Exploring Employability Factors: A Machine Learning Approach Using Association Rules in Business and Economics Graduates at Qassim University

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***Abstract*—The growing number of business and economics graduates raises concerns about employability in a competitive job market. Furthermore, scrutiny from the Saudi Education and Training Evaluation Commission on educational outcomes highlights the relevance of this research for university administrations. Current literature often overlooks the factors affecting employment outcomes for recent graduates. Understanding these factors is essential for addressing concerns. This study aims to fill these gaps by focusing on graduates from the College of Business and Economics at Qassim University, using association rule mining to uncover patterns and relationships among academic performance, skills, and employment status. This analysis uses a dataset of 407 graduates to examine factors such as gender, major, cumulative GPA, and employment status. As the job market evolves, the findings offer valuable observations for universities on aligning educational programs with employer needs. The association rules model was utilized to predict graduates' likelihood of securing employment based on these attributes, showing that factors such as GPA and skills significantly impact employment outcomes. The proposed model demonstrated high accuracy in predicting employability and generated 147 association rules, indicating its effectiveness in identifying the factors that influence employment outcomes. It also reveals actionable knowledge for curriculum development. The effectiveness of the association rules in identifying the most impactful attributes related to employment outcomes reinforces the importance of addressing the skills and competencies sought by employers. The proposed model demonstrates its reliability for practical use. By aligning educational offerings with market demands, universities can enhance the employability of graduates, ensuring they are prepared for a dynamic environment. This research highlights the critical role of data mining in informing educational strategies and connecting academia with industry.**

***Keywords*—Machine learning; prediction; hidden patterns; employment rates; academic performance; data analysis; modeling**

I. Introduction

Graduate employability has become a key issue in higher education institutions around the world, particularly in an era characterized by rapid technological advancement, labor market volatility, and increasing competition among graduates. Universities are no longer evaluated solely on academic outputs, but more on how good graduates are at getting and keeping jobs with skills, knowledge, and good traits [1, 2]. This shift underscores the significance of understanding employability factors. Therefore, graduates have become a main sign of how good a school is, how well it works and how good it makes the economy [3]. This is even more true in Saudi Arabia, where Vision 2030 says the better the graduates, the more they can help the country. Schools in Saudi Arabia are watched closely, especially when it comes to jobs, as grads from business and economics classes are in big races and will be watched more as they get ready to work and show they have skills and traits that will help them keep and grow jobs. However, existing literature often overlooks the multitude of variables influencing employment outcomes, indicating a gap that this study aims to address. This has been true even after many changes to curricula and measures for good education in the past. Literature review says graduates still matter but are not enough alone to explain how well graduates do in jobs [4, 5].

More and more, people who want to hire graduates look for a mix of soft skills, digital skills, job training, and work skills along with good graduates [3, 6]. So, the idea of a single factor, like high grades, being all that grads need has given way to a new view that a lot of factors, including grades, make up a good "employability" score and reflect how well schools do their job in making grads ready for work and life. This new view has made data mining tools more and more popular as they can look deep into big sets of student info and find hidden links that tell the story of what makes grads successful or not in jobs [7, 8]. People are now turning to methods like classification, clustering,

regression and associative rules to check how grads can do in jobs and how schools should change their curricula [9,10]. One kind of data tool, association rules, is especially good for schools because it can tell clearly what makes a good job candidate and what links together factors like grades, skills, training and work experience [11, 12]. People who study how students work and grow have used these rules to find how grades and other traits link to good jobs for graduates [13, 14]. Such things are important for schools and staff who plan curricula and want proof that what they do will help students get good jobs and improve how well schools do in the eyes of the world and the local areas. This research specifically focuses on graduates from the College of Business and Economics at Qassim University to facilitate solutions for their employability challenges. Though many schools have tried to use data mining for jobs and how well schools do in the past, most such work looks at how well students do in STEM or Tech classes and is mostly from Europe or Asia, not from the Gulf, where most schools focus on business and econ and where little work has been done on how to make student info into a clear picture of how well a school does and how well it can make students ready for the world. Therefore, this work takes a closer look at the employability of students who will leave the Business and Economic schools of Qassim University and uses association rules as the main way to check how well graduates will do after work.

It takes in data on 407 graduates to check for links between where they come from, their grades, skills, training and work skills and the jobs they get. The goal is to provide actionable insights for improving curricula, aligning educational offerings with market demands, and contributing to the growing research on graduate employability in Saudi and Gulf educational contexts. The goal is to give schools good ideas to improve curricula, match what students learn with what jobs want and add to the growing research on how to check for the best graduates in Saudi and Gulf schools. The structure of this study is as follows: Section II examines data mining in education and its implications for employability, providing a foundation for understanding the role of data analytics in educational outcomes. Section III explores stakeholder perspectives on employability, including employer expectations and challenges, educator observations on curriculum alignment and faculty development, student experiences regarding feedback and career services assessment, and collaborative efforts that highlight partnerships and future directions. Section IV presents a comprehensive literature review, identifying key themes and gaps in the current research. Section V outlines the research methodology, detailing data collection methods and the dataset, feature selection processes, the theoretical framework that guides the study, and the statistical analysis employed. Section VI reports the results of the study, emphasizing significant findings. Section VII discusses these findings in relation to previous research, examining implications for educational practice, validating association rules, and acknowledging limitations and constraints. Finally, Section VIII concludes the study by summarizing the key findings, outlining limitations, and suggesting directions for future work.

II. Data Mining in Education and Employability

Educational Data Mining (EDM) has become an essential field at the intersection between data mining and education research, with more efficient methods for studying and improving educational processes. Data mining is the application of computational and statistical approaches to discover significant patterns from complex educational datasets [15]. Some of the approaches widely used for data mining include classification analysis, clustering analysis, association rule mining analysis, regression analysis, and decision tree analysis models [16, 17].

More advanced approaches, including ensemble learning, neural networks, and text mining, have been applied to complex educational datasets, although their interpretability remains a challenge in institutional decision-making [18, 19, 20]. Together, these methods form a comprehensive analytical framework that supports evidence-based decision-making in higher education [21]. This analytical framework enables the application of data mining across various facets of education, including the application of data mining in education covers multiple dimensions—student learning analytics, institutional management, and employability prediction. In the academic situation, data mining has been successfully used to predict student success and identify at-risk learners [22]. These models enable early interventions that help reduce dropout rates [23, 24]. Likewise, clustering methods have been used to adjust teaching strategies to distinct learner profiles [25].

In curriculum design, data mining helps assess course effectiveness by analyzing historical performance data. Universities use association rule mining to understand correlations between prerequisite courses and student outcomes [22, 26].

From an administrative perspective, institutions use data mining for strategic planning and resource optimization. Predictive analytics can forecast enrollment trends, helping universities allocate faculty and facilities more efficiently [16]. Crucially, the linkage between data mining in education and employability analysis is increasingly recognized in the literature [28, 29]. Addressing these ethical considerations is particularly crucial when applying data mining to enhance graduate employability, an area of increasing importance for higher education systems, as the implementation of data mining strategies provides substantial benefits for educational institutions. One key advantage is data-driven decision-making [30]. Predictive analytics help identify students who are struggling and allow for proactive interventions that improve retention and graduation rates [31].

Another key benefit is personalized learning [32, 33]. Despite its benefits, the ethical use of data remains essential. Issues such as privacy, bias, and informed consent must be carefully addressed [34].

The issue of graduate employability has become increasingly prominent as higher education systems face intensifying competition and rapidly changing labor-market expectations. A recurring challenge concerns the gap between university training and employer expectations. Research shows that while graduates often possess theoretical knowledge, they lack workplace-ready competencies such as communication, teamwork, analytical reasoning, and digital literacy [35, 36, 37]. Structural factors further complicate employability. Many countries have experienced increased higher-education

enrollment, creating a surplus of graduates relative to available entry-level positions [38]. Demographic factors also influence employability outcomes [32]. Research consistently shows that combinations of academic indicators and non-academic experiences shape employment prospects [39]. These complexities highlight why universities are increasingly adopting data mining and machine learning techniques to interpret graduate data. A range of models have been successfully applied to predict employability and identify influential variables [29, 40]. In addition to predictive analytics, other data mining methods, such as association rule mining, play a crucial role in predictive analytics has become an important tool in higher education because it allows institutions to anticipate student outcomes instead of reacting after problems occur [15]. Early research in this area relied mainly on statistical approaches such as linear and logistic regression [41, 42]. These methods remain useful because they are relatively easy to interpret [43]. Machine learning techniques have increasingly been applied in predictive education research. Methods such as decision trees, random forests, support vector machines, and k-nearest neighbors have demonstrated stronger predictive performance [28, 44]. Findings consistently show that employability outcomes are shaped by combinations of factors rather than single academic indicators [45]. More recent studies have explored neural networks and deep learning models [32, 46]. However, their limited interpretability presents challenges in educational settings [31, 47]. Despite these advantages, ethical considerations remain central to the use of predictive analytics in education [48, 49, 50].

Association rule mining is a fundamental data mining method used to detect meaningful relationships among variables in large datasets [51]. In the context of employability, association rules allow researchers to uncover hidden relationships among academic performance indicators, skills, demographic features, and employment outcomes. Importantly, association rules complement machine learning classification models [52, 53, 54]. However, there are important limitations. Association rules identify correlations rather than causation, which limits their use for high-stakes decision-making without expert validation [55, 56, 57, 58, 59].

Employability has emerged as a central concept in educational research, labor-market policy, and human-resource development [60, 61]. Employability involves the attributes individuals obtain that increase their chances of obtaining a job [62, 63]. Employability concept encompasses multiple domains such as human capital [64] and social capital [65, 66]. Graduate employability models such as the CareerEDGE model define employability as having a set of skills, knowledge, understanding, and personal attributes that make a person more likely to secure employment [6]. Employability can be viewed across micro, medium, and macro levels, encompassing individual capabilities, organizational practices, and broader economic and policy contexts [67]. Finally, the framework of this study is introduced in detail in the methodology section.

III. Stakeholder Perspectives on Employability

While Section II focuses on analytical and data-driven methods for understanding employability, these methods alone do not fully capture how employability is experienced in practice. Stakeholder perspectives provide the real-world context in which patterns identified through data mining and predictive analytics gain meaning. Employers, educators, and students interact with these factors daily, and their experiences help validate and refine the associations uncovered through analytical models [68, 69].

Transitioning from school to work is a key moment for all students who complete their education, especially those studying business and economics. How well these students can get jobs shows whether they are ready to work and is also a significant indicator of how well higher education institutions (HEIs) perform. In today's world, where the economy is becoming more knowledge-based and increasingly dynamic, students studying business and economics must bring new ideas, keep up with rapid change, and help grow the economy. But there is a significant issue with how employers, teachers, and students view the concept of "employability.

Students need to learn many skills to get jobs, including technical skills, soft skills such as communication and teamwork, and thinking skills like problem-solving. Employers say students lack the real-world experience and skills to meet the needs of the job, while teachers say they provide a strong foundation of knowledge that prepares students for many careers. Also, many students say they do not feel ready for the complex world of work, indicating a gap between school and the real world. This complex issue needs a deep look that considers all these views.

From a data analytics perspective, these differences in how employability is perceived help explain why employability outcomes cannot be predicted using academic performance alone. Such variation supports the use of approaches like association rule mining, which capture combinations of academic, behavioral, and experiential attributes rather than relying on single indicators [70, 71]. Looking into what makes a student ready for work, how they struggle to learn skills, and how schools can address gaps, such as curriculum gaps, a lack of time for internships, and poor career guidance, will help identify reasonable solutions. These solutions will better prepare students for work and help HEIs better prepare them for successful careers in a constantly changing economy.

A. Employer Perspectives: Expectations and Challenges

Studies say that good book knowledge is needed for many jobs, but having good people skills and being able to adapt is what really helps you get hired. For example, one extensive study of many job ads conducted by [1] found that business grads need to know tools such as Tableau and Google Analytics, how to work with ERP systems such as SAP and Oracle, and digital marketing skills such as SEO, paid ads, and content tools. But having those skills alone is no longer enough; job seekers need to demonstrate soft skills that align with a company's values and culture. According to what [2] studies show, things like solving complex problems, thinking deeply, and making good ethical choices are what bosses want most, and sometimes they mean more than the degree you got in school. The idea of "learnability", that is, the skill and desire to learn new things fast, is now seen as very needed in today's fast-paced jobs. One extensive study by [69] found that bosses in fast-growing fields

like fintech and e-commerce want workers who can learn new things and adapt quickly, rather than those who do not change.

Even though more people are leaving school each year and becoming job-ready, it is often challenging for most businesses to find the right people for the job. This shows a significant skill gap between what students learn in school and what companies need from them. One example from reference [69] is a poor example of students' analytical skills. Students often receive intense training in theory and numbers, but they struggle to apply it in complex real-world situations. These are the skills we call storytelling with data: the ability to read data and turn it into a story that can inform a business plan or idea.

These expectations help explain why employability models discussed earlier consistently show that employment outcomes are driven by skill combinations rather than degree titles alone. Employer priorities provide practical meaning to the patterns identified through employability analytics and association rules [67, 68, 70, 71].

Another issue is the disconnect between students and business communication. A study in [72] reports that a large share of students cannot get their message across to businesses. Students often struggle to explain to employers how what they did in school, such as projects or research, helps the company. Many of them lack good interview manners, which also lowers their chances of getting hired.

These are the issues in the current system, and the data show that what students are taught in school does not match what they need in the workplace. This makes it essential to change what students learn so they can gain the skills they need to succeed.

B. Educator Perspectives: Curriculum Alignment and Faculty Development

Teachers are increasingly recognizing the need for schools to align with current employer expectations. This collaboration can break down barriers in education, ensuring classes are relevant to real-world job demands. It's not just about changing what students learn, but also how they learn. According to [73], traditional methods fail to adequately prepare students for the workforce. Therefore, there's a consensus on the necessity of moving away from outdated teaching approaches, emphasizing hands-on learning and practical preparation.

There are many ways to do this like project work, where students do hard, real projects; case games, that help students think better and work in teams; and role playing, that can help students learn by doing what they do at work and that can help students learn better by doing things that they do at work.

The effectiveness of a teaching program hinges on a teacher's ability to present content authentically and practically, drawing on industry practices. This underscores the importance of robust teacher training rather than treating it as a secondary concern. Research shows that teachers who experience industry settings through internships and externships can provide more relevant examples, enhancing student engagement and learning. Therefore, schools should prioritize hands-on opportunities for teachers over minimal training days. Without strong professional development, even the best programs may fall short of meeting workplace needs.

From an analytical standpoint, this focus on applied learning aligns with educational data mining studies, which indicate that practical exposure and skill integration are crucial for employability outcomes [73, 75]. Schools that equip teachers to learn new skills and stay connected to industry will better prepare students for a rapidly evolving job market. This approach benefits both teachers, who enhance their effectiveness, and students, who gain valuable insights and problem-solving skills for future employment [75].

C. Student Experiences: Feedback and Career Services Assessment

Recent research [76] shows that graduates who engage in hands-on learning—like live client projects, capstone experiences, and business simulations—experience a significant boost in confidence. These opportunities help ease the transition to professional life, allowing graduates to apply their theoretical knowledge practically and bridging the gap between school and the workplace.

However, many graduates still feel unprepared for the workforce, particularly regarding essential practical skills. Research [77] reveals that numerous recent business graduates struggle with industry-standard tools like Salesforce for customer relationship management, SAP for enterprise resource planning, and advanced Excel functions critical for data analysis. This skill gap often results in extensive on-the-job training, complicating the alignment of expectations for both graduates and employers.

Addressing this gap presents a valuable opportunity for educational institutions to update their curricula. By equipping students with the necessary skills for today's job market, schools can improve graduates' readiness for employment. Incorporating more hands-on training and industry-specific software can greatly benefit both students and employers seeking skilled professionals.

Student feedback offers an important validation layer for employability analytics. The experiences reported by graduates closely mirror patterns identified in employability-focused data mining, particularly those linking hands-on learning, technical exposure, and career support to stronger employment outcomes [76, 77, 78, 79].

University career services are a significant factor in linking students with jobs after graduation. Still, the question of their effectiveness is frequently raised. It turns out that these services are significantly more effective when they are provided from the first year of a student's studies. The study cited in [78] demonstrates that early incorporation of career support enables students to create a solid professional identity and have a clear understanding when choosing their courses and experiences.

On the other hand, many career centers are too standard and treat students as mere numbers. [79] states that these institutions usually limit their activities to resume writing and basic interview skills only. Such an approach does not meet each student's personal needs, and thus, they feel unprepared for the labor market. The study suggests a different approach - a more individualized one. It would be possible through personal consultations, the creation of industry-specific mentorship programs, and training in networking skills.

D. Collaborative Efforts: Partnerships and Future Directions

Collaboration between higher education institutions (HEIs) and industry is one of the most potent means of improving graduates' employability. The first point of the research states that these collaborations offer the best scenarios for effective collaboration. For example, a reference [80] discusses the relationship a university had with multiple banks to develop a FinTech and Digital Banking" module.

In the same vein, well-organized mentorship schemes are among the most powerful links between the academic and professional environments. Reference [81] describes the event in which a mentoring program was established, pairing seasoned industry professionals with students in their penultimate year of study. The deep relationships created in these pairings allowed students to get individualized career advice and, at the same time, get a sneak peek into the workplace culture. Also, the participants disclosed that they learned about the expectations and standards of their future careers, including professional conduct and moral principles, through the program. Mentorships such as these not only broaden students' perceptions of the workplace but also help them acquire the necessary skills and self-assurance for successful [80, 81].

Improving and expanding these collaborative efforts requires innovative, integrated strategies. One major proposal is to establish Industry Advisory Boards (IABs) with real power to influence curriculum review and development. Furthermore, to address the logistical issues of traditional internships, which often involve unpredictable schedules and administrative obstacles, experts suggest using "micro-internships" or project-based learning modules.

Another beneficial concept is establishing shared research and development (R&D) and innovation labs. These labs can be places where faculty members, students, and industry partners [82] work together to solve real business problems.

This review of graduate employability highlights the perspectives of employers, educators, and students, emphasizing the need for a more interconnected and responsive education system to equip students with the skills required in the labor market.

The Employer-Student Disconnect: Employers seek adaptable graduates who excel in communication and are proficient with digital tools [67, 68, 69, 70, 71]. In contrast, many graduates feel unprepared and lack the specific skills needed to meet these expectations [11]. This gap underscores the urgent need for schools to upgrade their programs.

The Educator-Institution Tension: Educators acknowledge the need for modern teaching methods and relevant topics [72, 73]. However, they face challenges from strict institutional regulations, outdated materials, and limited resources. Effective professional development support is crucial for educators to thrive in their roles [74, 75], yet there is often a lack of programs that connect educators with industry.

The Systemic Role of Collaboration and Support: Strong career services play a key role in linking education with job opportunities [78, 79]. Schools lacking comprehensive career services may struggle to connect with the labor market effectively. Additionally, robust industry partnerships are essential for aligning academic programs with market needs [80, 81], but resource limitations can hinder these services' effectiveness.

In summary, improving graduates' employability in Business and Economics demands a collaborative effort from all stakeholders. Higher education institutions (HEIs) must provide support and guidance to help teachers update their courses. Career services should transition from mere facilitators to comprehensive support throughout students' academic journeys. Additionally, building strong industry partnerships is crucial for enhancing the student experience, from curriculum design to internships. By addressing employability collaboratively, universities can better prepare graduates for both their initial jobs and long-term career success.

The diverse perspectives of stakeholders enrich the data mining and predictive approaches discussed earlier, anchoring analytical findings in real-world educational and labor market contexts. Collectively, these insights promote a more actionable and realistic understanding of graduate employability.

IV. Literature Review

Employability today is understood as much more than simply getting a job. It reflects a person's capacity to keep learning, adjusting, and making a meaningful contribution in different work and social contexts [83]. Early work in the field, especially [84], described employability in terms of what graduates possess: their skills, knowledge, and personal qualities, all of which increase their chances of securing work and performing well once hired. Later, Dacre Pool & Sewell added an important psychological dimension by showing that students' beliefs about their own abilities, particularly their confidence and self-efficacy, can determine whether learning turns into real employment opportunities. Taken together, these perspectives shift the understanding of employability away from "getting a job once" and toward the broader capability to build and sustain a career in a labor market that keeps changing [83, 85].

A key point in the literature is the distinction between employment and employability. Employment is a status having a job at a particular moment, while employability is a collection of capabilities, attitudes, and behaviors that help individuals secure, maintain, and move between roles over time [83]. This difference has major implications for universities and policymakers. Rather than focusing narrowly on short-term employment outcomes, they are encouraged to prioritize students' long-term adaptability and growth [86]. Byrne's own findings reinforce this argument. His experiments reveal that perceptions of "employability" are influenced not only by skills but also by social cues such as gender, ethnicity, and institutional prestige, suggesting that employability is partly socially constructed, not simply earned through talent or performance [86, 87].

Recent discussions highlight that employability has both personal and relational components. On the personal side, it is shaped by what the graduate brings: skills, knowledge, experiences, and psychological strengths like motivation, resilience, and optimism [88]. On the relational side, it depends

on external factors such as networks, professional identity, and knowledge of workplace norms, which help graduates recognize and access opportunities [5, 88]. This dual perspective emphasizes that employability is not only about having skills but also about being able to use those skills effectively in real organizational settings [85].

Employability matters because it now sits at the center of how governments and universities think about the relationship between higher education and the labor market. In many countries, employability indicators have become proxies for university quality and even national economic competitiveness [85, 89]. This trend has encouraged institutions to integrate employability into curricula, assessments, and quality assurance practices [83, 90, 91]. At the same time, scholars caution against reducing employability to a purely economic agenda. When higher education becomes overly responsive to immediate labor-market demands, broader educational purposes such as ethics, citizenship, and sustainability risk being neglected [64]. In response, researchers argue for a more holistic view in which universities support not only work readiness but also lifelong learning, social responsibility, and the capacity to adapt as the world changes [83, 88].

These debates have become even more urgent in an era defined by digitalization, automation, and rapid economic change. Research indicates that graduates with higher levels of self-direction, emotional intelligence, and openness to continuous learning are better able to navigate uncertainty and shifting career paths [3, 92]. This framing treats employability as a dynamic process rather than a fixed outcome, a capability that evolves across a person's career [83, 85]. Around the world, employability is gaining attention as governments aim to align education with technological change, automation, and global competition [85]. In countries like the UK and Australia, national frameworks such as TEF and QILT use employability outcomes to evaluate the performance of higher education institutions [85, 89]. These systems reflect a policy push for accountability, measurable skills, and job readiness. In contrast, U.S. research approaches employability from the angle of vocational psychology, focusing more on individual adaptability, self-efficacy, and long-term career development [85, 93, 94]. Note that this split has created disciplinary silos, limiting opportunities for shared learning across regions.

In developing economies, employability is often more challenging due to structural factors, including high youth unemployment and weak connections between universities and industry [86]. For example, in Ghana, fewer than 10% of graduates secure work within a year, largely due to outdated curricula and limited entrepreneurial preparation [90]. Similar obstacles appear across Africa and Asia, where education systems struggle to balance global standards with local economic realities [95,96]. These regional variations underline the importance of context: employability reforms must reflect local labor-market needs, cultural norms, and digital readiness [85, 96].

A global shift is also visible in the movement from "first job" preparation to lifelong employability. The pandemic accelerated remote work and digital transformation, highlighting the value of digital literacy, flexibility, and continuous learning [96, 97]. Many universities across Asia and the GCC especially Saudi Arabia now link employability efforts to national transformation agendas such as Vision 2030 [83].

A critical debate concerns fairness. If employability is treated solely as an individual responsibility, structural inequalities risk being ignored. [85] shows that even when qualifications are identical, hiring decisions are influenced by social and institutional biases. This means employability is shaped by national policies, labor-market dynamics, and cultural norms, not just personal effort [86, 87].

The literature consistently shows that employability is multi-dimensional: it is shaped by academic performance, digital and soft skills, practical experience, gender, and field of study. Although grades are a common signal of competence, they cannot capture the full range of skills needed for long-term success [85]. Employers often associate high grades with reliability and discipline, but these impressions only tell part of the story [86]. Indeed, Byrne's research demonstrates that a first-class degree increases perceived employability by around 15%, and postgraduate qualifications lift perceptions even more. Yet other scholars argue that academic performance must be paired with adaptability, professional identity, and career management skills to be meaningful in fast-changing workplaces [83].

Digital capabilities and soft skills have become equally essential. [3] using AI-enabled models, found that communication, self-confidence, and presentation ability were stronger predictors of employability than grades. Emotional intelligence, teamwork, and problem-solving consistently emerge as core components of employability worldwide [6, 90]. At the same time, digital literacy from analytics to collaboration tools has become a baseline expectation in most sectors [83, 97]. Universities that embed digital and interpersonal competencies into their programs tend to produce graduates who are more adaptable and competitive [90, 97].

Practical experience is one of the strongest determinants of employability. Byrne's research shows that well-structured internships raise perceived employability by almost 18%, while unrelated part-time work can lower it. This is echoed in studies demonstrating that capstone projects and hands-on learning help students connect classroom theory to real work settings [96]. However, access to valuable internships is uneven. Students from lower-income backgrounds may struggle to secure placements due to limited networks or resources [86], raising concerns about equity.

Gender also plays a role; [86] found that female candidates were slightly more likely to be rated as employable, but this pattern may reflect social desirability rather than actual labor-market equality. Persistent gender pay gaps and workplace barriers suggest that perceptions of employability do not always translate into equitable outcomes [98]. Scholars therefore stress the need for employability strategies that are sensitive to gender and structural bias [83, 85].

Field of study remains a major differentiator. Graduates from STEM and business disciplines generally enjoy clearer career pathways and stronger alignment between what they study and what employers need [90]. Humanities and social science graduates often face a more ambiguous job market, where they

must work harder to demonstrate the relevance of their skills [86]. Nevertheless, studies show that students from all disciplines can improve their employability through interdisciplinary learning and opportunities that help them apply academic knowledge to real-world contexts [96]. This reinforces the idea that employability development should be tailored to discipline-specific needs while still equipping all students with transferable competencies [83, 85]. Employability research has increasingly integrated data mining (DM) techniques to analyze, predict, and enhance graduates' employment outcomes [99]. Data mining has been widely used to analyze and predict employability, applying both supervised and unsupervised machine learning (ML) techniques [100]. Data mining is a process that consists of applying data analysis and discovery algorithms that produce a particular enumeration of patterns over the data under acceptable computational efficiency limitations [101]. As stated by [17], the general process of discovering knowledge from data consists of five steps as follows: 1) State the problem, 2) collect the data, 3) Preprocess the data, 4) Estimate the model, 5) Interpret the model and conclude.

Data mining has become a central methodological approach in employability research because it allows scholars to detect hidden patterns in large educational datasets and identify the factors that most strongly influence graduate employment outcomes [101, 102]. Across the literature, classification, clustering, regression, and association-rule mining emerge as the most commonly applied techniques for modelling employability, predicting student job readiness, and informing curriculum and policy reform [8, 100].

Most studies confirm that classification algorithms remain the primary tools for predicting employability outcomes because they can categorize graduates as "employable" or "not employable" based on academic and demographic attributes [103]. [100] identified Decision Trees (J48), Multilayer Perceptron, SVM, Naïve Bayes, Logistic Regression, and Random Forest as the top six algorithms used between 2008 and 2021, reporting accuracies ranging from 70% to 100%. Decision Trees and Multilayer Perceptron achieved particularly high performance, reaching up to 100% and 98% accuracy, respectively [100]. Similarly, [99] found that Logistic Regression, J48, and Artificial Neural Networks frequently produced accuracy rates above 90%, reinforcing the dominance of classification techniques.

[105] demonstrated that Logistic Regression yielded the highest accuracy (78.4%) for predicting IT-related employment in the Philippines. [106] further showed that Support Vector Machines (SVM) outperformed Decision Trees and Random Forests, achieving 91.22% accuracy, demonstrating SVM's strength in high-dimensional employability datasets. Likewise, [106] found that CART achieved 93.6% accuracy when predicting early employment among Vietnamese graduates, confirming the interpretability and practical relevance of tree-based models. Across these studies, classification consistently proves to be the most robust approach for employability prediction.

Unsupervised learning techniques such as Principal Component Analysis (PCA) and Ward's clustering have been applied to reveal latent structures in graduate data and categorize students into meaningful employability profiles [100]. [12] introduced an improved K-means method, SA-K-means, enabling more stable clustering with an error rate around 10%, significantly outperforming traditional K-means. Similarly, [107] applied hierarchical clustering to categorize graduates into 55 distinct groups, showing how combinations of demographic, academic, and attitudinal variables can shape employment probabilities. These findings suggest that clustering is especially useful for policymaking, as it uncovers subgroups that require targeted intervention.

Association-rule mining uncovers relationships among skills, academic behaviors, and employability outcomes [12]. Developed the MW-Apriori algorithm, an optimized version of Apriori that uses Boolean matrices and parallel processing, reducing computation time from ~30 seconds to <5 seconds and achieving precision above 96%. This method identified relationships between course engagement, employability training, and performance indicators, demonstrating how associations can guide curriculum design. [108] Similarly, used association rules to show that communication, teamwork, financial abilities, and time management are consistently linked to specific job categories in Sri Lanka. Broader research confirms this trend: association rules combined with neural networks enhance interpretability and predictive strength, as demonstrated by [14]. These studies show that association-rule mining not only predicts outcomes but also prescribes employability-enhancing strategies.

Emerging work integrates deep learning to capture complex, nonlinear relationships in student data. [3] employed LSTM and GRU networks, achieving 91.46% and 90.48% accuracy, outperforming traditional models such as Logistic Regression (58%). Importantly, the authors used SHAP explainability, identifying self-confidence, idea presentation, and general appearance as the strongest predictors of employability. These findings critique earlier studies for overemphasizing academic variables while undervaluing soft skills. As such, deep learning not only improves accuracy but also reshapes theoretical interpretations of employability by highlighting behavioral and psychological dimensions.

Across data-mining studies, academic performance consistently emerges as the most influential employability factor. [106] showed that third-year GPA and final-year GPA were the strongest predictors in Vietnam. [103] emphasized the centrality of CGPA, appearing in 27 of 30 studies and showing a strong correlation with employability. [108] also found IT core and professional subjects to be significant predictors. However, researchers note that technical skills alone are insufficient [109] demonstrated that soft skills appear in 70% of models, while [3] proved that soft skills, especially self-confidence, outperform academic metrics in deep learning models [27]. [108] reinforced this finding, identifying communication and teamwork as the most influential skills across job sectors. Importantly, multiple studies critique existing models for neglecting socio-economic, psychological, and institutional factors, despite their strong influence on employability [100, 107]. These omitted variables include family background, economic constraints, regional disparities, and institutional reputation—factors essential for holistic modelling. Although data mining has become

increasingly common in employability research, most existing studies rely heavily on classification-based prediction models rather than association-rule approaches. Prior works, including those by [99, 100, 103, 104, 105, 106, 108], primarily use algorithms such as Decision Trees, Random Forest, SVM, Logistic Regression, and Neural Networks to classify graduates as employable or not, demonstrating that prediction dominates the methodological landscape. In contrast, association rule mining remains underused and, where it does appear [12, 14, 108], it is typically employed only as a supplementary technique or combined with other models rather than serving as the core analytic method for generating actionable and interpretable rules for curriculum decision-making. Furthermore, the majority of empirical studies focus on STEM, IT, and engineering graduates, with limited attention to business and economics programs, despite the growing pressure on these disciplines to demonstrate employability outcomes. Major reviews [100, 103, 109] also show that employability analytics research is geographically concentrated in Europe and South/Southeast Asia, revealing a significant lack of data-mining–based employability studies within the Saudi or Gulf context, particularly for Business and Economics graduates, despite Vision 2030 reforms and scrutiny from the Education and Training Evaluation Commission (ETEC). Additionally, scholars consistently highlight the need for more interpretable, prescriptive, and context-aware models; existing prediction-focused studies tend to overemphasize academic and technical indicators, underrepresent contextual and program-specific variables, and rarely translate findings into clear, actionable rules that quality committees and curriculum designers can use. This study fills these gaps by focusing specifically on Business and Economics graduates at Qassim University, employing association rule mining as the primary analytical technique to derive interpretable, curriculum-relevant rules within a Saudi higher-education context, directly supporting program evaluation and strategic alignment with employer expectations.

V. Methodology

A. Data Collection Methods and Dataset

Data were gathered from graduates of the College of Business and Economics at Qassim University using structured questionnaires that included closed-ended and Likert-scale items. The survey focused on various aspects, including academic achievement, professional certifications, internship experiences, skill development, and the duration of job searches. Academic records such as GPA, major, and participation in training programs were verified through university databases and alumni records to ensure accuracy. The instrument's reliability was established, with Cronbach's Alpha reported at 0.76 for the main construct, indicating an acceptable level of internal consistency. All collected data were consolidated into a single repository, and preprocessing steps were undertaken to address missing values, inconsistencies, and illogical responses.

The final dataset comprised 407 graduates with diverse attributes, including demographics (gender, age, city of residence), academic profile (GPA, awards, major), professional experience (training, internships, volunteer work, mentorships, club participation, certifications), skills (leadership, teamwork, communication, problem-solving, English proficiency, technical skills), digital engagement (social media activity), and employment outcomes (employment status and job search duration).

After data cleaning and screening for variance and relevance, attributes with low analytic value (like nationality and Arabic proficiency) were excluded. Employment status remained as the target label to prevent information leakage, while job alignment and job title were included for descriptive purposes. The final set of 21 predictive features includes gender, age, city, GPA range, major, awards, technical and soft skills, training participation, and duration of job search. These predictors operationalize Human Capital Theory within an Educational Data Mining framework for the predictive models in the theoretical framework.

B. Feature Selection

To prepare for this analysis, the collected data were organized into tables that were suitable for applying Association Rules. We prioritized the most relevant features, as including irrelevant attributes could skew the findings. Data standardization and thorough cleaning were essential steps to enhance quality. Preparing the dataset for analysis required significant effort. Certain features were excluded due to their limited impact; for instance, Arabic language proficiency was rated uniformly high by all participants, rendering it ineffective for our analysis. Additionally, since all respondents were Saudi nationals, that attribute was removed as it did not contribute any meaningful variance. Other fields, such as open-ended comments, were considered irrelevant because only a few respondents provided additional observations. In some cases, we also needed to convert attribute types to numeric forms, as Association Rules rely on numerical data to identify meaningful patterns. Table I offers a detailed description of these attributes.

TABLE. I. The Symploic Attribute Description

Attributes	Values
Gender	Male, Female
Age	1 = 22-24 2= 25-27 3= 28-30 4= > 30
Current City of Residence	Categorical
GPA Range	1= 4.5 -5 2= 4 – 4.5 3 = 3.5 -4 4 = 3 – 3.5 5 = < 3
Major	Categorical
Academic Awards	Yes, No
Communication	1 to 5 (5 highest)
Teamwork	1 to 5 (5 highest)
Problem solving	1 to 5 (5 highest)
Leadership	1 to 5 (5 highest)
English	1 to 5 (5 highest)
Training Participation	Yes, No
Training Duration	1 = 1-3 2 = 3-6 3 = 6 -9 4 = 9-12

	5 = > 12 months
Participation in clubs and organizations	Yes, No
Volunteer Work	Yes, No
Employment Status	Unemployed, Employee
Social Media Activities	Yes, No
Mentorship Programs	Yes, No
Professional Certifications	Yes, No
Duration of the job search	1 = 1-6 2 = 6-12 3 = 12 -18 4 = 18-24 5 = > 24 months

C. Theoretical Framework

This framework begins with the Data Collection phase, where relevant data is gathered about graduates from the College of Business and Economics at Qassim University. This foundational step ensures a comprehensive dataset that captures the multifaceted nature of employability factors. Following data collection, the Data Preparation phase is initiated. This involves organizing and structuring the data for analysis, ensuring that it is in a usable format. The final step of this phase is Data Preprocessing, which includes cleaning the data by handling missing values, removing duplicates, and normalizing the data to enhance its quality and reliability.

The next phase is Data Analysis, where the prepared data is examined to extract meaningful information. The Validation of Data occurs during this phase, ensuring the integrity and accuracy of the dataset before proceeding to further analysis. Once the data is validated, the focus shifts to Feature Selection. This crucial step identifies the most relevant attributes that contribute to employability, allowing for a more efficient and targeted analysis.

Following feature selection, the Model Development phase commences, during which the Algorithm Selection takes place. In this study, the Apriori Association Rules algorithm is chosen for its effectiveness in identifying relationships among multiple factors. Key parameters are configured, including the Minimum Metric, the Number of Rules (147 rules), the Lower Bound for Minimum Support, and the specification of Class Association Rules. These configurations are critical for optimizing the algorithm's performance and ensuring that the generated rules are robust and relevant.

The framework then progresses to the Knowledge Discovery/Patterns phase, where the association rules are analyzed to uncover hidden knowledge and patterns that influence graduate employability. Model assessment and accuracy evaluation are conducted to gauge the effectiveness of the Apriori algorithm in generating valuable associations. Finally, the Results phase presents the findings derived from the analysis. These observations offer practical knowledge that can be utilized by educational institutions to inform decision-making and enhance employability programs for graduates. The framework supports a data-driven approach to improving graduate outcomes in the competitive job market, as shown in Fig. 1.

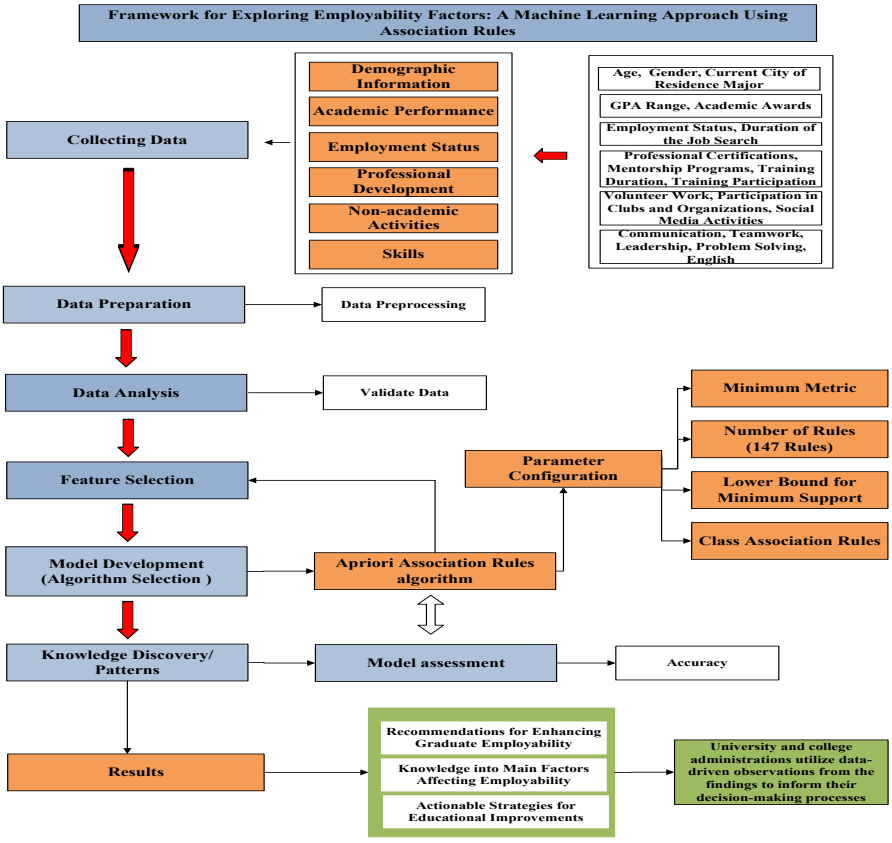

Fig. 1. Framework for exploring employability factors: A machine learning approach using association rules.

D. Statistical Analysis

In this section, we focus on analyzing the statistical aspects related to the students in the college, with an emphasis on their classification according to demographic, academic, and professional characteristics. The study began by categorizing students by gender to determine the distribution between males and females, which represents an essential initial step in understanding the sample's characteristics. Subsequently, the different academic majors within the college were analyzed to provide a comprehensive overview of the students' composition and their distribution across various fields, which helps in understanding academic diversity and its potential impact on future career paths. The study relied on descriptive statistics, including frequencies, percentages, and charts, to visually present the data and analyze the fundamental patterns within the sample. This approach enabled comparisons across different student groups and facilitated the observation of differences between genders and academic majors.

The main part of the study focused on analyzing the relationships between various categorical variables. To achieve this, the Chi-square test was employed to determine the strength and significance of these relationships, providing precise information into how academic backgrounds influence students' employment opportunities and professional certification status.

Through this statistical analysis, the study aims to offer an in-depth understanding of the interactions between students' demographic and academic characteristics and their career paths, while also providing an informative foundation to support researchers and policymakers in developing academic and professional policies that align with labor market needs. Due to the extensive amount of data collected in this study, it is not feasible to include all figures and tables in the report. Instead, we will describe key findings and discuss select figures and tables that illustrate the most important results. This approach allows us to focus on critical insights while providing a clear summary of the overall data.

Table II illustrates the gender and the distribution of the sample across different academic majors. It shows that females represent the majority, comprising 58% (236 individuals) of the total participants, while males account for 42% (171 individuals). Overall, the total sample consists of 407 participants, indicating a higher representation of females compared to males. This distribution is critical for understanding the demographic composition of the study and may have implications for interpreting the findings related to employability and other variables. As well as, the distribution of the sample across different academic majors. The results indicate that the highest proportion of participants are enrolled in Business Administration (33.4%), followed by Management Information Systems (31.4%). Accounting accounts for 21.1% of the respondents, while smaller proportions are observed in Economics (10.8%) and Finance (3.2%). Collectively, these findings suggest that the majority of participants are concentrated in Business Administration and Management Information Systems, which together represent nearly two-thirds of the total sample (64.8%).

TABLE. II. GENDER AND THE DISTRIBUTION OF THE SAMPLE ACROSS DIFFERENT ACADEMIC MAJORS

Demographic	Frequency	Percent	Academic Major	Frequency	Percent
Gender Distribution			Accounting	86	21.10 %
Female	236	58.00 %	Business Administration	136	33.40 %
Male	171	42.00 %	Economics	44	10.80 %
Total	407	100.00 %	Finance	13	3.20%
			Management Information Systems	128	31.40 %
			Total	407	100.00 %

Fig. 2 shows the distribution of students by major and gender. Overall, females (236) outnumber males (171) in the sample. Females are the majority in Accounting, Economics, and Finance, while the distribution is more balanced in Business Administration and Management Information Systems, although females still slightly exceed males. This indicates that female students are more represented across most majors, with smaller gender gaps in certain fields.

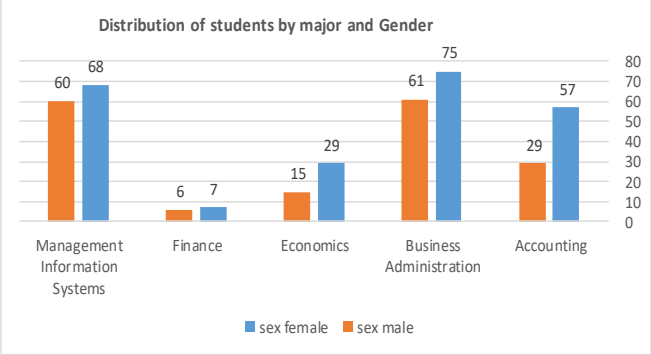

Fig. 2. Distribution of students by major and gender.

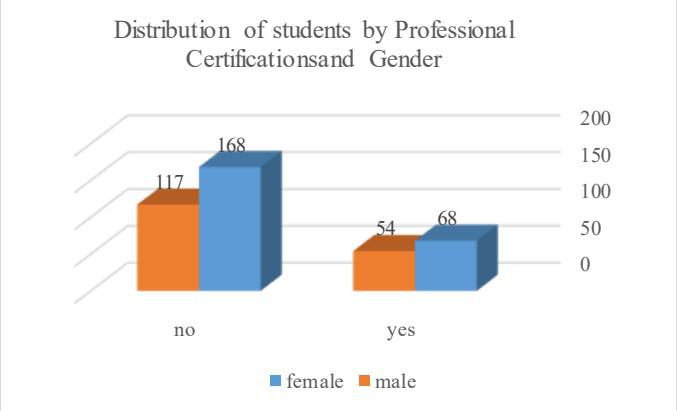

Fig. 3. Distribution of students by gender and professional certifications.

Fig. 3 shows the distribution of students by gender and professional certifications. Out of the total 407 participants, 122 have professional certifications, while 285 do not. Notably, females with certifications (68) slightly outnumber males (54), although the overall difference between genders is small. This distribution highlights the participation of both genders in obtaining professional certifications, indicating a trend towards professional development among graduates.

Table III shows the distribution of students by major and employment status. Out of 407 participants, 187 are employed, 162 are unemployed, and 58 work in misaligned positions. Business Administration (136) and Management Information Systems (128) record the highest numbers of employed graduates, while Finance has the lowest employment figures, with only 13 participants. This distribution highlights the varying employment outcomes across different academic majors, indicating that certain fields may offer better job prospects for graduates. The distribution of students by gender and employment status reveals that out of 407 participants, 236 are female and 171 are male. Among females, there are 107 employees, 97 unemployed, and 32 in misaligned positions, while males have 80 employees, 65 unemployed, and 26 in misaligned roles. Overall, employees constitute the largest group at 187, followed by the unemployed at 162, with 58 in misaligned positions. This distribution indicates that female graduates are more represented among employees than their male counterparts. Additionally, there is a significant relationship between possession of professional certifications and employment outcomes. Among those in misaligned positions, 126 individuals lack certifications. Overall, 120 graduates hold professional certifications, while 287 do not. This suggests that graduates without certifications are more likely to occupy roles that do not match their qualifications, emphasizing the importance of obtaining professional certifications to enhance employability and secure suitable job positions.

TABLE. III. DISTRIBUTION OF STUDENTS BY MAJOR AND EMPLOYMENT STATUS

Major	Employment Status			Total
	Employed in a misaligned position	employee	Unemployed	
Accounting	6	49	31	86
Business Administration	14	62	60	136
Economics	10	20	14	44
Finance	0	8	5	13
Management Information System	28	48	52	128
Total	58	187	162	407

VI. RESULTS

In this study, we employed Association Rules as our primary analytical technique to uncover patterns and relationships that could inform predictions about graduate employability. This method enhances the comprehension of the key determinants of employability and paves the way for potential enhancements in educational practices and student support services. The analysis highlighted several significant findings: Graduates with higher GPAs showed markedly improved employment outcomes. For example, those achieving GPAs between 4.5 and 5 had an impressive employment rate of 93%, compared to only 16% of graduates with GPAs below 3.0 who found jobs. Moreover, holding professional certifications was strongly linked to employability, with certified graduates experiencing a higher employment rate (90 employed vs. 30 unemployed) compared to their uncertified peers, where 97 were employed and 132 were unemployed. Additionally, graduates who excelled in communication, leadership, and teamwork skills were significantly more likely to secure employment; for instance, 90% of those with strong communication abilities obtained jobs, while only 10% faced unemployment.

The gender breakdown of the graduates revealed that 42% were male and 58% were female, underscoring the necessity for focused support initiatives for underrepresented groups. The data also indicated that around 29.5% of graduates found employment within 1 to 6 months, while 17.7% took more than 24 months, showing variability in job search durations influenced by factors such as chosen fields and personal connections.

Throughout the analysis, we performed various correlation assessments to explore the interplay between GPA and skills, professional certifications and skills, major and employment status, duration of job search and skills, and gender and employment status. The use of Association Rules provided critical knowledge into the relationships among these factors, deepening our understanding of employment outcomes.

Examining the distribution of graduates across various majors is vital for evaluating employability rates within different fields. A significant portion of graduates, approximately 33.4%, pursued degrees in Business Administration, closely followed by 31.4% in Management Information Systems. This distribution could impact employability outcomes; as certain fields tend to present more job opportunities than others.

In terms of gender representation, the analysis revealed that 58% of graduates are female, which may influence employability trends given current job market dynamics. The employment status of graduates indicates that about 60.2% are currently employed, with a noteworthy 76.33% of these individuals in suitable roles, suggesting the effectiveness of their education. Conversely, 39.8% remain unemployed, highlighting a need for a deeper investigation into job market dynamics.

The analysis of job search durations indicated that 29.5% of graduates secured employment within the first six months, reflecting variations in the timeline for job acquisition influenced by various factors. When examining the distribution of graduates by major and gender, it is essential to connect these demographics to employment outcomes. For instance, graduates in Business Administration and Management Information Systems tend to have higher employment rates than those in fields such as Economics and Finance. By emphasizing these disparities, we can better understand how specific majors may align with job market demands, thereby affecting employability.

The gender distribution, which shows a greater percentage of female graduates, raises important questions regarding the

impact of gender dynamics on job opportunities and outcomes. By elucidating these connections, we can offer a more nuanced analysis of the factors influencing employability, facilitating targeted initiatives to support all graduates in their career pursuits. These observations will be elaborated further in the statistical section.

The study includes a series of tables that illustrate the relationships between diverse factors and graduate employability. These tables offer insights into how cumulative GPA, professional certifications, soft skills, and other attributes correlate with employment outcomes. Through this analysis, we aim to enhance our understanding of the determinants of employability among graduates of the College of Business and Economics.

Fig. 4- Fig. 6 illustrate the preprocessing steps undertaken for key attributes in the dataset using Weka Explorer. Preprocessing is a critical stage in data analysis, as it ensures that the data is clean, consistent, and suitable for modeling. In Fig. 4, the preprocessing for the Duration of the Job Search attribute is depicted, showcasing how this variable was formatted and standardized to facilitate accurate analysis. The preprocessing of this attribute is essential, as it directly impacts the model's ability to predict employment outcomes based on how long graduates take to secure jobs. Fig. 5 highlights the preprocessing steps for the Training Duration attribute, emphasizing the importance of capturing the length of training programs that graduates have participated in. This attribute can correlate with employability, as longer training durations may enhance skill sets and job readiness. Lastly, Fig. 6 illustrates the preprocessing for the Gender attribute, which, although categorical, requires careful handling to ensure it appropriately contributes to the analysis. Proper preprocessing of gender data is crucial for understanding its influence on employability outcomes. Overall, these figures demonstrate the meticulous approach taken to prepare the dataset, ensuring that each attribute is ready for effective modeling and analysis.

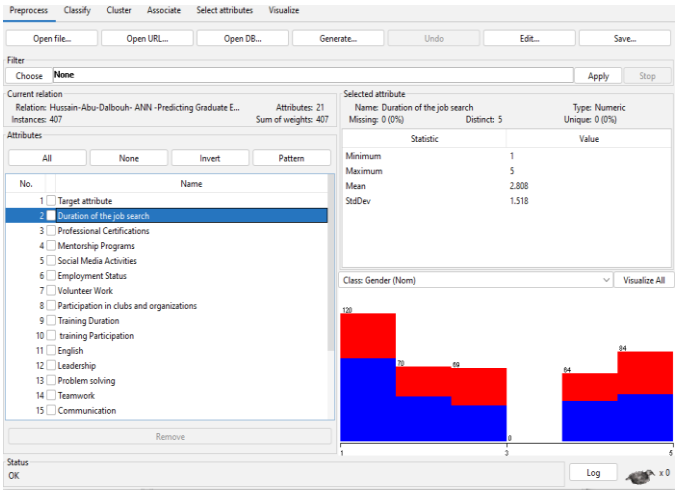

Fig. 4. Preprocess weka explorer for duration of the job search attribute.

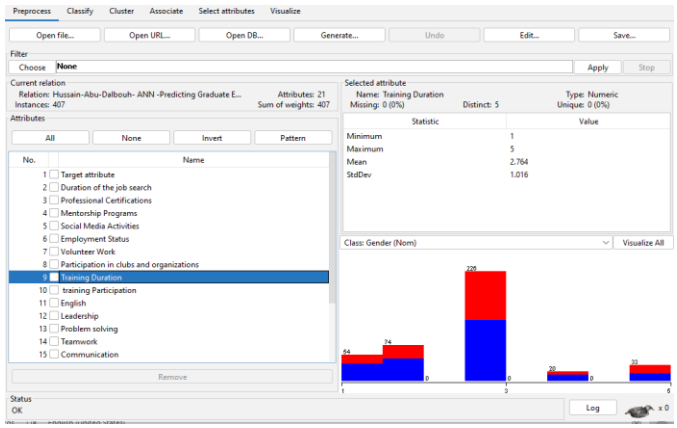

Fig. 5. Preprocess weka explorer for training duration attribute.

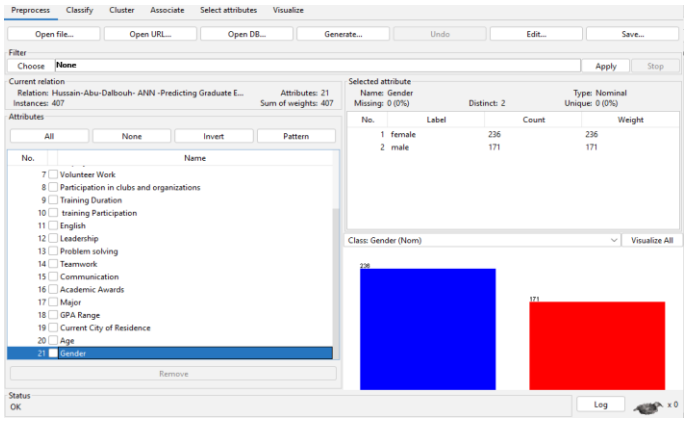

Fig. 6. Preprocess weka explorer for gender attribute.

To prepare for this analysis, the collected data were organized into tables suitable for applying Association Rules. We prioritized the most relevant features, as including irrelevant attributes could skew the findings. Data standardization and thorough cleaning were essential steps to enhance quality, requiring significant effort. Fig. 7 shows the attribute ranking.

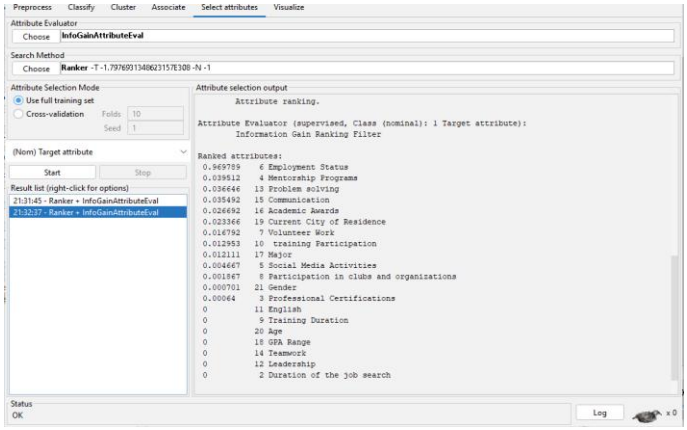

Fig. 7. Attribute evaluator information gain ranking filter.

The model utilized 10-fold cross-validation, enhancing performance assessment and generalizability by reducing bias across different data subsets. It was trained on 405 instances and generated 147 rules, as shown in Fig. 8 and 9, indicating its ability to capture complex relationships within the data. A forward search approach began with no attributes, expanding until five nodes were reached. This method identified relevant feature subsets, with the best subset scoring 85.185, reflecting strong predictive capability. Key attributes chosen included professional certifications, mentorship programs, and social media activities, which are crucial for employability. While the model showed reasonable predictive accuracy for graduates' employment status, it needs improvement in predicting employed graduates. Further refinement, such as exploring additional attributes or alternative modeling techniques, could enhance its overall effectiveness in forecasting graduate employability outcomes.

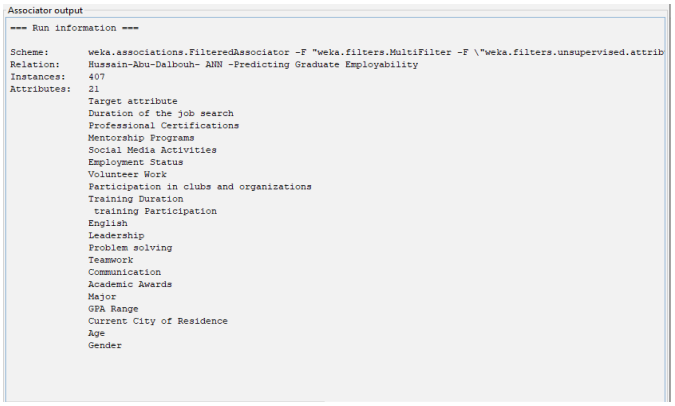

Fig. 8. Association output.

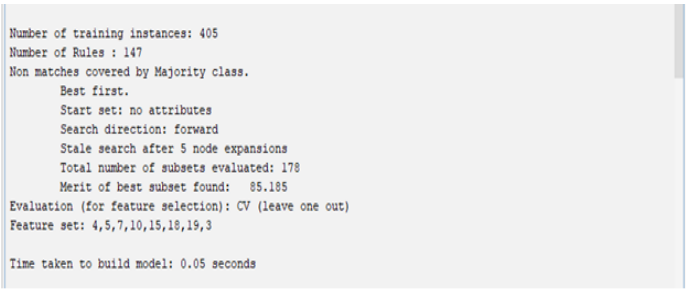

Fig. 9. Number of rules.

The model identifies key patterns influencing graduate employability outcomes. Age emerges as the primary decision factor, indicating that younger graduates face different employment trends than older ones. The current city of residence is also crucial, highlighting how geographic factors impact job availability. Leadership skills significantly affect employability, with graduates scoring higher in this area enjoying better job prospects. The academic major plays a vital role, especially in fields like Finance and Business Administration, where pathways to employment are defined by attributes such as English proficiency and social media engagement. Additionally, practical experience is emphasized; training duration and involvement in clubs are linked to favorable employment outcomes. The importance of social media activities and professional certifications reflects modern hiring practices, which increasingly value digital presence and ongoing education.

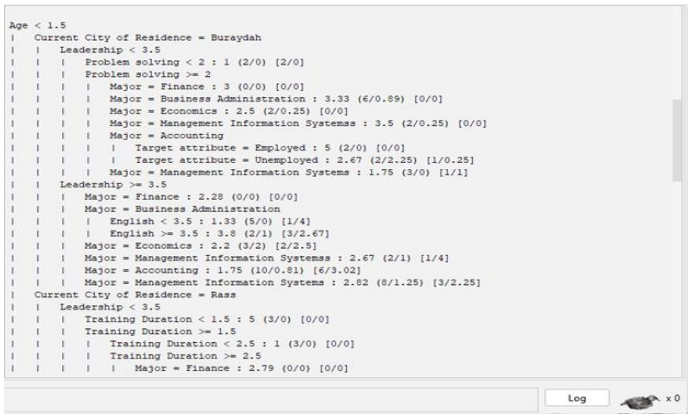

Fig. 10. Representation of association rules and hierarchical decision tree indicating factors influencing graduate employability.

VII. Discussion

This study examines the variables influencing graduate employability for students at Qassim University's College of Business and Economics. One important finding is that academic achievement, especially cumulative GPA, is a critical predictor of employability; higher GPAs result in better career outcomes, underscoring the necessity for educational institutions to promote high academic standards. Universities should establish comprehensive academic programs, such as support and tutoring, to assist at-risk students in raising their GPAs. Additionally, it is evident how important internships are; graduates who take part in them have better employment rates and shorter job searches. Universities should collaborate with nearby companies to develop comprehensive internship programs that provide students with priceless practical experience. Furthermore, fulfilling employment requires both technical and soft skills. Universities should incorporate skills training into their curricula through workshops and group projects since graduates with strong communication, teamwork, and leadership abilities are more successful. Fig. 10 illustrates the key factors influencing graduate employability, highlighting the relationships between various attributes and their impact on employment outcomes. The hierarchical decision tree effectively visualizes these associations, providing a clear framework for understanding how different influences contribute to graduate success in the job market.

There is a significant number of female graduates, according to the gender distribution analysis, which raises concerns about employment placement in some areas. Initiatives like mentorship programs should be put in place by universities to assist these graduates by putting them in touch with accomplished women in their areas. Additionally, the relationship between professional certificates and employability highlights their importance; graduates with certifications are more likely to find employment. By emphasizing long-term advantages and integrating preparation into their curricula, universities could promote certification endeavors. Lastly, employability outcomes have been analyzed using association rule mining, which has yielded insightful results. This strategy demonstrates how data-driven methods can increase

comprehension of intricate educational datasets, highlighting the necessity of concentrating on important indicators like GPA and internship experience in order to improve graduation outcomes.

Among the discovered rules, several intriguing patterns emerge that can inform classifications of graduate employability. For instance, Rule 1 indicates that graduates aged under 24 years with low leadership skills and residing in Buraydah, who have a major in Finance, are likely to be unemployed. In contrast, Rule 3 reveals that graduates aged 28 to 33 with high leadership skills and a major in Business Administration, who demonstrate proficiency in English, are categorized as employed. Additionally, Rule 4 highlights that graduates with a major in Finance, who participate in clubs and have a strong social media presence, are also classified as employed. Interestingly, Rule 5 suggests that graduates over 25 with a training duration of over 3.5 are seen as more likely to be employed. Furthermore, the rules demonstrate that practical engagement plays a crucial role; Rule 6 shows that graduates with high social media engagement and professional certifications are classified as employed. This information underscores the diverse factors influencing employability and the potential for targeted interventions to enhance job readiness. Some of the discovered interesting rules are:

1) Rule 1: IF Age is under 24 AND Leadership is low AND Current City of Residence is Buraydah AND Major is Finance, THEN classify the graduate as Unemployed.

2) Rule 2: IF Training Duration is less than 1.5 AND Social Media Activities is No AND Major is Economics, THEN classify the graduate as Unemployed.

3) Rule 3: IF Age is between 24 and 28 AND Leadership is high AND Major is Business Administration AND English proficiency is high, THEN classify the graduate as Employed.

4) Rule 4: IF Major is Finance AND Participation in clubs is Yes AND Social Media Activities is High, THEN classify the graduate as Employed.

5) Rule 5: IF Age is over 25 AND Education is MIS AND Training Duration is over 3.5, THEN classify the graduate as Employed.

6) Rule 6: IF Training Duration is less than 2 AND Leadership is low AND Current City of Residence is Unayzah, THEN classify the graduate as Unemployed.

7) Rule 7: IF Major is Management Information Systems AND English is low AND Communication skills are low, THEN classify the graduate as Unemployed.

8) Rule 8: IF Major is Business Administration AND Age is between 25 and 35 AND Training Participation is Yes, THEN classify the graduate as Employed.

9) Rule 9: IF Social Media Activities is High AND Professional Certifications is Yes AND Age is between 30 and 45, THEN classify the graduate as Employed.

10)Rule 10: IF Current City of Residence is Rass AND Training Duration is medium AND Leadership is medium AND Major is Management Information Systems, THEN classify the graduate as Medium value.

These rules illuminate the critical factors affecting graduate employability, highlighting the importance of skills, education, and engagement in determining job readiness. The following table presents a sample of rules that classify graduates based on various attributes affecting their employability outcomes. Each rule captures specific conditions under which graduates are classified as employed, unemployed, or of medium value, indicating the interplay of demographic factors, skills, and engagement activities.

Table IV shows some samples of Rules presents a selection of association rules derived from our analysis. This table illustrates the key relationships identified within the data, showcasing how different factors interact and influence the outcomes related to graduate employability. Each rule details the specific conditions under which certain attributes are associated with positive employment results.

TABLE. IV. SAMPLE OF RULES

Rule No	Sample of Rules	Instances	No of Attributes	Matched Instances
1	IF Gender is Male AND Age is 1 (22-24) AND Major is Finance OR Business Admiration, AND Leadership is High AND English is 5 AND Communication is 4 AND Teamwork is 3 AND Volunteer Work is Yes AND Training Participation is Yes, THEN classify the graduate as Employed.	407	9	123
2	IF Current City of Residence is Buraydah AND GPA Range is 1 (4.5-5) AND Training Duration is 3 (6-9 months) AND Volunteer Work is Yes AND Participation in clubs is Yes AND Social Media Activities is High, THEN classify as Employed.	407	6	92
3	IF Age is 2 (25-27) AND Volunteer Work is Yes AND Social Media Activities is High AND Communication is 5 AND Teamwork is 4 AND Leadership is 3 AND Problem Solving is 4, THEN classify the graduate as High value.	407	7	83
4	IF Major is Management Information Systems AND Training Participation is No AND Problem Solving is Low AND Duration of the Job Search is 3 (12-18 months) AND Age is 3 (28-30), THEN classify the graduate as Unemployed.	407	5	67
5	IF Leadership is Low AND Current City of Residence is Rass AND Duration of the Job	407	6	48

	Search is 4 (18-24 months) AND Teamwork is 2 AND English is 3 AND Training Duration is 2 (3-6 months), THEN classify the graduate as Unemployed.			
6	IF Age is 3 (28-30) AND Training Duration is 1 (1-3 months) AND Academic Awards is Yes AND Teamwork is 4 AND Communication is 4 AND Leadership is 5 AND Social Media Activities is Yes AND Professional Certifications is Yes, THEN classify the graduate as Medium value.	407	8	56
7	IF Gender is Female AND Age is 4 (>30) AND Professional Certifications is Yes AND Leadership is 5 AND Problem Solving is 4 AND Training Participation is Yes AND Volunteer Work is Yes AND Current City of Residence is Unayzah, THEN classify the graduate as High value.	407	8	72
8	IF Social Media Activities is Yes AND Participation in Clubs is Yes AND Problem Solving is 3 AND Training Duration is 4 (9-12 months) AND GPA Range is 2 (4-4.5) AND Age is 2 (25-27) AND Leadership is 3, THEN classify as Employed.	407	7	81
9	IF GPA Range is 2 (4-4.5) AND Age is 1 (22-24) AND Mentorship Programs is No AND Communication is Low AND Leadership is 2 AND Problem Solving is 2 AND Teamwork is 2, THEN classify the graduate as Unemployed.	407	7	49
10	IF Volunteer Work is Yes AND Training Participation is Yes AND Duration of the Job Search is 2 (6-12 months) AND English is 3 AND Teamwork is 3 AND Leadership is 4 AND Current City of Residence is Buraydah, THEN classify as Medium value.	407	7	66
11	IF Age is 4 (>30) AND Major is Accounting AND Training Duration is 5 (>12 months) AND Communication is 5 AND Leadership is 4 AND Volunteer Work is Yes AND English is 4 AND Social Media Activities is Yes AND Problem Solving is 3, THEN classify the graduate as High value.	407	9	75
12	IF Gender is Male AND Age is 3 (28-30) AND GPA Range is 3 (3.5-4) AND Teamwork is 5 AND Leadership is 5 AND Training Participation is Yes AND Duration of the Job Search is 1 (1-6 months) AND Current City of Residence is Rass AND Professional Certifications is Yes, THEN classify the graduate as Employed.	407	9	90

The generated rules provide valuable knowledge into the factors influencing graduate employability outcomes. Rule 1 indicates that male graduates aged 22-24 majoring in Finance or Business Administration, with high leadership skills, are likely to be employed, supported by 123 instances. This highlights the importance of gender and age in employability, particularly in leadership-centric fields. Rule 2 shows that graduates residing in Buraydah who possess a high GPA and actively participate in volunteer work and clubs are also likely to find employment, with 92 instances validating this pattern. Rule 3 classifies graduates aged 25-27 as high value when they engage in volunteer work and demonstrate strong social media presence, communication, and problem-solving skills, reflecting the significance of social engagement in enhancing job prospects. Conversely, Rule 4 illustrates that graduates majoring in Management Information Systems who exhibit low problem-solving skills and a longer job search duration tend to be unemployed, emphasizing the challenges in specific fields. Similarly, Rule 5 indicates that low leadership skills and extended job search duration correlate with unemployment, particularly for graduates in Rass. In contrast, Rule 6 suggests that graduates aged 28-30 with recent training and strong teamwork skills are classified as medium value, highlighting the role of ongoing professional development. Rule 7 identifies female graduates over 30 with professional certifications and high leadership capabilities as high value, underscoring the importance of continuous education in career advancement. Moreover, Rule 8 emphasizes that social media engagement and club participation significantly enhance employability for graduates aged 25-27. Rule 9 reveals that younger graduates who lack mentorship opportunities and exhibit lower communication skills are more likely to be unemployed, suggesting a need for improved support systems. Additionally, Rule 10 indicates that graduates involved in volunteer work and training are classified as medium value, showcasing the importance of practical experience. Rule 11 highlights that older graduates majoring in Accounting with extensive training and strong communication skills are viewed as high value, while

Rule 12 shows that male graduates aged 28-30 with strong teamwork and leadership skills, along with relevant certifications, are likely to be employed. These rules illustrate the multifaceted nature of employability, emphasizing the interplay between demographics, skills, and engagement, and providing critical areas for educational institutions and policymakers to enhance graduate job readiness.

A. Comparison with Previous Research

The findings of the proposed study are in agreement with [110], a study which revealed that employers frequently think highly qualified graduates have a good work ethic, discipline, and commitment to learning, qualities that might improve their employability. The study also emphasizes that while academic brilliance, as measured by GPA, continues to be an important aspect in the employability equation. Moreover, a study conducted by [111] demonstrated that employers appreciate higher grades and they frequently use them as key indicators in the selection processes to examine resumes of applicants. [106] noted that the most significant predictors of early employment factors are the GPA. [106] concluded that graduates of almost all majors, except Tourism, with a high GPA are employable within 6 months after graduation. From these findings, we concluded that higher academic performance is likely to improve employability, particularly for fresh graduates with limited work experience, because it offers a quick signal of ability and commitment. Regarding internship/training, this study found that Internship participation and longer training durations correlate with higher employment rates and shorter job-search durations. This finding agreed with the [112] study, which revealed that the practical training includes the potential for curriculum revision, adjusting the curriculum to better align with the needs of the labor market, and ensuring that graduates have the relevant skills and are needed by the employers. Also, [113] study stated that the employer plays an important role in providing work-based learning through internship programs to support learning in vocational education, which ultimately encourages the improvement of job skills for vocational students. In addition, [114] noted that internships play a crucial role in improving the employability of vocational students by bridging the gap between academic knowledge and practical skills, making them more attractive to potential employers. [115] claimed that internships are considered a means for preparing for future employment through developing personal abilities and skills, including self-confidence, communication skills, teamwork, social interactions, problem-solving abilities, time management, and resilience under pressure. These findings concurred with [116], study findings which demonstrated that certifications could build trust and credibility without employers spending the time and effort to design customized tests or evaluation mechanisms. Moreover, the [117] study findings indicate that micro-credentials can help individuals better align their careers with their skills and experience, ultimately boosting employability. The analysis highlights the necessity of both technical and soft skills in securing meaningful employment. Graduates who outperformed in communication, teamwork, and leadership were significantly more successful in the job market. These analysis findings agreed with [113]. In addition, [118] study highlights the importance of soft skills and self-awareness in university education, revealing that current curricula must adapt to the rapidly changing job market. Finally, [119] stated that soft skills are critical for success in the workplace and social life.

B. Implications for Educational Practice

The findings of this study, which employed association rule mining to predict graduate employability, have significant implications for educational practice at the College of Business and Economics at Qassim University. The identified rules illuminate critical factors influencing employability, such as high GPAs, strong leadership skills, and active participation in extracurricular activities, suggesting a need for curriculum revisions to emphasize these competencies. Educational institutions should focus on developing soft skills, including teamwork and communication, by integrating skill-building workshops and experiential learning opportunities into their programs. Moreover, the analysis highlights the importance of practical experience and networking, advocating for partnerships with local businesses to establish internship programs that allow students to apply theoretical knowledge in real-world contexts. Encouraging students to pursue relevant professional certifications is also essential, as seen in the rules indicating that such qualifications significantly boost employability. Additionally, addressing gender dynamics through targeted initiatives and mentorship programs can foster an inclusive environment, particularly for underrepresented graduates. Finally, the study underscores the value of utilizing data-driven knowledge; by continually analyzing graduate outcomes and employment trends, institutions can adapt their programs to meet evolving labor market demands. By addressing these implications, the College of Business and Economics can better prepare its graduates to navigate the complexities of the job market and enhance their overall employability.

C. Association Rule Validation

This section delves into the validation process of the Association Rules approach used to analyze employability outcomes for graduates from the College of Business and Economics. With a background in data analysis, the author highlights the importance of understanding the relationships within the data rather than focusing solely on technical aspects.

In this study, the Apriori algorithm was employed to uncover association rules that illuminate the factors influencing graduate employability among the College of Business and Economics graduates at Qassim University. The Apriori algorithm is particularly suitable for this analysis as it iteratively reduces the minimum support threshold to identify robust rules that exhibit significant correlations between educational attributes and employment outcomes.

The dataset was formatted in ARFF (Attribute-Relation File Format) to facilitate processing within Weka. This dataset included various attributes, such as academic performance, skills, and demographic information. The Apriori algorithm was selected from Weka's "Associations" section, known for its efficiency in mining association rules in large datasets. This algorithm allows for the mining of both general and class association rules, providing a comprehensive view of the relationships among educational factors. A minimum confidence level was set to ensure that only reliable rules were generated, and a target number of rules was specified to limit the

output to the most relevant findings. The lower bound for the minimum support parameter was adjusted to filter out less significant item sets, focusing on those likely to influence employability. The algorithm was configured to mine class association rules, linking educational attributes directly to employment outcomes.

Upon configuring these parameters, the algorithm was executed, generating a set of association rules that highlight key factors affecting employability. The generated rules were analyzed based on their support, confidence, and lift metrics. For instance, one significant rule indicated that graduates with high GPAs and internship experiences are more likely to secure employment. This finding supports the need for universities to enhance academic performance and provide practical experiences.

The application of the association algorithm in this study has revealed critical knowledge into the factors influencing graduate employability. The algorithm demonstrated good accuracy and reliability, effectively generating meaningful association rules, which were subsequently verified through manual inspection. By utilizing this robust algorithm, the research uncovered associations that inform educational strategies and improve alignment with market demands. This methodological approach enhances the credibility of the findings and contributes to the ongoing discourse on optimizing graduate outcomes in a competitive job market.

D. Limitations and Constraints

This study faces several limitations that should be considered when interpreting the findings. First, the analysis is confined to graduates from the College of Business and Economics at Qassim University, which may limit the applicability of the results to other educational contexts. The specific demographic and geographic focus may not capture the broader trends affecting employability across different institutions or disciplines. The dataset reflects a cross-sectional snapshot, which means it does not account for variations in employability outcomes over time. This limitation restricts our ability to assess the long-term effectiveness of educational programs or the evolving nature of job market demands. Additionally, challenges in data collection arose from inconsistent engagement levels among graduates. Some respondents may have provided superficial or inaccurate answers, impacting the data's reliability. This inconsistency highlights the importance of ensuring thorough participant engagement in future surveys. While the study examined various factors influencing employability, it may not have encompassed all relevant variables. For instance, aspects such as mentorship opportunities, internships, and personal networks were not explored, potentially omitting key influences on job readiness.

Moreover, the focus on quantitative measures may overlook qualitative factors, such as personal resilience and adaptability, which significantly contribute to employability but are harder to quantify. Although association rule mining is a powerful analytical tool, its success depends on the dataset's quality. Any limitations in the data can affect the robustness of the discovered patterns, necessitating cautious interpretation of the results. Lastly, the sample size of 407 graduates, while adequate for initial knowledge, may pose challenges in achieving broader generalizability. Smaller datasets can lead to overfitting in machine learning models, which may impact the reliability of predictions. Acknowledging these limitations is crucial for contextualizing the findings and identifying areas for future research to enhance the understanding of graduate employability.

VIII. Conclusion and Future Work

This study offers a detailed examination of the factors influencing employability among graduates from the College of Business and Economics at Qassim University, utilizing association rules to uncover 147 significant patterns. The findings reveal critical determinants of employability, including academic performance, practical experience, skills development, and social engagement. The analysis indicates that specific attributes, such as cumulative GPA and participation in internships, are pivotal predictors of job placement. Graduates with higher GPAs find employment more easily and secure positions that align closely with their qualifications. This underscores the importance of academic achievement in preparing students for the job market. Additionally, the results highlight the increasing value of professional certifications, which enhance employability by demonstrating a commitment to ongoing learning and skills enhancement. While the findings show that a substantial percentage of graduates are employed, the data also reveal a concerning number of graduates who remain unemployed. This gap emphasizes the urgent need for educational institutions to reevaluate and adapt their curricula to better align with the evolving demands of the labor market. Integrating practical experiences, such as internships and project-based learning, into academic programs is essential for bridging this disconnect. The use of association rules in this study has illuminated hidden knowledge about the relationships between various employability factors. By identifying these patterns, educational institutions can make informed decisions to enhance their support services and ultimately improve student outcomes. The observations gained from the analysis provide a robust framework for understanding the complex interplay of factors that contribute to graduate employability. This study recommends an approach to education that prioritizes academic success, practical experience and skill development. By creating an environment that fosters both technical and soft skills, universities can better equip graduates for the challenges of the job market. Furthermore, promoting networking opportunities and mentorship programs can significantly enhance students' employability prospects. While this study contributes valuable knowledge, several avenues for future research can deepen the understanding of graduate employability. Longitudinal studies that track graduates over time could provide insight into the long-term effectiveness of educational interventions and how employability evolves in response to changing market conditions. Qualitative methods, such as interviews and focus groups, could offer a richer contextual understanding of graduates' experiences in the job market. Future investigations should also explore the impact of extracurricular activities on skill development and how social media engagement influences networking opportunities and job placement. Expanding the dataset to include graduates from various universities or disciplines would facilitate a comparative analysis, enhancing the comprehension of the broader employment environment. By

building on the findings of this study, future research can delve into the dynamic factors that influence employability, fostering collaboration among educational institutions, industry stakeholders, and policymakers. Continued exploration of these critical issues will enhance the preparedness of graduates for successful transitions into the workforce, ultimately contributing to a more skilled and adaptable labor market.

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