minimum support threshold. This process gradually refines the set of frequent itemsets, which are combinations of items that occur frequently in the dataset. From these frequent itemsets, association rules are generated by considering various levels of confidence. In the context of the study, the association rule mining method will be applied to analyze the dataset of academic advising interactions. The goal is to uncover patterns in student advising behaviors, preferences, and outcomes. For example, the method might reveal that students who frequently attend advising sessions early in the semester tend to have higher final grades. Alternatively, it could identify that students with a certain course background are more likely to seek advice on specific majors. By applying association rule mining, the study aims to provide valuable insights that can inform the design of the proposed academic advising system. These insights might help optimize advising strategies, tailor recommendations to individual student needs, and improve overall student success rates. The association rule mining method is a powerful technique for uncovering hidden patterns and relationships within large datasets. By adopting this method in the study, the researchers intend to gain valuable insights into student advising behaviors and preferences, which can guide the development of an enhanced academic advising system.

V. SYSTEM MODEL

The system model serves as a blueprint that visually represents the architecture, components, and interactions of a proposed system (Oestereich, 2010). It provides a clear and comprehensive overview of how the various elements of the system will function together to achieve its intended objectives. The system model is a crucial tool in the software development process, as it facilitates communication among stakeholders, guides the implementation phase, and ensures that the final product meets the specified requirements. The system model typically consists of different diagrams and representations that capture different aspects of the system's structure and behavior. One common type of system model is the use case diagram, which depicts the interactions between different actors (users or external systems) and the system itself. Use case diagrams help identify the main functionalities the system must provide and the user roles involved. Another integral component of the system model is the system architecture diagram. This diagram illustrates the high-level structure of the system, including its various modules, components, and their interconnections. It highlights how data and control flow through the system and provides a visual reference for developers during the implementation phase.Furthermore, the system model may include sequence diagrams, which illustrate the chronological order of interactions between different components of the system. These diagrams showcase the flow of actions and messages, helping to visualize how the system responds to various inputs and triggers. The class diagram is another essential component of the system model, particularly in object-oriented software development. It represents the classes, attributes, methods, and relationships between different classes in the system. Class diagrams provide a foundation for implementing the system's object-oriented structure. The system model is not only beneficial during the development phase but also serves as a valuable communication tool with stakeholders. Non-technical stakeholders can easily grasp the system's functionalities, interactions, and features through visual representations, fostering a shared understanding of the project's scope. Moreover, the system model helps identify potential issues, inconsistencies, or missing functionalities before the actual implementation begins. This proactive approach minimizes the likelihood of costly revisions or changes during later stages of development. The system model is a vital component of the software development process. By providing a visual representation of the system's architecture, components, interactions, and behaviors, it facilitates communication among stakeholders, guides implementation, and ensures that the final system meets the specified requirements. Through a combination of different diagrams and representations, the system model serves as a blueprint for creating successful software solutions.

VI. DISCUSSION OF RESULTS

This phase provides valuable insights into the system's performance, effectiveness, and alignment with its intended objectives. Through a thorough examination of the results, researchers and stakeholders gain a deeper understanding of how well the system meets the needs of students and advisors. One aspect of the results discussion is system functionality . Researchers analyze whether the system successfully generates accurate and relevant recommendations based on the mined association rules. They assess whether the recommendations align with students' academic interests, majors, and goals. This analysis helps determine the system's efficacy in providing valuable guidance to students during the course selection process.

The user experience is a crucial aspect of the discussion. Researchers delve into how user-friendly and intuitive the system interface is, taking into account feedback from students and advisors. Usability testing results can reveal areas where improvements are needed to enhance navigation, readability, and overall satisfaction with the system. Performance metrics play a significant role in the discussion of results. Researchers interpret metrics such as response times, throughput, and scalability data collected during performance evaluation. They identify trends, potential bottlenecks, and areas where the system excels or requires optimization. For instance, if response times are consistently low and throughput remains high under various user loads, this suggests a well-performing system.

The accuracy and relevance of the generated recommendations are key factors under scrutiny. Researchers assess how often the system's recommendations align with students' actual academic choices and outcomes. If the system consistently provides relevant recommendations that contribute to successful academic paths, this reinforces its value to students and advisors. The impact on advising efficiency is another critical discussion point. Researchers analyze whether the system streamlines advising processes, allowing advisors to offer more personalized guidance based on data-driven insights. If the system reduces

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manual workload and enhances the quality of advising sessions, it demonstrates its potential to enhance the advising experience.

Incorporating user feedback is essential in the results discussion. Researchers consider the perspectives of students and advisors who interacted with the system during testing. Feedback on usability, recommendations, and overall satisfaction provides qualitative insights that complement quantitative metrics. To contextualize the results, researchers can refer to existing literature and related studies on academic advising systems, data mining techniques, and user experience design. Comparing their findings with the findings of others in the field adds depth and credibility to the discussion. The discussion of results in the context of the student advising system involves an in-depth analysis of system functionality, user experience, performance metrics, recommendation accuracy, impact on advising efficiency, and user feedback

VII. SYSTEM SETUP

The system setup and user manual for the student advising system using association rules are essential components that guide users and administrators through the process of deploying, configuring, and using the system effectively. These documents provide step-by-step instructions, guidelines, and troubleshooting information to ensure a seamless experience for both students and advisors.

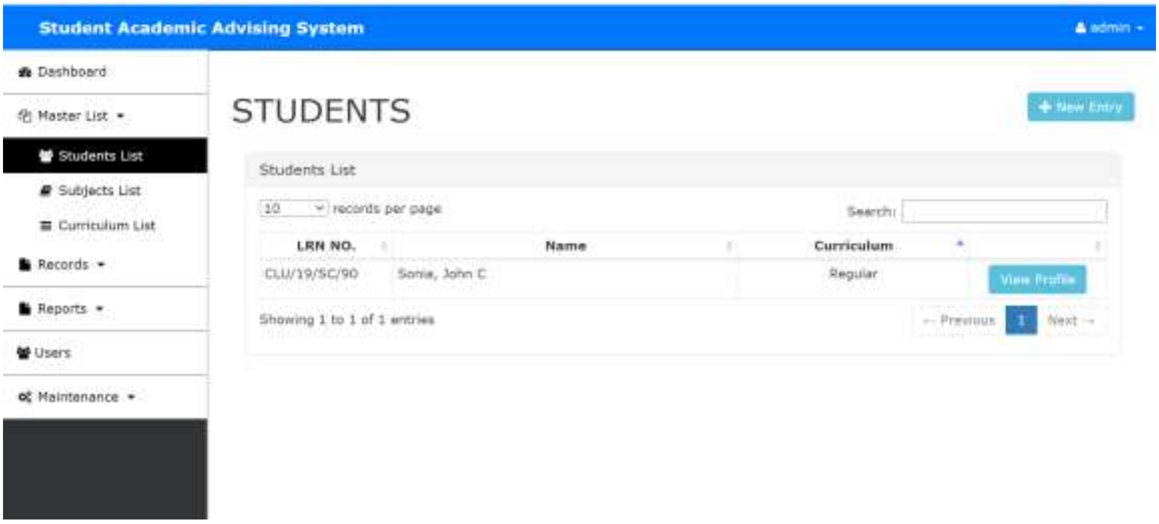

Figure 4.3 Students page

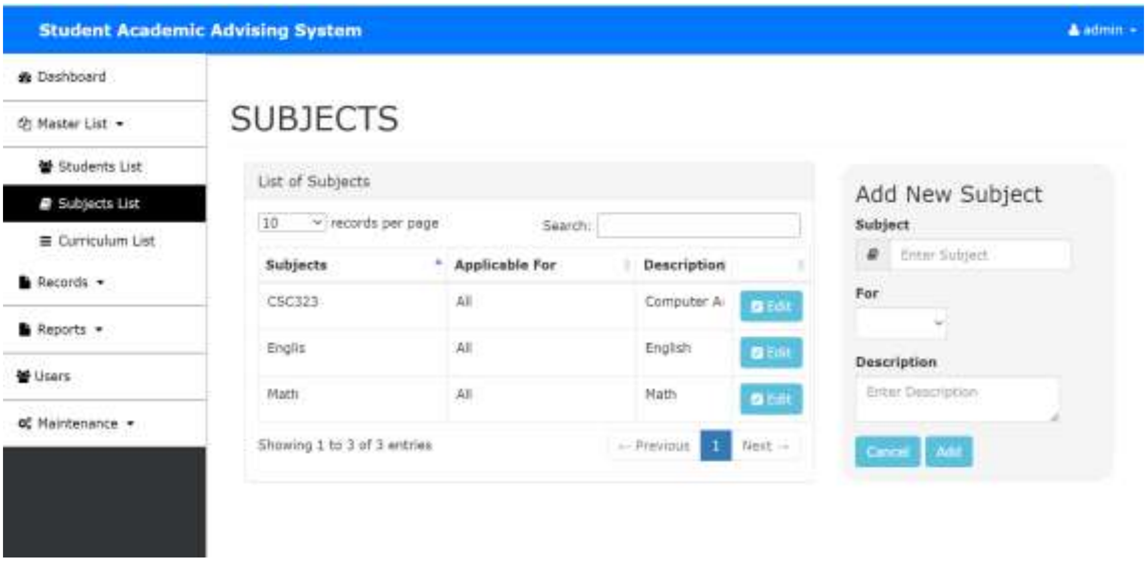

Figure 4.4 Subjects page

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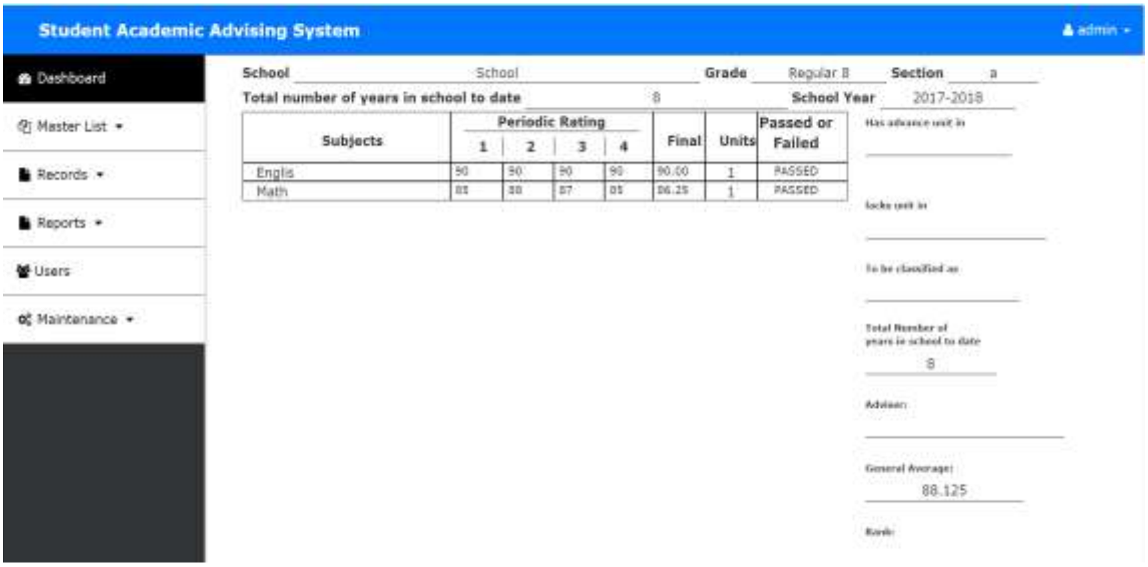

Figure 4.5 grading page for advice

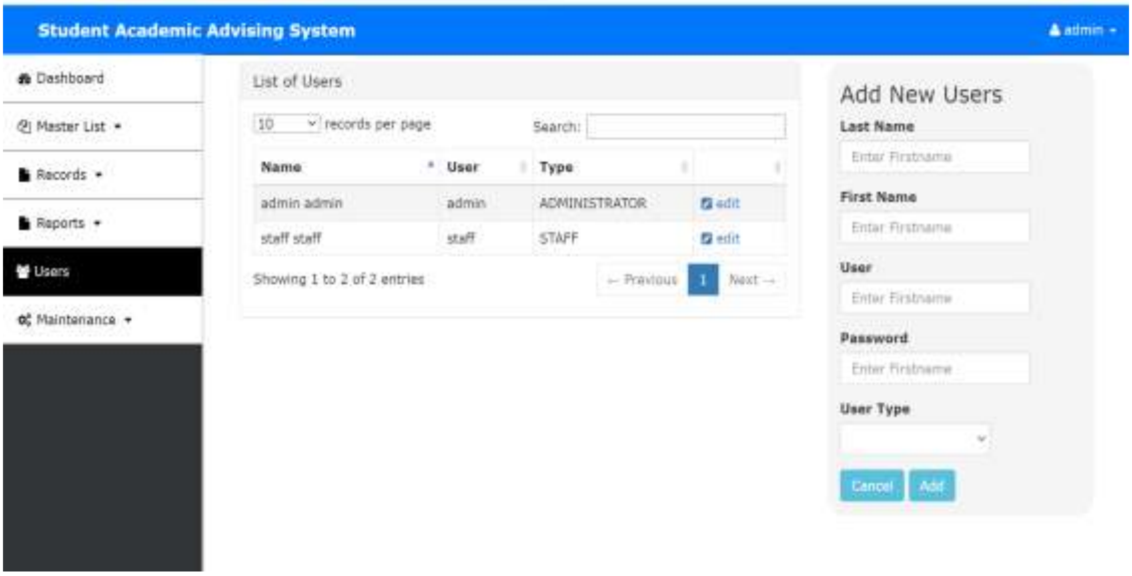

Figure 4.6 System users page

VIII. CONCLUSION

In conclusion, the research presents a comprehensive approach to revolutionizing the academic advising process through the utilization of association rules and data mining techniques. By leveraging these advanced technologies, the student advising system offers personalized course recommendations to students, enhancing their decision-making and academic progression. The system's architecture, coupled with a user-friendly interface, fosters efficient interactions between students and advisors. The successful implementation and rigorous performance evaluation of the system underscore its potential to significantly improve the quality of academic advising. The research not only highlights the technical achievements in developing the system but also emphasizes the practical benefits it brings to students and advisors. The system empowers students to make informed choices aligned with their academic goals while facilitating advisors in delivering tailored guidance. Moreover, the research contributes to the broader field of educational technology by showcasing the application of data mining in academic contexts. The combination of association rule mining and advising system design demonstrates how innovative technologies can positively impact student success and academic institutions' efficiency. As educational institutions strive to provide effective guidance and support to students, the student advising system represents a valuable tool that bridges the gap between technology and academia. This research lays the foundation for future advancements in academic advising methodologies, emphasizing the transformative potential of data-driven approaches in enhancing student outcomes and educational experiences.

IX. RECOMMENDATIONS

The successful implementation of the student advising system using association rules opens avenues for further enhancement and expansion. To optimize its effectiveness, it's recommended to:

1. Integration with Learning Management Systems: Explore integration with existing learning management systems to streamline data exchange, course enrollment, and academic planning.
2. AI and Machine Learning Enhancements: Consider incorporating machine learning algorithms to further refine course recommendations based on evolving academic trends and user behaviors.
3. Mobile App Development: Develop a mobile application to enable students and advisors to access the system conveniently on their smartphones or tablets.

X. SUGGESTIONS FOR FUTURE STUDIES

Future studies could explore the long-term influence of the advising system's recommendations, predictive analytics integration, sociodemographic impacts, ethical considerations, usability enhancements, user feedback mechanisms, interdisciplinary collaboration, and scalability across diverse educational contexts. Investigating these areas will deepen our understanding of the system's effects, ensure fairness and transparency, refine user experience, and facilitate broader implementation.

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