Qualified but Not Quite Employable? AI Uncovers the MBA Skill Gap in India

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Abstract

An MBA degree is traditionally regarded as a gateway to managerial careers, but does it necessarily guarantee industry readiness? In an era increasingly shaped by artificial intelligence (AI), automation, and digital transformation, the employability of Indian MBA graduates has emerged as a critical concern. While business schools continue to produce management graduates equipped with academic qualifications and leadership aspirations, employers increasingly demand specialised technical competencies, analytical capabilities, industry certifications, and practical experience. This study critically examines the widening disconnect between what MBA graduates offer and what contemporary employers actually seek, using AI-driven analytical techniques to uncover skill gaps across major management disciplines.

The study employs an AI-enabled Exploratory Data Analysis (EDA) framework to systematically compare MBA students' résumés with industry job descriptions. The methodological approach integrates Natural Language Processing (NLP), sentiment analysis, topic modelling, clustering, Google Trends analysis, and comparative visualisations to identify patterns in skill representation, employer expectations, and industry-specific competency requirements. Google Trends analysis provides contextual insights into the geographical and seasonal patterns of interest in MBA education across India, particularly in economically active regions such as Delhi, Maharashtra, and Haryana.

The findings reveal a notable mismatch between graduate-reported competencies and employer expectations. MBA résumés predominantly emphasise conventional soft skills, including communication, teamwork, leadership, and problem-solving, alongside basic digital proficiencies. In contrast, employers increasingly prioritise advanced analytics, AI-enabled business applications, industry-recognised certifications, domain-specific expertise, and demonstrable practical experience. Functional analysis further identifies distinct competency gaps across Marketing, Human Resources, and Finance. Marketing positions increasingly require digital analytics and AI-supported marketing capabilities; HR roles emphasise workforce analytics, compliance, and HR technology; while Finance positions demand financial modelling, analytical proficiency, and technology-enabled decision-making. Sentiment analysis additionally highlights a contrast between the aspirational language of student résumés and the performance-oriented expectations reflected in job advertisements.

The study challenges the assumption that possessing an MBA qualification necessarily translates into employability, highlighting the distinction between academic credentials and industry-relevant competencies. It demonstrates the potential of AI-driven skill mapping and labour-market analytics to support evidence-based curriculum redesign, personalised learning pathways, experiential education, and industry-aligned certifications. By positioning AI as both a driver of changing employer expectations and a tool for diagnosing competency gaps, the research offers actionable implications for management institutions, recruiters, policymakers, and MBA graduates seeking to strengthen employability in India's evolving digital economy.

Keywords: MBA Employability; Artificial Intelligence; Skill Gap Analysis; Exploratory Data Analysis; Natural Language Processing; Industry–Academia Alignment; Management Education; India

Introduction

Artificial intelligence (AI) is transforming the contemporary organizations by changing the way people organize work, make decisions, and create value in all industries around the globe [1][2]. Improvements in machine learning, deep learning, robotic process automation, predictive analytics, and generative AI systems have increased the speed of the digital transformation of the enterprise, with algorithmic intelligence now integrated into both strategic and operations processes [2][3]. These

technologies are increasingly being adopted in forecasting, customer segmentation, talent analytics, financial risk assessment, supply chain optimization, and performance management through AI-enabled systems and, thus, reshaping the composition of skills necessary in managerial positions [2][4].

As organizations are increasingly adopting AI-enabled systems and routine tasks, they are placing greater emphasis on cognitive agility, data literacy, analytical reasoning, digital fluency, and the capacity to work effectively with intelligent technologies [5][6]. As a result, management graduates should not only have traditional leadership and administrative skills but also knowledge of AI, technological flexibility, and the capacity to analyze the algorithm-based knowledge to make strategic decisions [2][4]. The swift institutionalization of AI technologies has also transformed the recruitment and talent management practices. Companies are actively adopting applicant tracking systems, resume screening applications, predictive recruitment, and employee analytics systems based on AI to find the right applicants and predict performance results [7]. This change is an indication of how employability is evaluated, measured and operationalized within the labor market. Graduates are not judged by academic qualifications or theoretical understanding anymore but by provable skills in line with digital and AI-converged workplaces [8][9]. The use of intelligent recruitment systems further increases the demand on graduates to have quantifiable and technology-related skill sets that can be identified during automated screening [7]. In this context, management education plays an important role in equipping graduates with AI-supported skills. In India, MBA programs have experienced tremendous growth over the last ten years, giving rise to a large number of graduates; most of them are in the field of marketing, finance, human resources, operations, and new specialities [4][10]. However, this growth has also raised concerns about the employability and readiness of management graduates [1][11]. Companies increasingly seek MBA graduates to have hybrid skills that combine domain knowledge with AI-related skills (data decoding, business analytics, the implementation of digital strategies, knowledge of intelligent automation technologies) [2][4]. Despite a gradual growth in MBA graduates in India, unemployment rates have not been evenly distributed among institutions and disciplines, indicating that curriculum relevance and flexibility are questionable [4][11].

Existing literature on the employability of MBAs has focused mostly on the skills gaps, curriculum development, industry-academic fit, and graduate preparedness [1][3][12]. Previous studies have identified gaps in analytical skills, communication, digital skills, and problem-solving skills of management graduates [6][13]. Though these studies provide useful information about the issues of employability, their results mostly rely on perception-based surveys and employer feedback tools, which may not fully capture the dynamic and ever-changing skills requirements associated with artificial intelligence technologies [1][14]. The ability to transform operational functions, particularly in marketing analytics, fintech innovation, and HR analytics, and data-driven operations management, is typically captured in the dynamic ability of AI applications to transform functional roles, which is mostly not reflected in the framework of these technologies [2][4].

The increasing integration of AI in managerial areas has also introduced new competency requirements, including algorithmic thinking, ethical consciousness of AI application, and data governance literacy and strategic assessment of automated decision systems [2]. Such new competencies require formal evaluation methods that can determine dynamic changes in skills that are required in real time. However, very few studies have combined the application of artificial intelligence-based analytical methodologies with the systematic assessment of employability in management education [7][15]. The majority of traditional research on employability fail to utilise large-scale labour market data, resume-scale analytics, or machine-aided textual analysis to objectively investigate the issue of demand-supply mismatches [1][14]. Analytical methods based on artificial intelligence, in particular, natural language processing (NLP), text mining, and exploratory data analysis (EDA), promise significant improvements to these limitations in the methodology [7][15]. By analysing job descriptions and resume content, these techniques can help in identifying rising competencies and structural skill gaps. These methods can also help in comparison between technical, analytical, and behavioural competencies across different management roles and specialisations [7].

Despite these opportunities, there is a significant gap in empirical research related to the use of such AI-based frameworks in the context of Indian MBA employability [8][15]. Moreover, the growing importance of AI in strategic projection and performance analytics puts additional emphasis on the necessity to change the management curriculum in line with the needs of the digital era [2][4]. In the absence of the systematic integration of AI literacy, data-driven decision-making and analytics training, management education runs the risk of creating graduates who are not in line with modern labour market demands [1][12]. Besides its consequences to the individual outcomes of employability, this misfit has a wider implication to the organizational productivity and the competitiveness of the national economy [8][11].

At the institutional and policy levels, there is an increasing demand for objective, technology-enabled frameworks for assessing employability [8][9]. With the shift to intelligent automation and the digital ecosystems of industries, academic institutions

should implement empirical tools that would constantly track the changes in skill requirements. AI-powered analytical approaches can support this process by detecting curriculum deficiencies, informing pedagogic changes, and improving graduate preparedness for AI-enabled workplaces [7][15].

Based on this context, the present study aims to explore the alignment between the skills profile of MBA graduates and changing industry demands through the application of artificial intelligence-driven analyses. In particular, the study will examine the current industry demand trends in real time, measure skill profiles in MBA graduates' resumes, and determine the gaps in employability in management specialization. Using a combination of the exploratory data analysis tool and the natural language processing tool, this investigation suggests an AI-powered, data-driven model that can add to the academic literature and the policy discussion. The results provide practical information to academic institutions, students and policymakers in an effort to make MBAs more employable in an ever AI-dominated economy.

2. Literature Review

This is not a new topic that management graduates have been studied on in terms of gaining their employability particularly in the context of the rapidly changing economic and technological environments [1][2]. According to previous studies, employability does not solely depend on academic qualification but also on transferable skills, which are analytical reasoning, communication, flexibility and problem-solving skills [3][4].

In the management education scenario, different scholars have expressed that the gaps have existed between the curriculum content and what the industry requires and that the gap needs to be closed on the continuous basis of curriculum being revised to accommodate the changing requirements of the organization [3][5]. This literature points out that employability is a multidimensional construct, which is influenced by both the personal capabilities and structural economic changes, necessitating dynamism in terms of alignment between the institutions of higher education and the labor market requirements [1][6]. Along with the trend of increased adoption of digital technologies by businesses in their business processes, the recent literature has begun to draw attention to the ways in which artificial intelligence and digital competencies can shape graduate employability [2][7].

It has been shown that the landscape of management is shifting due to AI applications, data analytics, and automation and graduates must develop skills that are indicative of data interpretation, data decision making using technology, and working with intelligent machines [7][8]. Research has also demonstrated that AI literacy and digital fluency are emerging as important managerial competencies that employers cannot do without particularly in fields such as marketing analytics, financial modelling, human resource analytics and optimization of operations [7][9]. The proliferation of AI within the organizational ecosystem has altered the managerial functions more of supervising functions into data-driven strategic decisions functions and thus exacerbating the necessity of graduates to bear hybrid skills characterized by the ability to combine business skills and technological consciousness [2][7].

The new scholarship also accentuates the process of digital transformation as not being a technological change but a structural reorganization of business practices, business models, and performance indicators [2]. Within these settings, AI-powered systems have an impact on forecasting performance, customer interaction tactics, human resource planning and productivity. In turn, the efficacy of the managerial work becomes more and more dependent on the skill of interpreting the algorithmic outputs, estimating the reliability of the model, and incorporating predictive knowledge into the process of the implementation of strategic plans [7].

These advancements make AI competency more of a necessary legitimacy than optional addition to the employability in the modern-day management fields [2][9]. The other theory of literature examines the techniques of skill gap evaluation in management education [1][10]. The bulk of the existing research is rooted in the perception surveys carried out on students or faculty members or employers to identify the gap between the acquired and the required competencies [1][11]. Inasmuch as these methods provide useful information, they are usually limited by respondent bias and predetermined skills that cannot be capable of responding to rapidly evolving jobs in the industry [6][12].

Therefore, scholars have demanded less biased and more objective ways of determining employability on the basis of data which are reflective of the prevailing situation in the labor market [10][13]. It is also common in the context of the use of static survey tools; it usually prevents researchers to identify new skill demands that are made in response to technological shocks and the adoption of AI in the fields [1][13]. Over the last years, there has been a growing argument amongst scholars that methodologies based on data should be used to measure employability more objectively [10][13].

Instead of relying on subjective perceptions, these methods encourage the labor market analytics, job posts analysis, and competency mapping models as a way of eliciting evidence-based information about the skill demand patterns. This change is indicative of a wider trend of empirical, scalable and technologically mediated research methodologies that are able to capture real time evolving industry demands [10][14]. The increasing body of the literature suggests that the limitations of the traditional employability research can be overcome

using artificial intelligence-related data mining tools, such as natural language processing and exploratory data analysis [14][15]. According to AI, the analysis of a large piece of textual data (job descriptions and resumes) can be performed to identify the patterns of skills, discrepancies between demand and supply of skills to a greater extent [14]. The competency keywords, cluster of skill groups, and semantic mapping of industry requirements to graduate profiles can be obtained automatically using natural language processing techniques [14][15]. Exploratory data analysis also enhances the determination of the frequency distributions, the gaps in the specialization that are specific and new competencies trends in the dynamic labor market settings [14].

Nevertheless, considering the methodological potential of AI-based analytics, not many empirically conducted studies in the area of MBA employability references to the case in India by using the methods [9][15]. Current studies have mostly been descriptive, or perception based or have applied traditional methods of statistical analysis, without utilizing fully the power of artificial intelligence to analyze large volumes of text and labor market features [1][13]. It is this gap in the literature that demonstrates the necessity of AI-based, information-driven systems to evaluate the employability of management graduates based on the evolving industry demands. The lack of these frameworks limits institutions and policymakers to diagnose skill mismatches systematically and take evidence-based curriculum changes in line with the economic system that integrates AI [14][9].

Overall, the literature proposes the shift in the paradigm of traditional employability towards technologically embedded paradigms of competency. Still, empirical combination of artificial intelligence tools with MBA skill gap analysis is undeveloped especially in developing economies like India [9][15]. This gap highlights the necessity to implement AI-based analytical frameworks to balance the theoretical understanding of labor markets with the realities of the labor market.

3. Methodology

This paper was based on the quantitative and exploratory research design to investigate the match between the skill profile of the MBA graduates and the changing industry needs using artificial intelligence-based methods of analysis. The research method was deemed suitable because of the volatility of the occupational skills requirements in the AI-affected workforce and the scarcity of empirical research that had incorporated AI-related practices in the field of management employs managerial skills.

The analysis was done using secondary data sources. The data on industry demand was gathered using the job descriptions and labor market trends websites that were publicly available, to obtain real-time demands of skills in management fields. Simultaneously, the MBA students anonymized data in terms of resumes was processed to determine the current skills representations in each of the specializations. The secondary data helped to perform a big-scale analysis and reduce the respondent bias, inherent to the surveys based on perceptions.

An analysis was done in a manner that permitted data preprocessing in order to achieve consistency and accuracy. The text data on the job descriptions and resumes were cleaned using the tokenizing, stop word removal, normalization and lemmatization techniques. These preprocess procedures contributed to the successful use of artificial intelligence methods and ensured the accuracy of the further analyses.

Analytical approaches based on artificial intelligence were used to analyse the alignment of skills demand and supply. Textual data sources were processed using natural language methods to obtain and categorize the skills related to keywords. Exploratory data analysis has been used to determine patterns, frequency distributions and the differences between the skills required by the industry and those of MBA graduates. The cross-specialization of management activities allowed it to find gaps in employability domains.

The analytical model was aimed at lining industry demand cues with graduate skill profiles to identify employability preparedness. The outcomes produced by using AI-enables analysis presented an empirical foundation to establish key skill gaps and conduct further discourse based on the alignment of the curriculum and policy implications in the field of management education.

4. Result and Interpretation

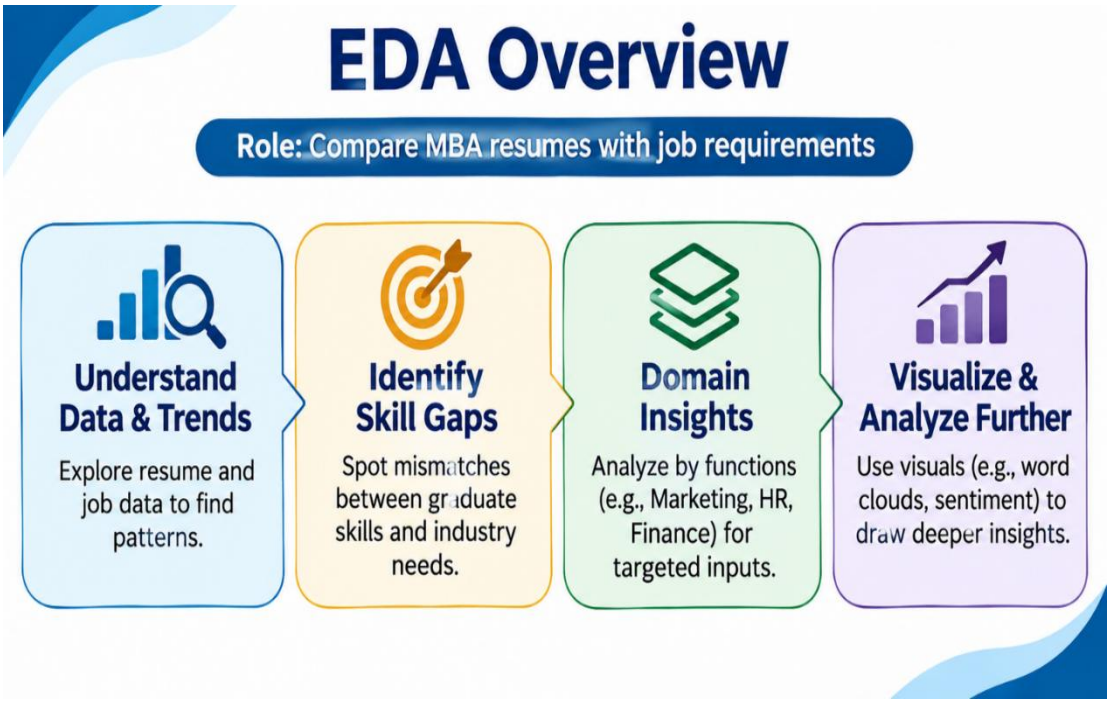


Figure 1: EDA Overview
Source: Created by authors using Powerpoint

4.1 Google Trend Analysis

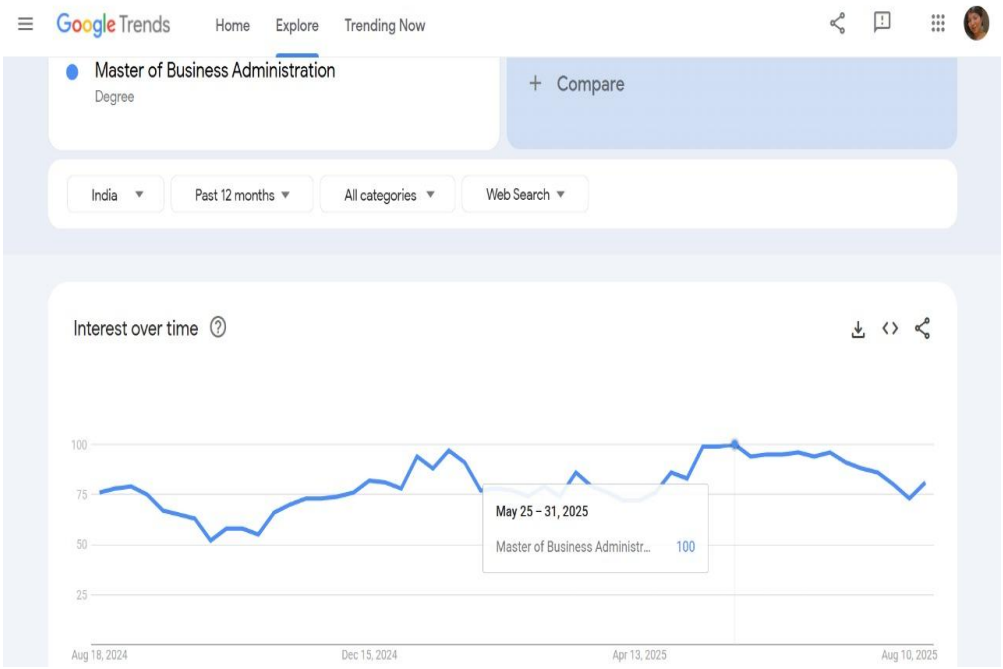


Figure 2: Interest over time
Source: Generated by authors using Google trends

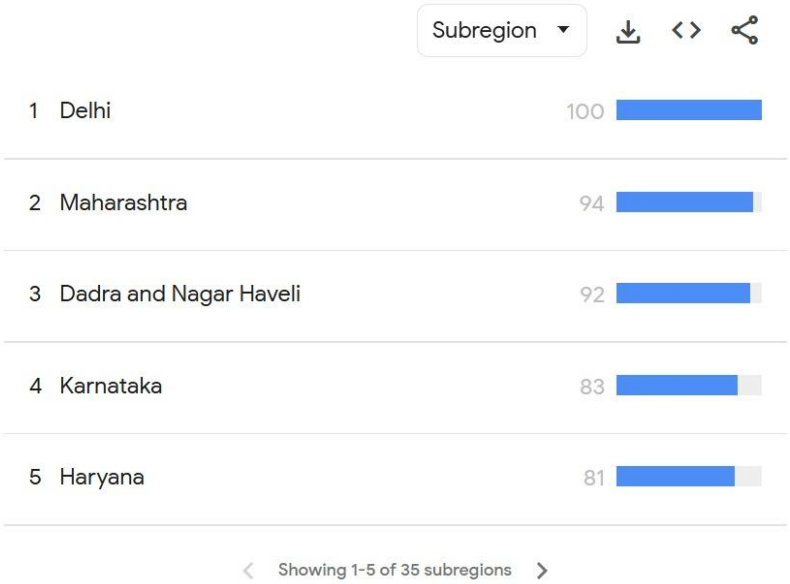


Figure 3: Location wise interest
Source: Generated by authors using Google trends

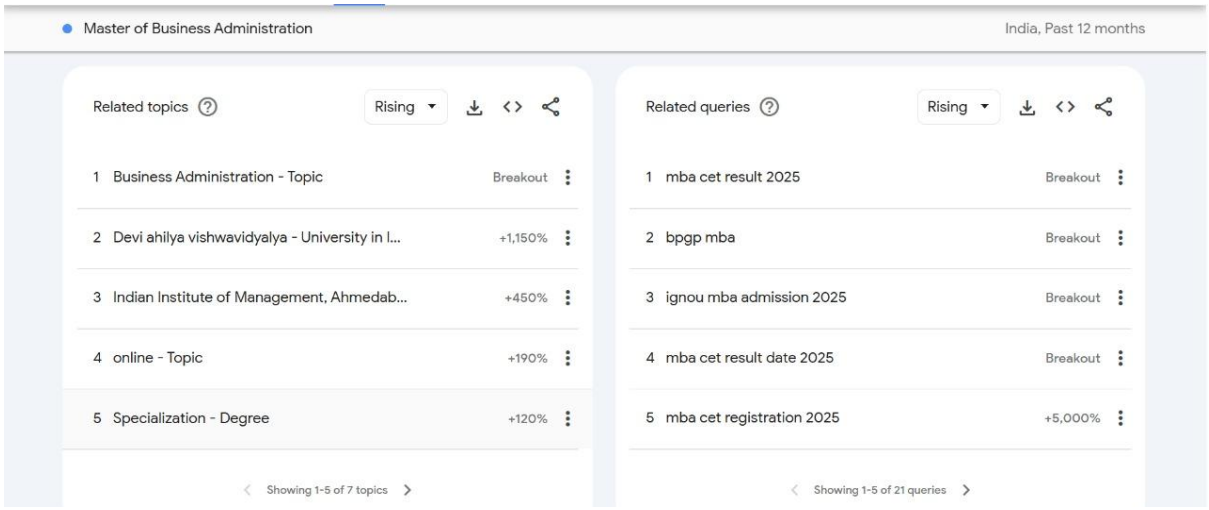


Figure 4: University wise interest
Source: Generated by authors using Google trends

As evident in figure 1,2,3 and 4 Google Trends analysis of search terms Master of Business Administration in India within the last one year shows that the level of public interest has steadily increased and is gradually growing with a significant peak noted in the late May 2025. This increase in intensity of searches must be related to the release of entrance examination scores, admission status and application dates of the top business schools. These seasonal peaks are an indication of the cyclicality of the MBA admissions in India where applicants are enthusiastic to get information about eligibility requirements, cut-off marks, counselling dates and institutional ratings at major times in the academic year.

A geographical analysis of the search popularity reveals that Delhi, Maharashtra, and Haryana are the states with the highest volume of search. These states are the large urban, industrial, and educational centers, with the large business schools and corporate headquarters. This increased attention to these regions can reflect better awareness of management education opportunities, increased concentration of competitive candidates, and more perceived rewards of MBA credentials in economic dynamic regions. This geographical trend also implies that the cities with well-established industrial eco-systems are more inclined to show the correlation between professional interests and post-graduate management studies.

The additional trending topics research and associated queries indicate that user searches are mostly on MBA entrance tests, university admission processes, program majors, online MBA program opportunities, and announcement of results. This has been demonstrated as a factor tracing to the competitiveness of the MBA education in India where candidates in their quest for education follow updates of exams including: CAT, XAT, MAT,

and state entrance exams. Moreover, the popularity of online and specialty MBA programs search results indicate a rise in the appeal of the types of flexible learning and niche specialization in accordance with the new requirements of the industry. In general, the information provided by Google Trends does not only indicate the long-term need in MBA education but also a change in preferences toward the expedient access to information, preferences to specialization, and management education that could be offered digitally.

Demographics

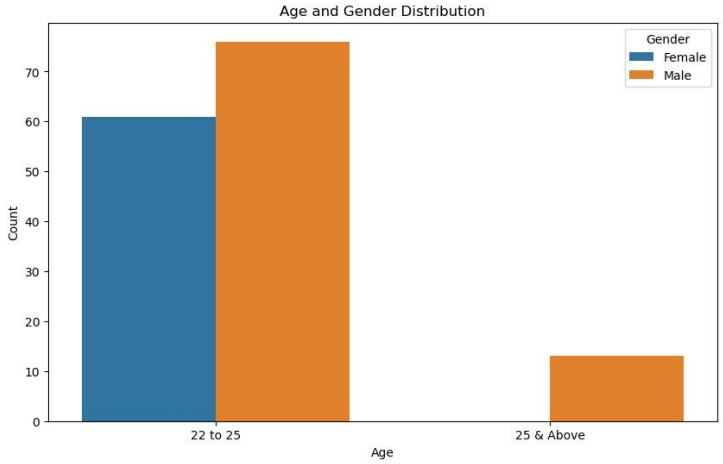


Figure 5: Age distribution
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

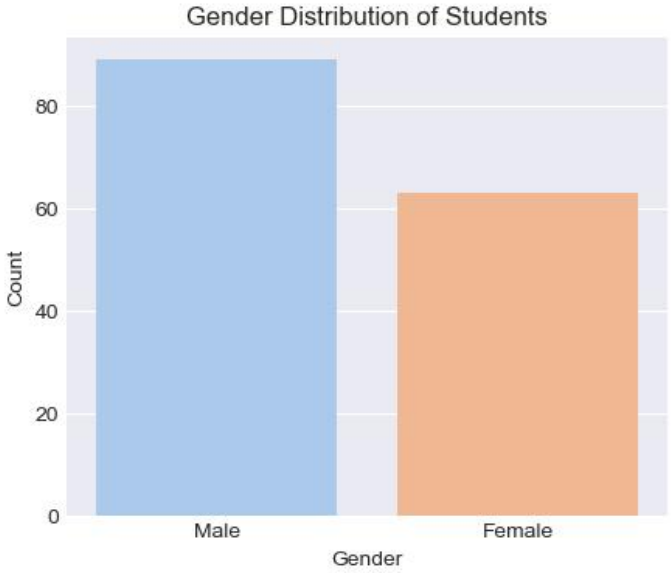


Figure 6: Gender distribution
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

As shown in figure 5, most MBA applicants on the dataset are between 22 and 25, males outnumber females slightly, and the overall talent pool in the industry is young and gender diverse, actively pursuing industry preparedness. Figure 6 again validates that though the major percentage falls on the male students, the percentage of females is still high indicating that both sexes are contributing well in skill-building and professional growth as far as MBA careers in the Gurgaon job market are concerned.

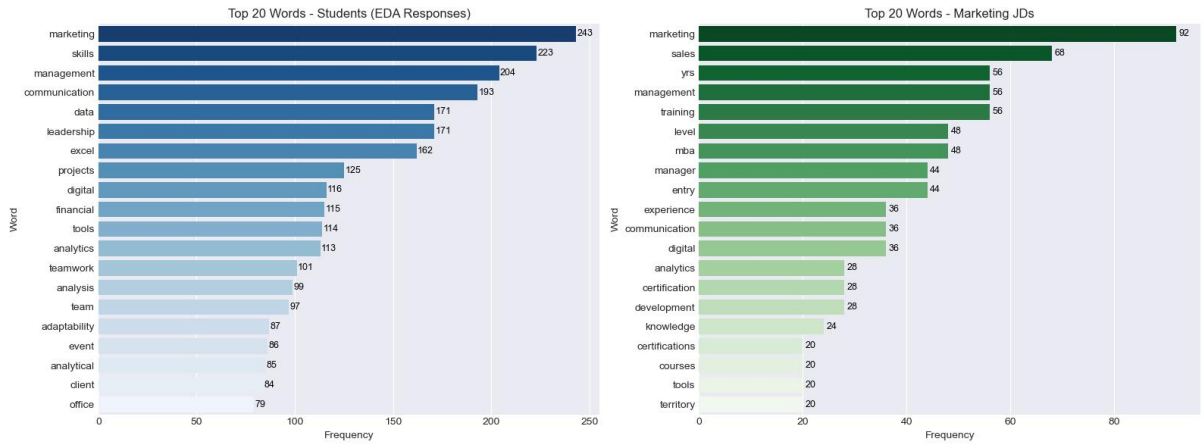


Figure 7: Student vs stream
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

As evident in figure 7 direct comparison reveals that, although both students and employers focus on marketing, management, and communication, students are heavy on general skills such as leadership, teamwork, and Excel, but job descriptions are more interested in specific skills and requirements such as sales, training, analytics, certifications, and experience.
According to the thematic analysis, there is a general correspondence but also indicates gaps especially on some of the qualifications and certifications that the students should complete in order to best fit the requirements of the industry.

4.2 Marketing Domain Analysis

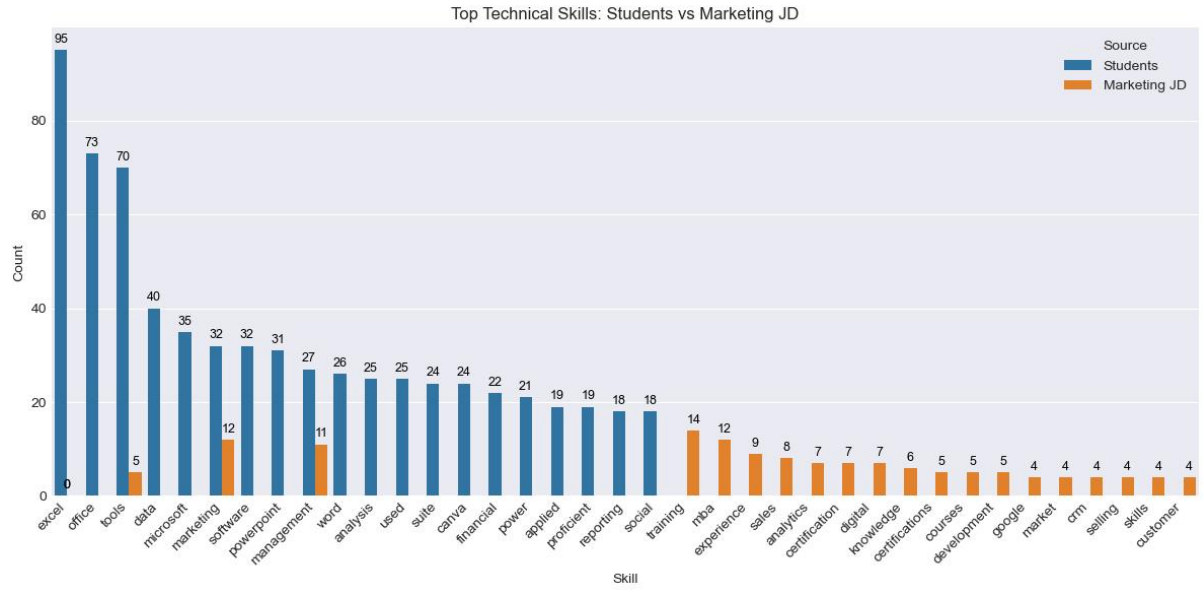


Figure 8: Technical skills- student vs. marketing JD
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

Figure 8 demonstrates that there is a vast difference in the student and employer focus on technical skills. As an example, students use the word "excel" 95 times and marketing JDs use it 0 times, whereas the word mba is used 14 times in JDs and 0 times in student resumes.
Also, although students often mention office (73) and powerpoint (31), job descriptions tend to mention experience (12), sales (9) and certification (8), indicating that students are more concerned with software skills as compared to employers who are more concerned with official qualifications and skills. This is a measure of a definite skilled misfit gap..

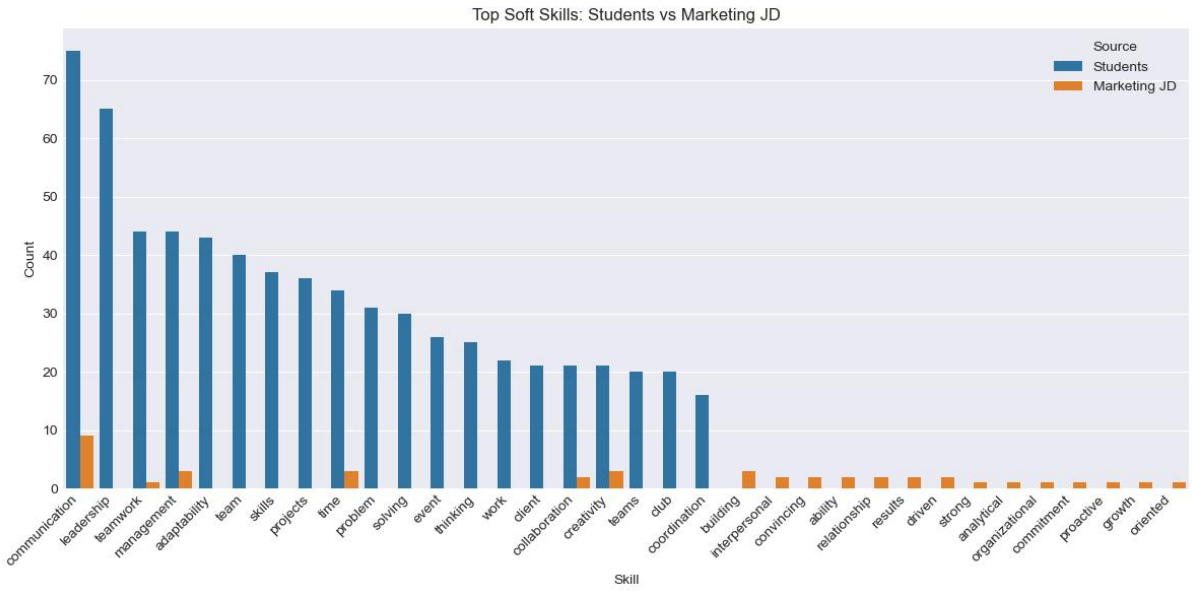


Figure 9: Soft skills- student vs. marketing JD
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

Figure 9 shows, students focus much, much more on soft skills, including communication (76 mentions), leadership (65), teamwork (44) and management (43) than employers mention them in the marketing job descriptions; here, there are only 9 mentions of communication and 8 mentions of leadership. The infrequency of JD mentions on other skills identified by students (teamwork (3) adaptability (3), problem solving (3) etc.) suggests a poor fit as students emphasize general soft skills when employers want more role-specific or outcome-driven skills.

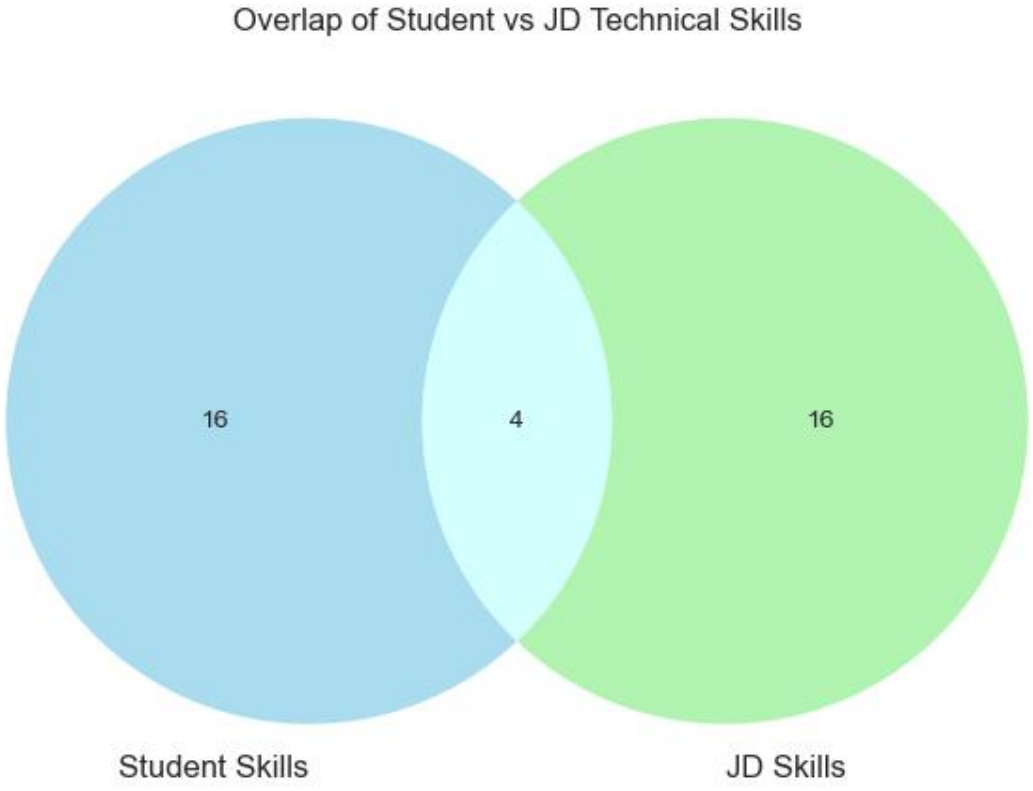


Figure 10: Venn diagram
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

This Venn diagram in figure 10 indicates that the overlap between technical skills mentioned by MBA students and those mentioned in job descriptions is very small: there are only 4 skills that are shared by both parties, whereas 16 are specific to each party.

This shortcoming highlights the necessity of more specific curriculum changes and student education to further match candidate skillsets with industry needs to be more job ready.

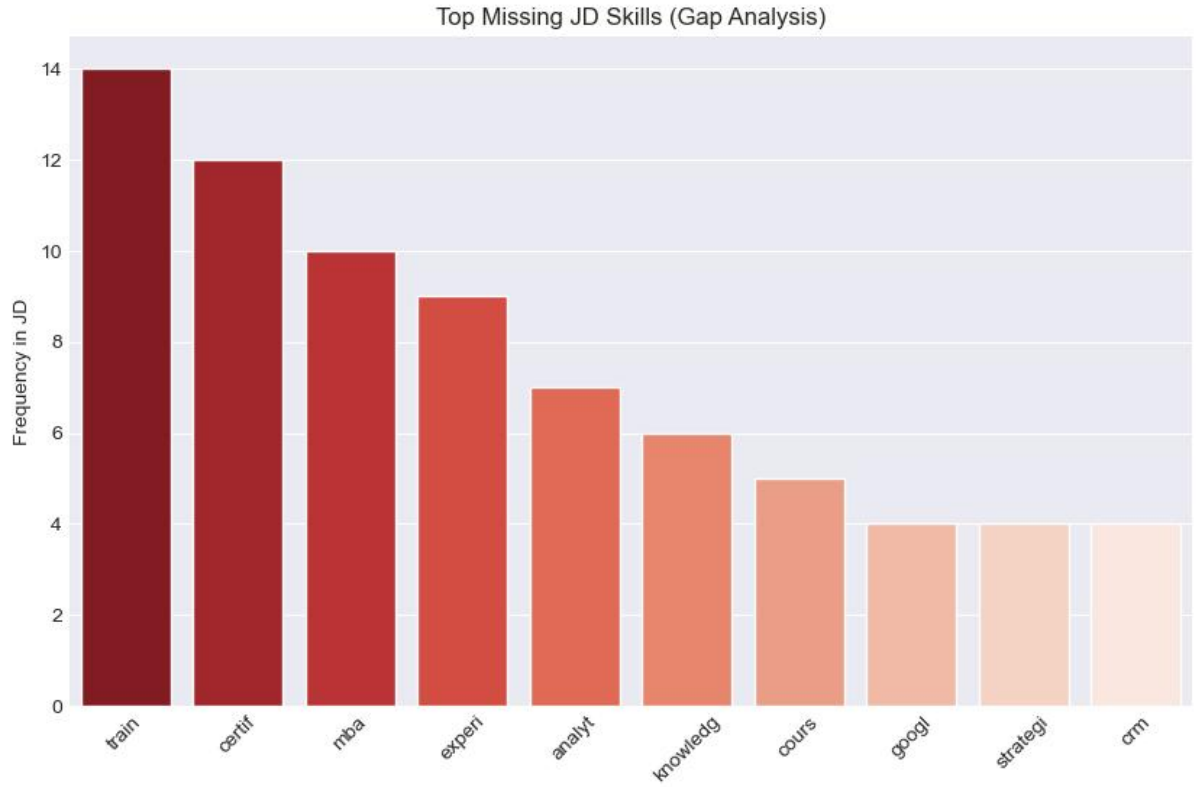


Figure 11: Gap Analysis
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

Figure 11 gap analysis shows the best technical skills that have been required in job descriptions but lacking in resumes of MBA students, the best gaps being train, certif, and mba.
Sealing these gaps, particularly in training, certification, analytics, and strategic areas, will go a long way in making MBA graduates more industry-ready and employer-aligned.

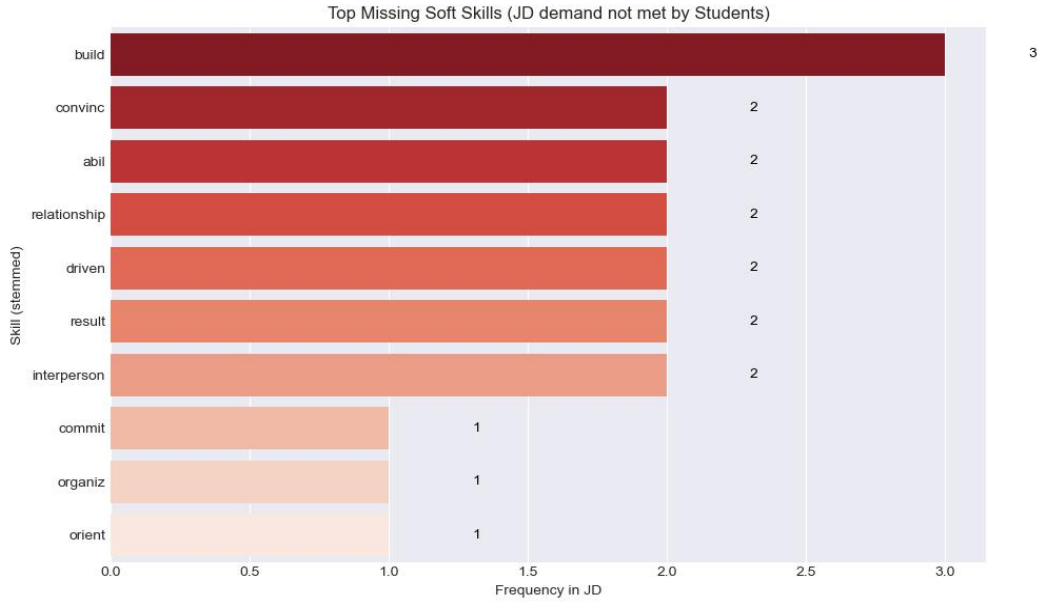


Figure 12: Top missing soft skills (Gap Analysis)
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

Figure 12 evidently indicates the highest ranked marketing JDs soft skills that employers desire in their marketing roles but are not prominently shown in student resumes and most prominently in the build (3 mentions), convinc

(2), abil (2), and relationship (2) skills.

The gaps point to the lack of opportunities by the students to demonstrate role-specific qualities such as relationship-building, result-driven, interpersonal, and organization commitment attributes, which recruiters consider important, but these qualities are not reflected in graduate self-presentation.

Word Cloud



Figure 13 Word Cloud

Correlation Heatmap

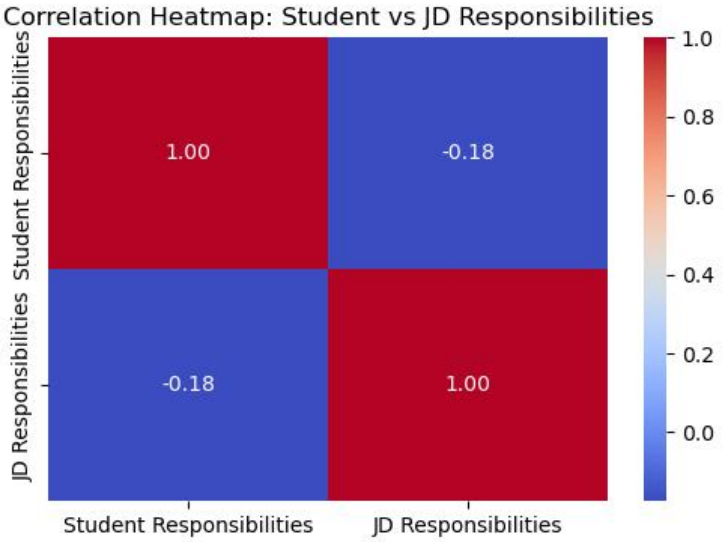


Figure 14 Correlation Heatmap: Student vs JD Responsibilities
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

Figure 14 heatmap shows that there is a weak negative relationship between the responsibilities that were found in the student resumes and what marketing job description had to offer (r= -0.18). Though the scale of the correlation is not that high, the negative trend is also notable, as it indicates the inverseness of the relationship between competencies focused on by students and responsibilities required by prospective employers. Put simply, the skills and job descriptions which students consider as the most important in their self-presentation seem to go against the requirements of the current marketing job role descriptions.

This observation shows that there may be mis-match between the strategies of self-presentation by the candidates and the real needs of the industry. There is a possibility that students are pointing to broad managerial capabilities or scholarly project experiences, but employers are looking to find data-driven marketing skills, digital analytics skills, and campaign performance measurement skills and familiarity with AI-driven marketing tools.

The difference indicates that resume building can be inadequate in reflecting the changing market reality, especially in the sectors where marketing activities are more technologically influenced and analytic-oriented. Also, the

negative correlation could mean that the gap is caused not only by the lack of the necessary skills but the focus on different or outdated ones. Such a mismatch has the potential to decrease the likelihood of employability, because recruitment systems (and in particular, the AI-powered applicant tracking system) favor a match between keywords in the resume and job description words. The outcome consequently highlights the necessity of industry education among students and curricular absorption of digitally applicable and role-specific marketing skills.

Sentiment Analysis

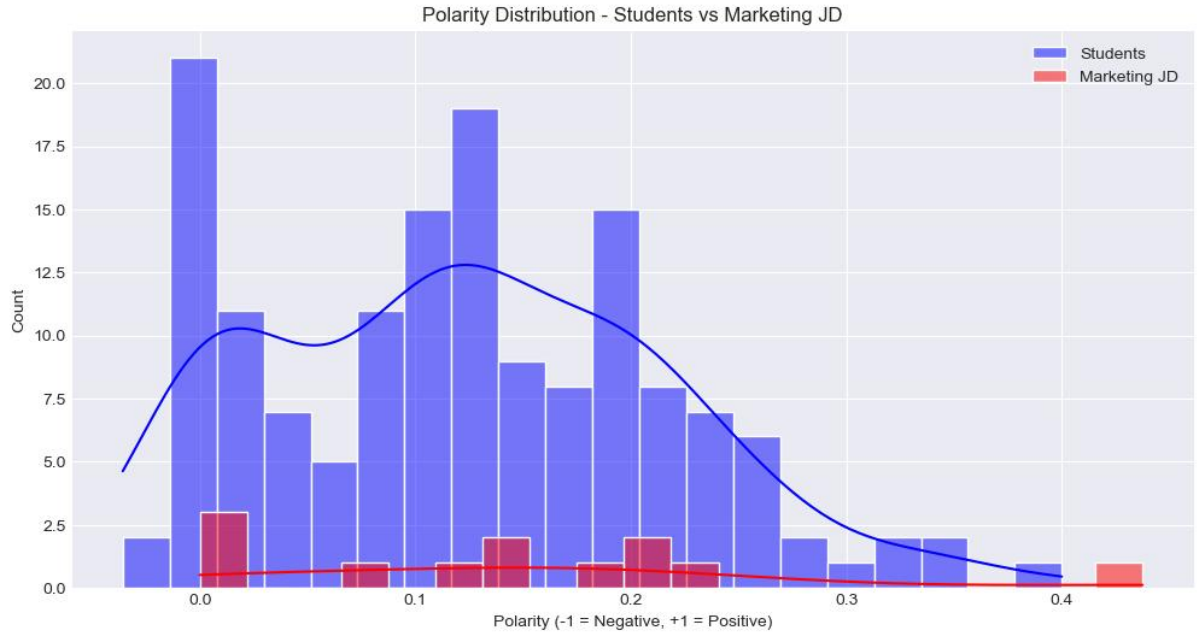


Figure 15: Polarity Distribution
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

Figure 15 is the comparison of sentimentality of the resumes of students and description of a marketing job, as both have mostly positive sentimentality, yet student statements have greater diversity and a little more positive. The general distribution indicates that MBA learners describe their abilities and experience more optimistically, and the content of JD does not have such characteristics but is more neutral and standardized.

4.3 HR Domain Analysis

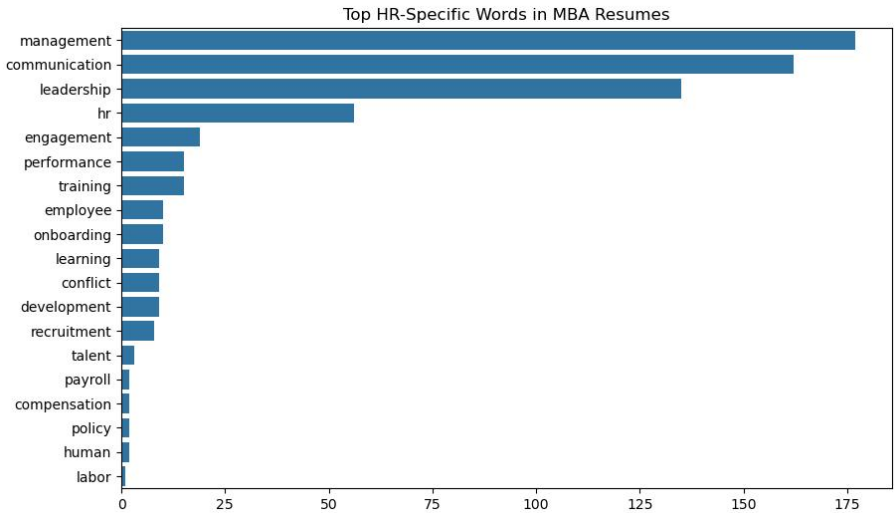


Figure 16: Words specified in resumes
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

This bar graph in figure 16 shows that management, communication, and leadership are the most common terms that MBA students list in their resumes, then there are such words as HR, engagement, and performance. Although

such basic HR terms as: training, employee and onboarding are there, more technical HR specific terms such as: payroll, compensation and labor are less frequent, which may reflect a tilt towards generalist skills rather than technical HR specialisms.

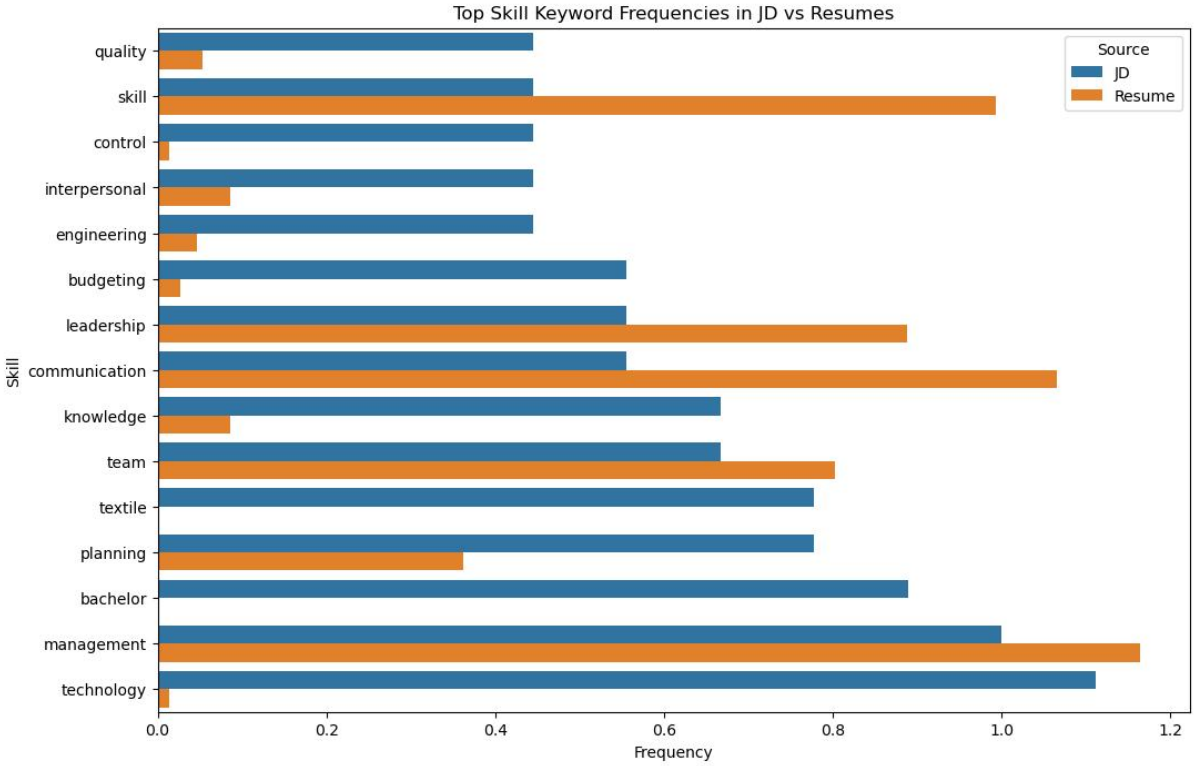


Figure 17: Skill keywords in JD vs Resume
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

As can be seen in this comparative bar chart in figure 17, whereas such skills as management, communication, leadership, and skill are highly represented in both job descriptions and resumes, some technical skills, such as textile, engineering, and technology, are much more highly represented in JDs than in candidate profiles. The visual dichotomy shows both both areas of high alignment and large areas of skill deficiency, indicating that MBA graduates would be more competitive through making clear their expertise in technical skills which are in demand by employers.

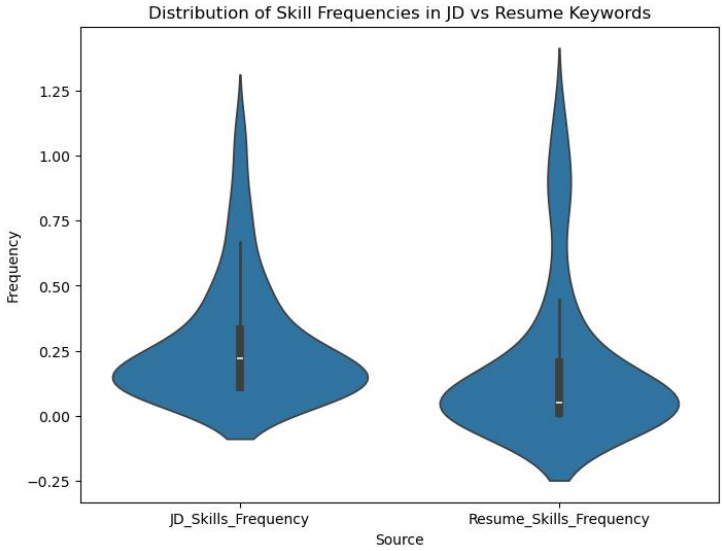


Figure 18: violin chart
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

This violin chart in Figure 18 shows the frequency distribution of skill keywords found in job descriptions (JD) and resumes to be similar in range and shape, but with most frequencies near the lower end.
The plot shows that although some of the skills are accentuated in both sources, most of them are mentioned less

frequently- indicating a similarity in the range of skills but potentially a difference in the focus on particular competencies that are in high demand.

4.4 HR Domain Analysis

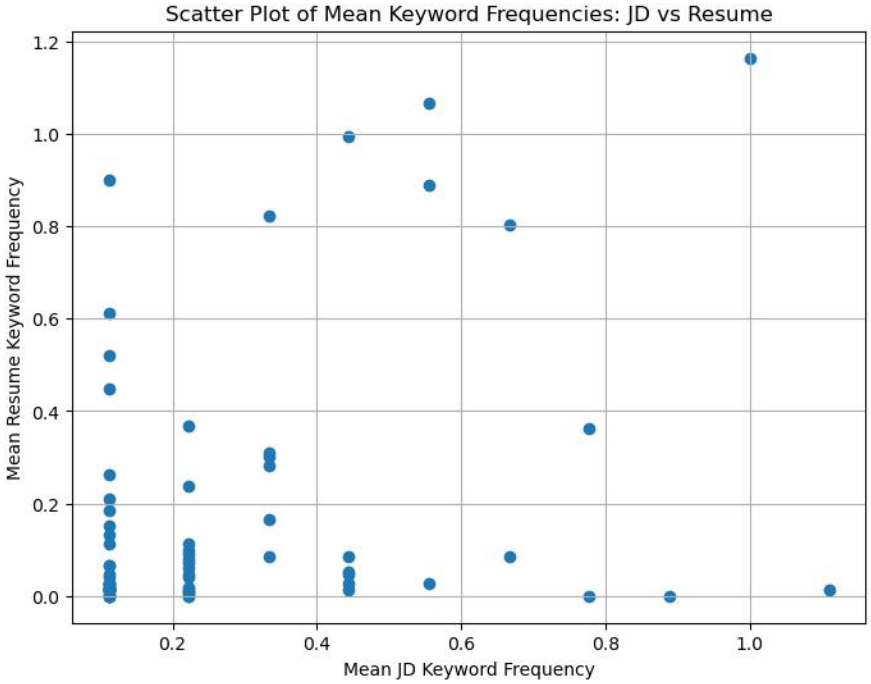


Figure 19: Scatter plot
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

The correlation shown in the scatter plot in figure 19 is between average occurrence of keywords in job description (x-axis) and student resumes (y-axis). Every point of data is a given skill or competency, and is graphed based on the frequency with which it is required by employers versus the frequency of it being emphasized by applicants. The allocation of the points on the graph portrays a certain level of dispersion and lacks a high order of clustering along the diagonal graph line, which would otherwise reflect the point of congruency between industry demand and the student self-representation.

The diffusion indicates that there is a low level of consistent fit between the demanded and the available skills. Ideally, the high positive correlation would be in the form of a clustering of the points around a linear upward direction, which implies that the often-requested skills are equally highlighted in the resumes. Nonetheless, the evaluated dispersion shows that a number of competencies are either overrepresented in the resumes compared to their level of demand in the job descriptions or underrepresented in spite of their high relevance to the industry.

This unequal's the asymmetry of the structural gaps in the expectations of the labor market and the articulation of graduate skills. Particularly, those skills found in the upper-left quadrant of the plot are those ones that are focused on by students but are not highly sought after by employers, which may be evidence of an outdated or generic resume placement. On the other hand, jobs skills in lower-right quadrant indicate high-demand competencies that are inadequately depicted on resumes indicating critical employability gaps.

This general trend supports the existence of demand-supply imbalance and implies that students are not strategically to suit their skill representation to the demands of the contemporary job market. Regarding the employability aspect, such mismatch may have the substantial effect on the recruitment processes, particularly in the setting where AI-based applicant tracking systems use keyword matching and semantic similarity algorithms to filter out applicants. The scatter plot thus presents empirical data of skill representation inequality and recommends strategies of using data-driven curriculum design and resume optimization tools to enhance fit between MBA graduates and industry demands.

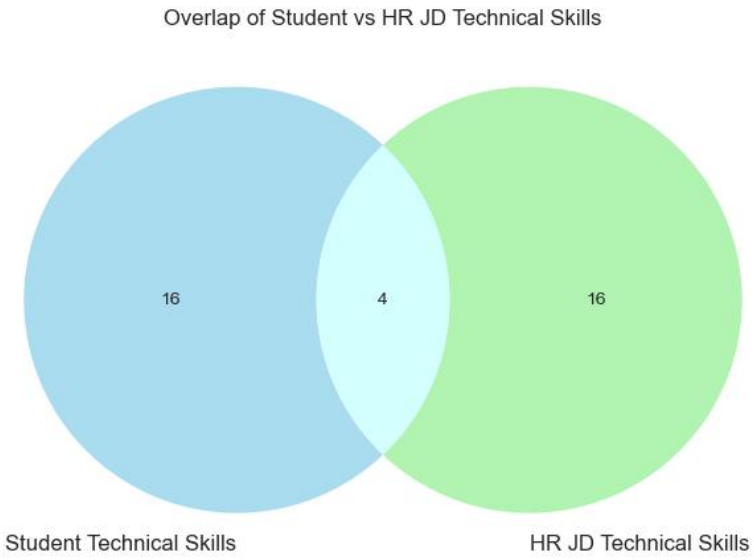


Figure 20: Venn diagram
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

According to this Venn diagram in figure 20, the overlap in technical skills is low: there are only 4 skills that overlap between students and the HR job descriptions, whereas 16 technical skills are specific to each of the two groups. This means there is a tremendous disparity, and therefore students need to learn and focus more on the highly demanded technical skills listed by employers.

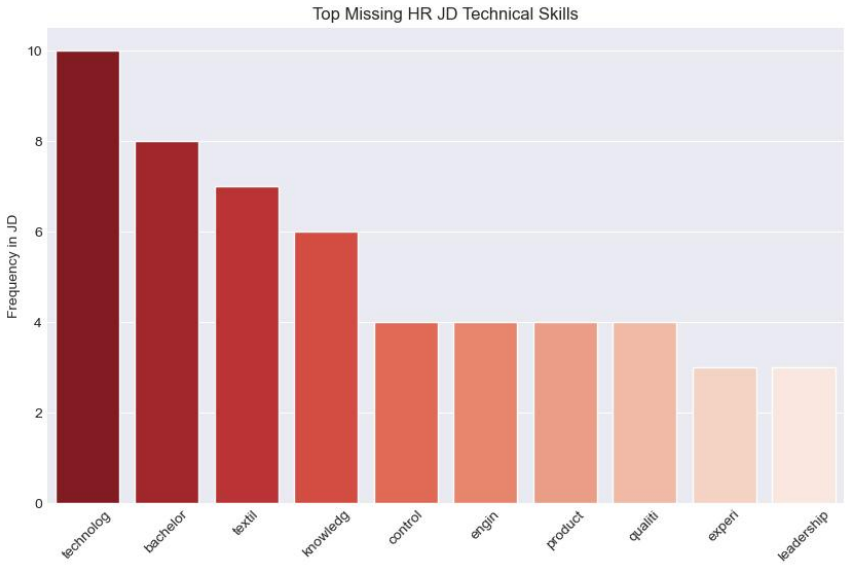


Figure 21: missing HR skills in JD (Gap Analysis)
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

The chart in figure 21 evidently shows the highest HR technical skills that are often required in job descriptions and absent in the student resume, with technology (10 mentions), bachelor (8), and textil (7) at the top.
Other significant gaps are highlighted as knowledge, control and engine, each being mentioned at least 4 times in JDs and there is clear indication of lack of these industry-relevant competencies in students and the need to demonstrate them in order to increase employability.

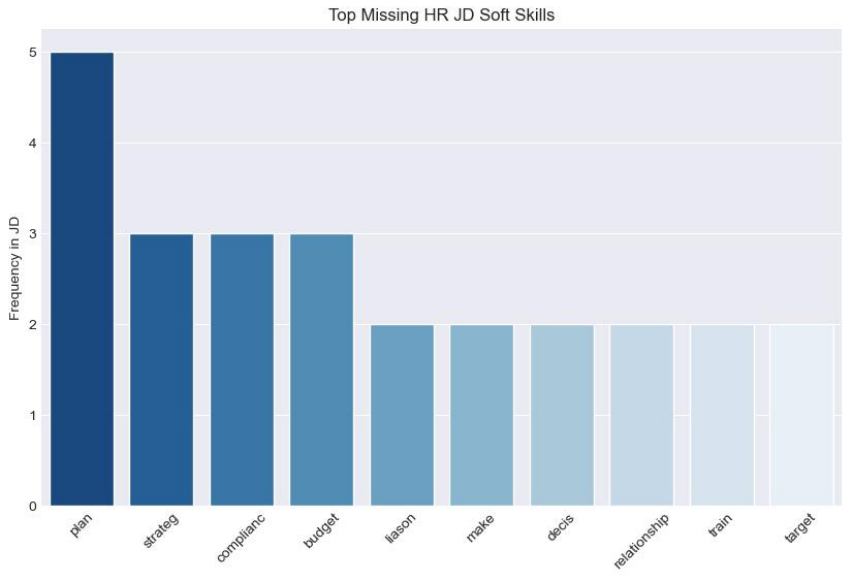


Figure 22: Missing HR soft skills
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

The following chart in the figure 22 lists those soft skills that are often sought after in HR job descriptions, but not well represented in student resumes, where plan (5 mentions), strateg (3), and complianc (3) are the top 3.
It also shows other skill gaps in such areas as "budget," "liaison," relationship, and train, which are mentioned by employers at least twice, which demonstrates that students can do a lot to improve these skills.

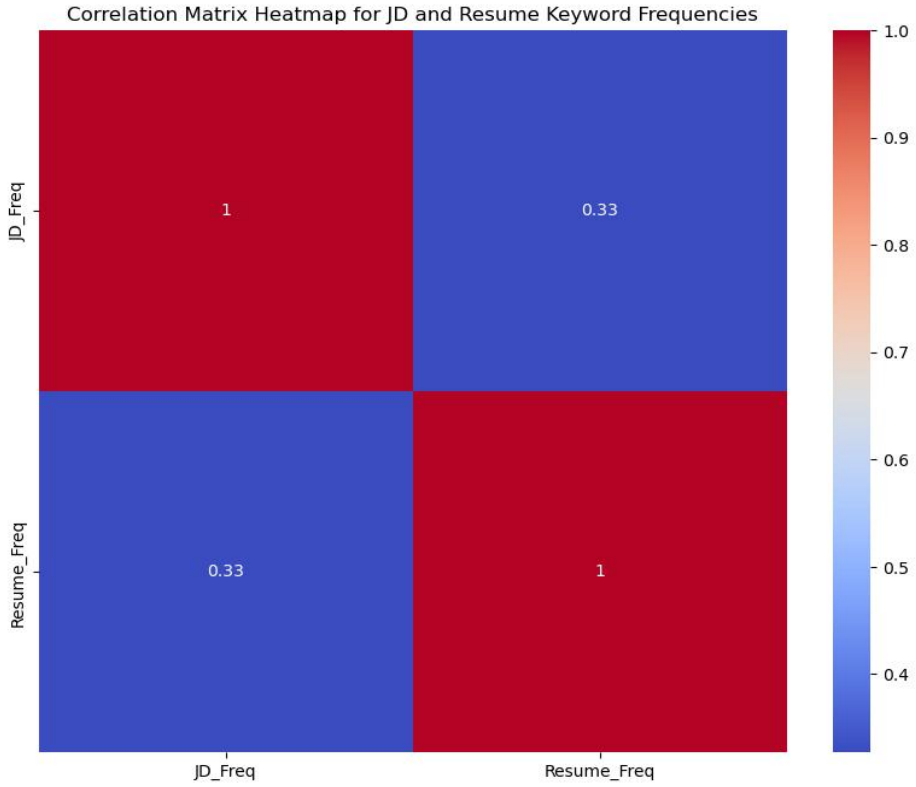


Figure 23: Correlation Matrix Heatmap for JD and Resume Keyword Frequencies
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

The heatmap in figure 23, the correlation matrix of the frequency of keywords used in job descriptions (JD) and resumes indicates that there is a moderate positive relationship of 0.33 between them.
It means that there is the presence of a similarity regarding the efficiency of some of the keywords that the employers are pursuing and the ones that could be found in the candidates but on the other hand there still are the significant differences and, therefore, the optimal skill and resume optimization could be offered by MBA graduates.

Word cloud



Figure 24: Word cloud
Source: Words extracted by authors using python with NumPy, pandas, matplotlib as libraries and created using Wordart

Sentiment analysis

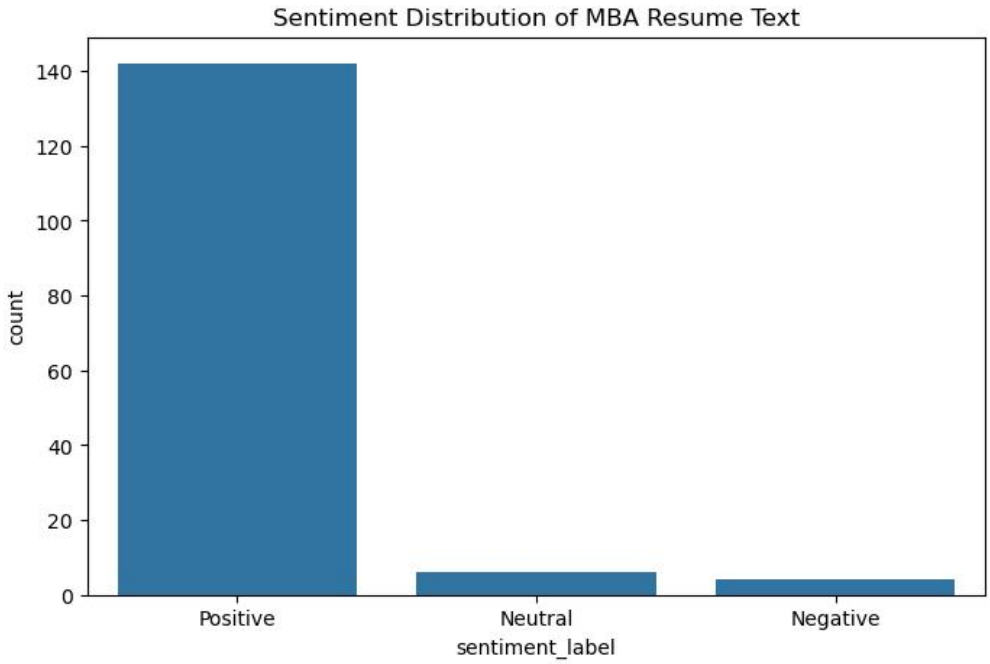


Figure 25: Sentiment analysis of MBA Resume Text
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

The chart in figure 25 indicates that most MBA resume texts are positive with very few belonging to the neutral and negative categories.
This implies that learners are highly inclined to use positive and affirmative words when listing their expertise and experience in resumes.

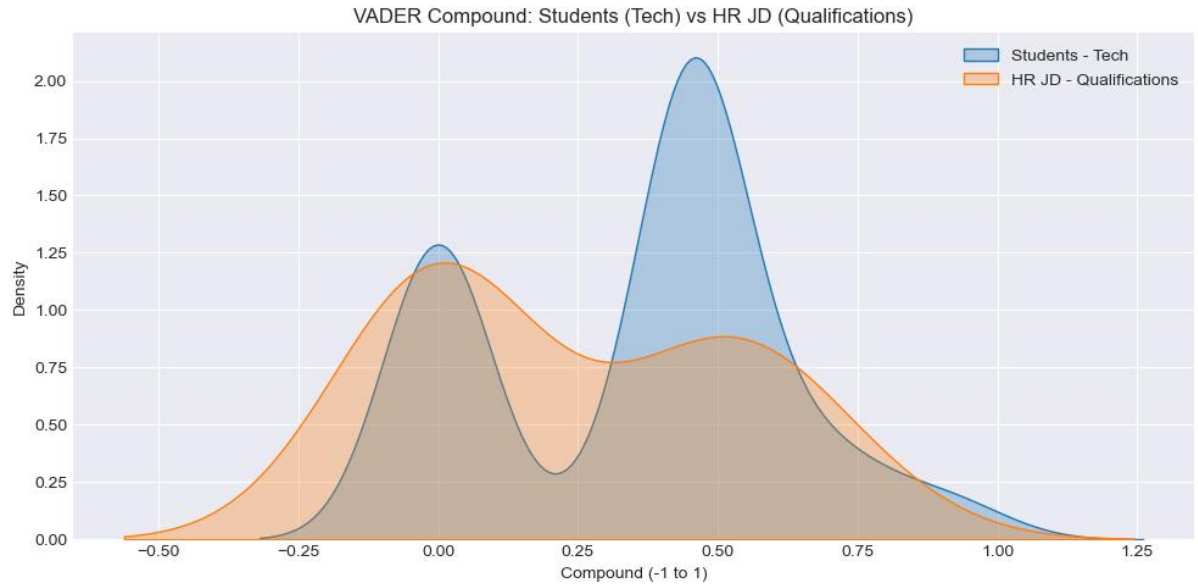


Figure 26: VADER Compound: Students (Tech) vs HR JD (Qualification)
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

In the figure 26 the tone analysis performed by Vader compound scores demonstrates the observable difference in the tone between student resume description and HR job description (JD) qualifications. In particular, the technical skill statements revealed by the students show a reasonably good positive attitude, with the mean compound score standing at around +0.5. This implies that the students are more likely to be aggressive, achievement oriented, and full of confidence when describing their technical competencies in words. Conversely, the sentiment distribution in the HR job descriptions seems more balanced and far-spread with a range of about -0.5 to +0.5, hence with neutral, cautionary, and sometimes restrictive language usage.

This disparity in feelings indicates a variance of the communicative aim. The student resume is always a self-promotional document, meant to emphasize the strengths and ability to perform, which in turn leads to a higher percentage of positively framed sentences. On the other hand, the employer job descriptions usually are more formal and requirement-oriented, and focus on the eligibility criteria, mandatory skills, and performance standards. The null or even weakly negative nature of the sentiment in HR requirements can indicate the rigorous qualification standards, the compliance standards, or the performance accountability standards that are reflected in recruitment documentation. In terms of employability, such a difference in the orientation of sentiment could be a sign of overconfidence among the students or optimistic self-presentation compared to the well-organized and even demanding preconditions expressed by employers. Though the confidence aspect could have a positive effect on the perception, excessive positivity with poor correlation to explicit JD specifications could hurt credibility, especially in AI-assisted applicant tracking systems that promote objective matching of keywords rather than the affective expression of language. Thus, sentiment analysis highlights not the tonal variations only, but also more profound differences between the ways in which competencies are expressed and perceived within the recruitment ecosystem.

4.5 Finance Domain Analysis

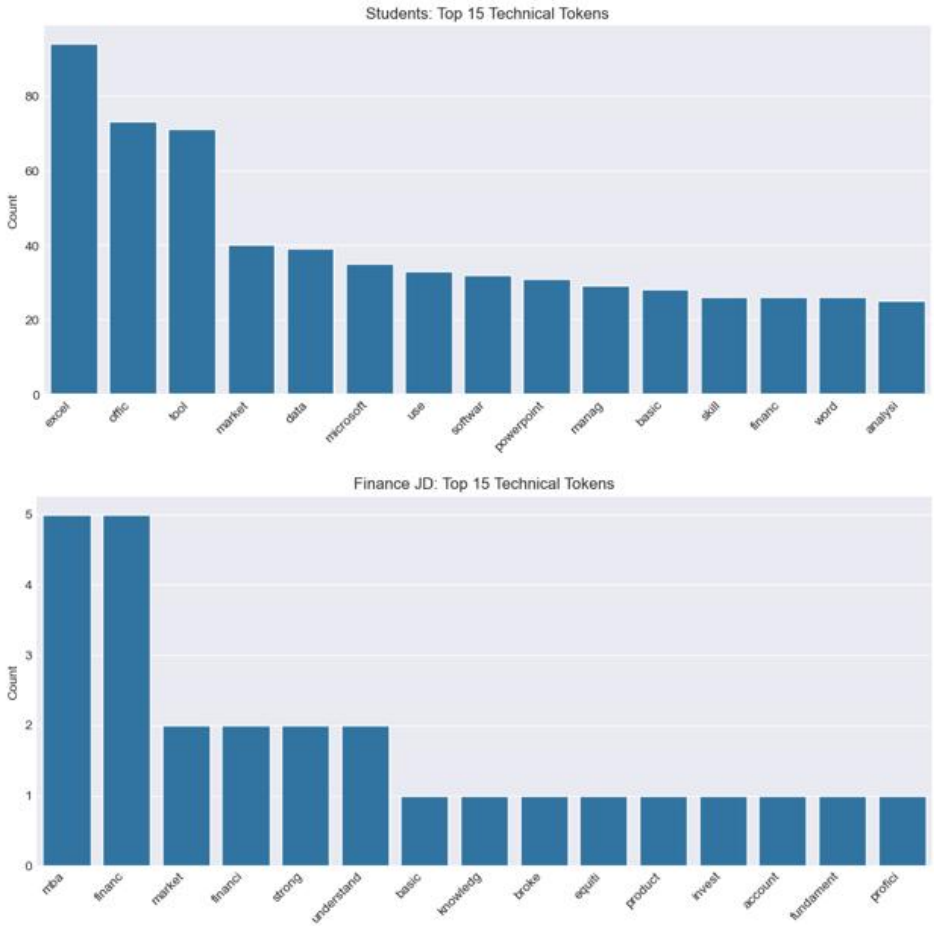
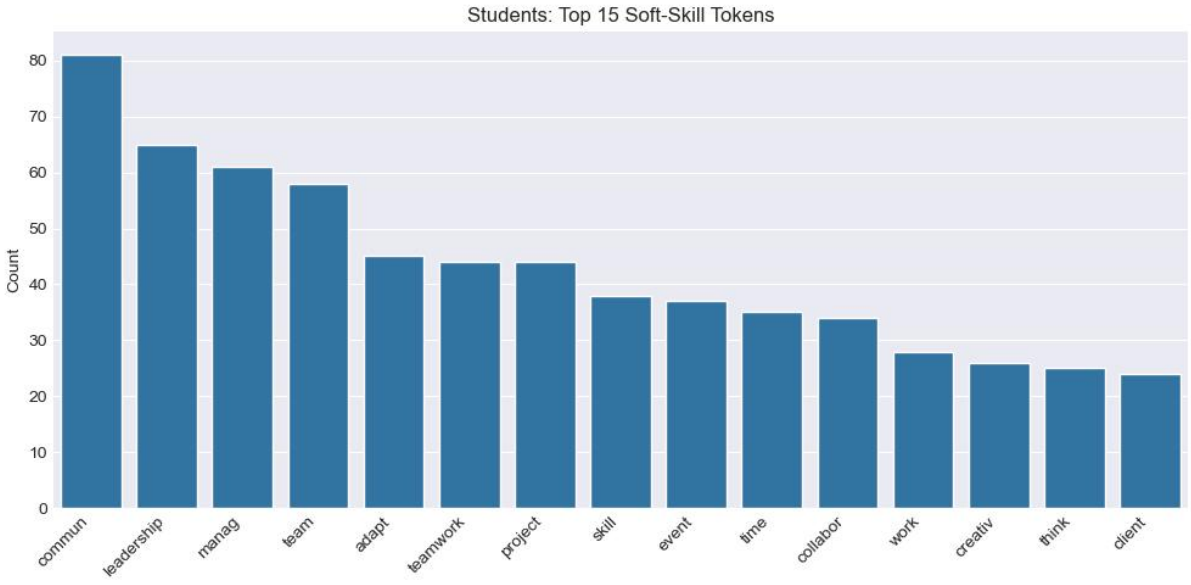


Figure 27: Resume vs. JD (Technical Skills)
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

The chart in figure 27 demonstrates that practical technical skills like "excel," "Office," and "tool" are the most common items MBA students note on their list, i.e., there is an accent on digital and analytic capability in their resumes. The second chart shows that finance job descriptions more emphasize broader technical words such as mba, financ, and market and domain terms such as equity, product, and invest, which reflect industry requirement of both academic and financial experience.



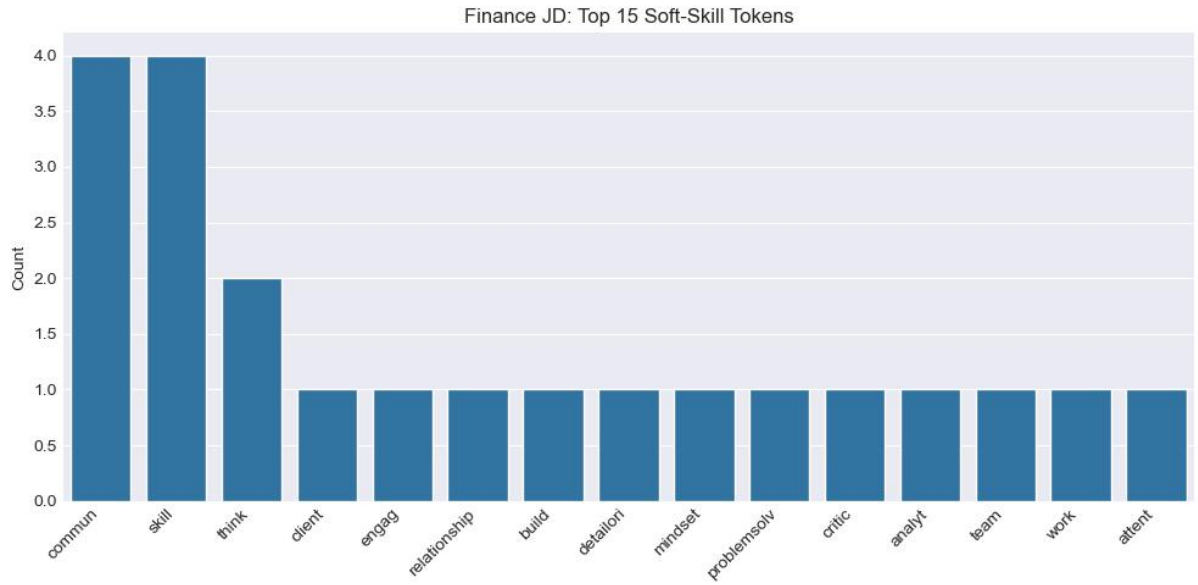


Figure 28: JD vs. Resume (Soft Skills)
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

As indicated in the figure 28, the most common soft skills that MBA students include in their resumes are communication, leadership, management, teamwork, and adaptability. The second chart shows that communication and skills are also important in the job description of finance, but with higher priority (compared to the resumes) is critical thinking, detail-orientation, client relationship and analytical mindset, where the student self-presentation can be more aligned to the employer expectations.

Word Cloud



Figure 29 Word Cloud
Source: Words extracted by authors using python with NumPy, pandas, matplotlib as libraries and word cloud was made using Wordart

Correlation Heatmap

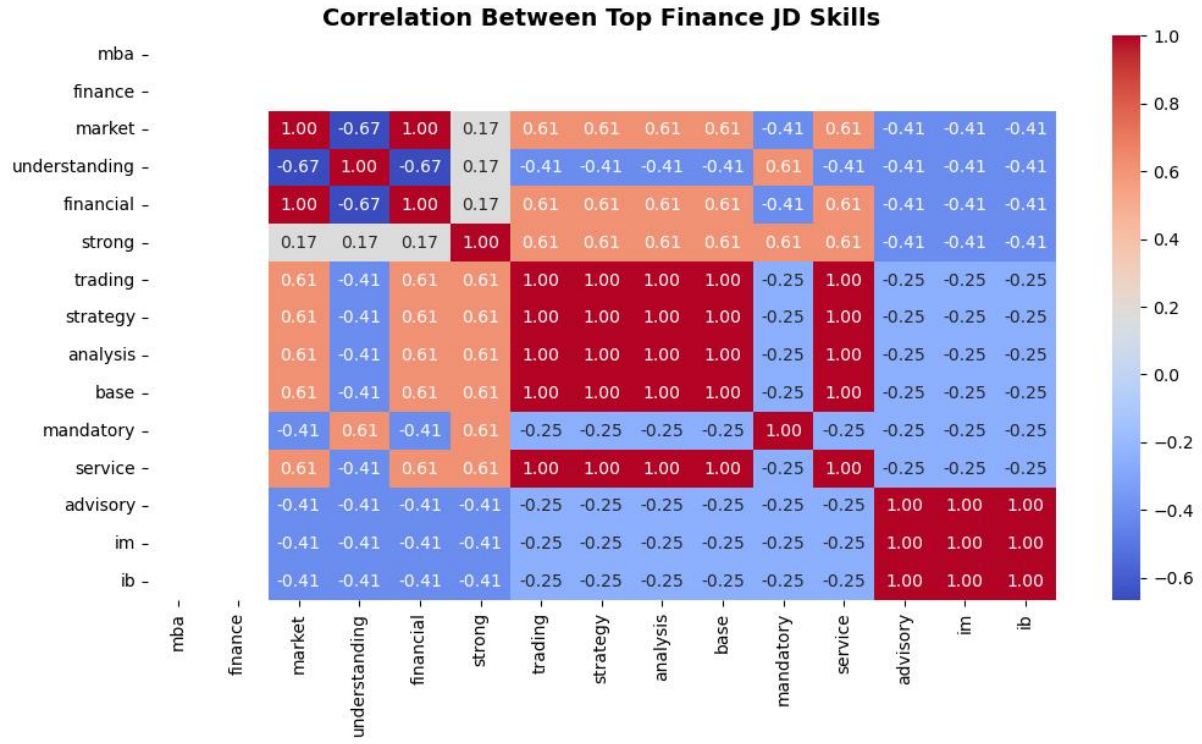


Figure 30: Correlation Heatmap Between Top Finance JD Skills
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

The correlation heatmap in figure 30 shows that there are distinguishing patterns of the job descriptions in finance. There are strong positive relationships, marked by deep red color and approaching +1 value, between core finance competencies of market, strategy, trading and analysis. The existence of these high correlation coefficients indicates that these skills are often co-occurring in the same job descriptions, and they construct a highly connected cluster of technical and strategic finance skills. The regular occurrence of these words together suggests that employers tend to pursue interwoven skills, i.e., a combination of market awareness, strategic thinking, trading skills, and analytical skills, but not separate skills. This cluster indicates the multi-dimensionality of current finance positions, in which it becomes crucial to make decisions based on an analytical model, an interpretation of the market, and a strategic implementation.

Conversely, there are a few individual words that show moderately high negative relations with the above skill group like MBA, Finance, and Understanding (blue shads, values close to -0.67). These negative relationships suggest that these broader or more general terms are less probable to overlap in the case that the highly technical cluster is more pronounced in the job descriptions. This trend indicates that there are certain sub-categories of posting connections in finance jobs. One cluster seems to be special, skill-based, finance jobs with analytical and market-oriented skills, and another cluster can be more generalized and less focused on technical expertise.

The presence of these two differentiated groups suggests division in the demand of finance jobs. Employers can identify it as advanced, data-driven finance jobs like trading analysts or strategy consultants, and more general finance management jobs or entry level jobs where more focus is on academic credentials or conceptual knowledge than on highly technical skills. Regarding an employability perspective, this segmentation indicates the relevance of representing the skills based on the sub-domain in finance. Graduates who focus on generic finance qualifications without matching the highly correlated technical skill group can experience a lower fit with any job role.

Overall, the heatmap offers empirical support to the structured clustering of skills in the job descriptions in the field of finance and indicates that the demand in the finance jobs is not homogeneous but is made of clusters of competencies. Identifying these clusters can help the academic institutions to create curriculum based on specialization and helps students to effectively position their resume information according to the desired category of the job in finance.

Sentiment Analysis

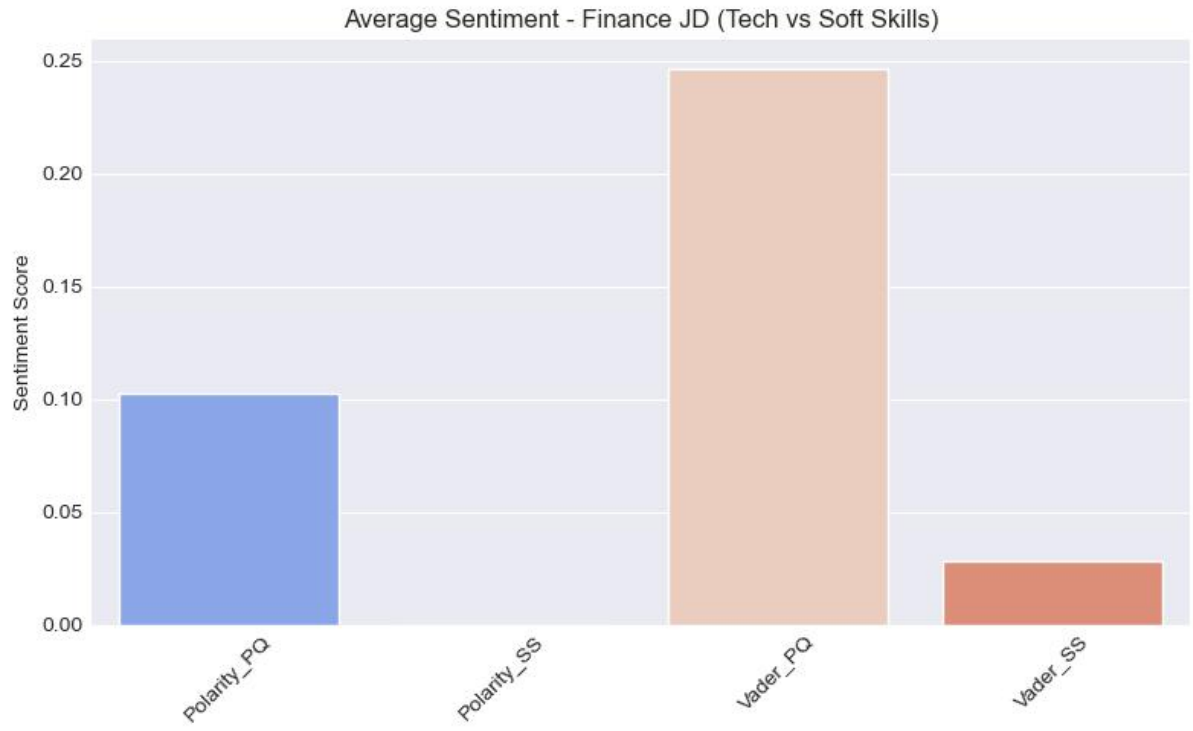


Figure 31: Sentiment Analysis
Source: Created by authors using python with NumPy, pandas, matplotlib, vader as libraries

The present bar chart in figure 31 compares the average sentiment scores of technical (PQ) and soft skills (SS) sections of a finance job description in terms of text polarity and VADER sentiment values.
It shows that sections on technical skills are more likely to be written in a positive key than those on soft skills, in particular when measured by the VADER analyzer, which implies more excitement or assertiveness on the part of the employer in the way they formulate technical specifications.

4.6 Topic Modeling

Student Topics
(0, '0.019*"management" + 0.017*"financial" + 0.017*"communication" + 0.016*"leadership" + 0.015*"excel" + 0.015*"skills" + 0.013*"data" + 0.010*"client"')
(1, '0.015*"data" + 0.013*"skills" + 0.009*"communication" + 0.009*"excel" + 0.009*"projects" + 0.008*"marketing" + 0.007*"like" + 0.007*"business"')
(2, '0.039*"marketing" + 0.020*"skills" + 0.020*"digital" + 0.016*"management" + 0.016*"leadership" + 0.015*"communication" + 0.013*"research" + 0.012*"analytics"')
(3, '0.012*"management" + 0.011*"event" + 0.008*"time" + 0.008*"skills" + 0.007*"coordination" + 0.007*"office" + 0.006*"business" + 0.006*"excel"')

Marketing JD Topics
(0, '0.056*"marketing" + 0.026*"training" + 0.021*"level" + 0.021*"mba" + 0.021*"entry" + 0.021*"development" + 0.021*"yrs" + 0.021*"manager"')
(1, '0.041*"marketing" + 0.041*"management" + 0.035*"sales" + 0.028*"yrs" + 0.028*"training" + 0.028*"analytics" + 0.028*"digital" + 0.021*"mba"')
(2, '0.047*"sales" + 0.030*"management" + 0.026*"marketing" + 0.026*"yrs" + 0.021*"training" + 0.021*"mba" + 0.021*"manager" + 0.021*"level"')

Finance JD Topics
(0, '0.051*"finance" + 0.051*"equity" + 0.029*"financial" + 0.029*"mba" + 0.029*"entry" + 0.029*"level" + 0.029*"years" + 0.029*"securities"')
(1, '0.071*"finance" + 0.037*"years" + 0.037*"mba" + 0.037*"level" + 0.037*"entry" + 0.037*"skills" + 0.037*"communication" + 0.026*"accounting"')
(2, '0.051*"finance" + 0.029*"level" + 0.029*"entry" + 0.029*"mba" + 0.029*"years" + 0.029*"communication" + 0.029*"skills" + 0.029*"analyst"')
HR JD Topics

(0, '0.045*"technology" + 0.037*"manufacturing" + 0.032*"planning" + 0.032*"welspun" + 0.032*"bachelor" + 0.032*"senior" + 0.032*"head" + 0.032*"yrs"')
(1, '0.034*"management" + 0.033*"data" + 0.033*"’" + 0.033*"s" + 0.019*"knowledge" + 0.019*"yrs" + 0.019*"level" + 0.019*"bachelor"')
(2, '0.037*"communication" + 0.037*"leadership" + 0.037*"skills" + 0.037*"sales" + 0.021*"level" + 0.021*"yrs" + 0.021*"training" + 0.021*"strong"')

4.7 Cluster analysis
Students (EDA Responses)

Cluster 0 → 46 documents
Cluster 1 → 42 documents
Cluster 2 → 44 documents
Cluster 3 → 20 documents
Cluster 0 keywords: ['communication', 'analysis', 'data', 'analytics', 'sales', 'market', 'digital marketing', 'digital', 'research', 'marketing']
Cluster 1 keywords: ['management', 'leadership', 'power', 'analytical', 'client', 'audit', 'excel', 'communication', 'finance', 'financial']
Cluster 2 keywords: ['digital', 'adaptability', 'design', 'skills', 'team', 'communication', 'management', 'marketing', 'leadership', 'event']
Cluster 3 keywords: ['internship', 'excel', 'finance', 'problem', 'problem solving', 'solving', 'analytics', 'like', 'skills', 'data']
Silhouette Score (quality): 0.010

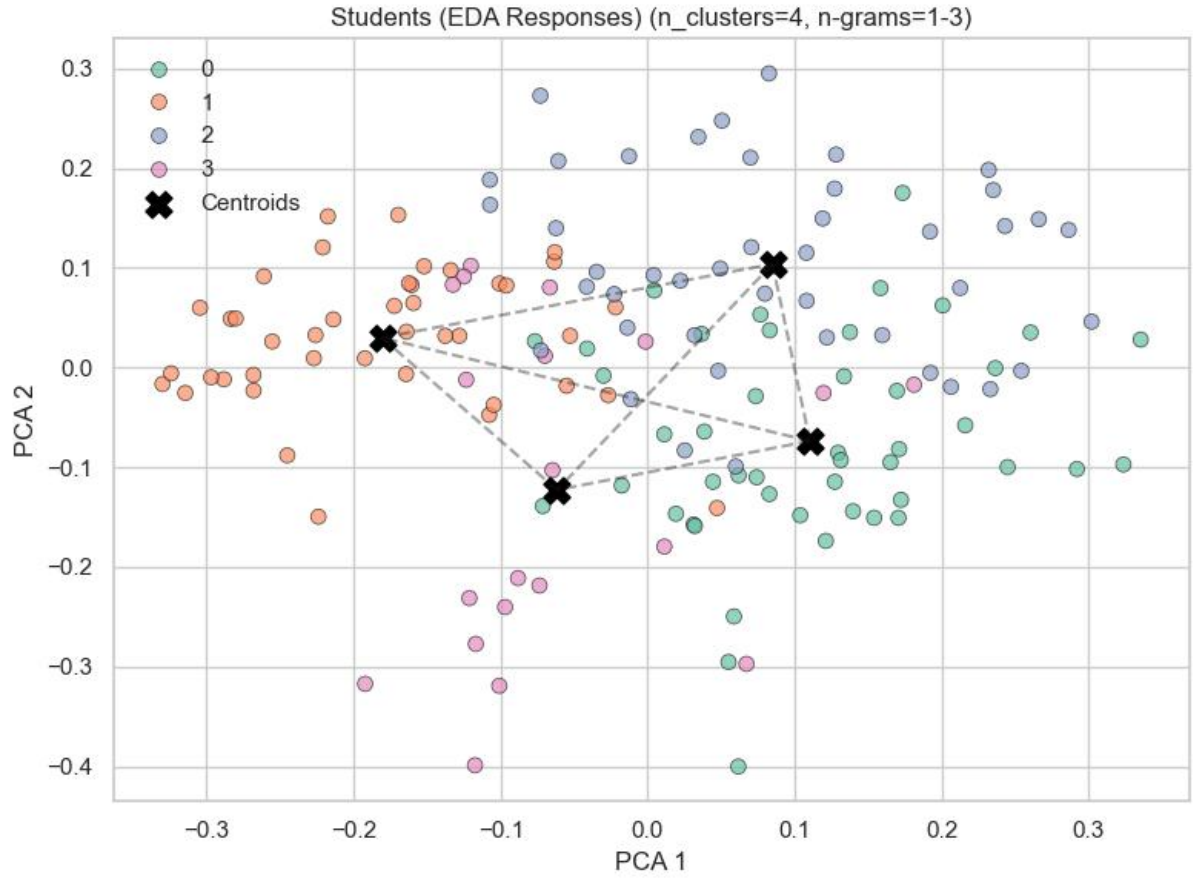


Figure 32 Students (EDA Responses)
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

In this PCA scatter plot in figure 32 shows that students survey responses are visualized in four different clusters, each cluster is denoted by a different colour.
The spatial division and centroid positions (black X marks) show distinct clusters of student attitudes or abilities and may imply that there exist patterns of articulation of student experiences or abilities.

Marketing JD

Cluster 0 → 4 documents
Cluster 1 → 5 documents
Cluster 2 → 3 documents
Cluster 0 keywords: ['manager marketing', 'manager marketing entry', 'mba marketing', 'marketing manager', 'marketing manager marketing', 'yrs mba marketing', 'google', 'digital marketing', 'analytics', 'marketing']
Cluster 1 keywords: ['certification', 'manager sales entry', 'sales entry', 'sales entry level', 'customer', 'management', 'manager sales', 'territory', 'selling', 'sales']
Cluster 2 keywords: ['data', 'innovation', 'functional', 'project', 'management', 'marketing', 'services', 'coursework', 'brand', 'development']
Silhouette Score (quality): 0.151

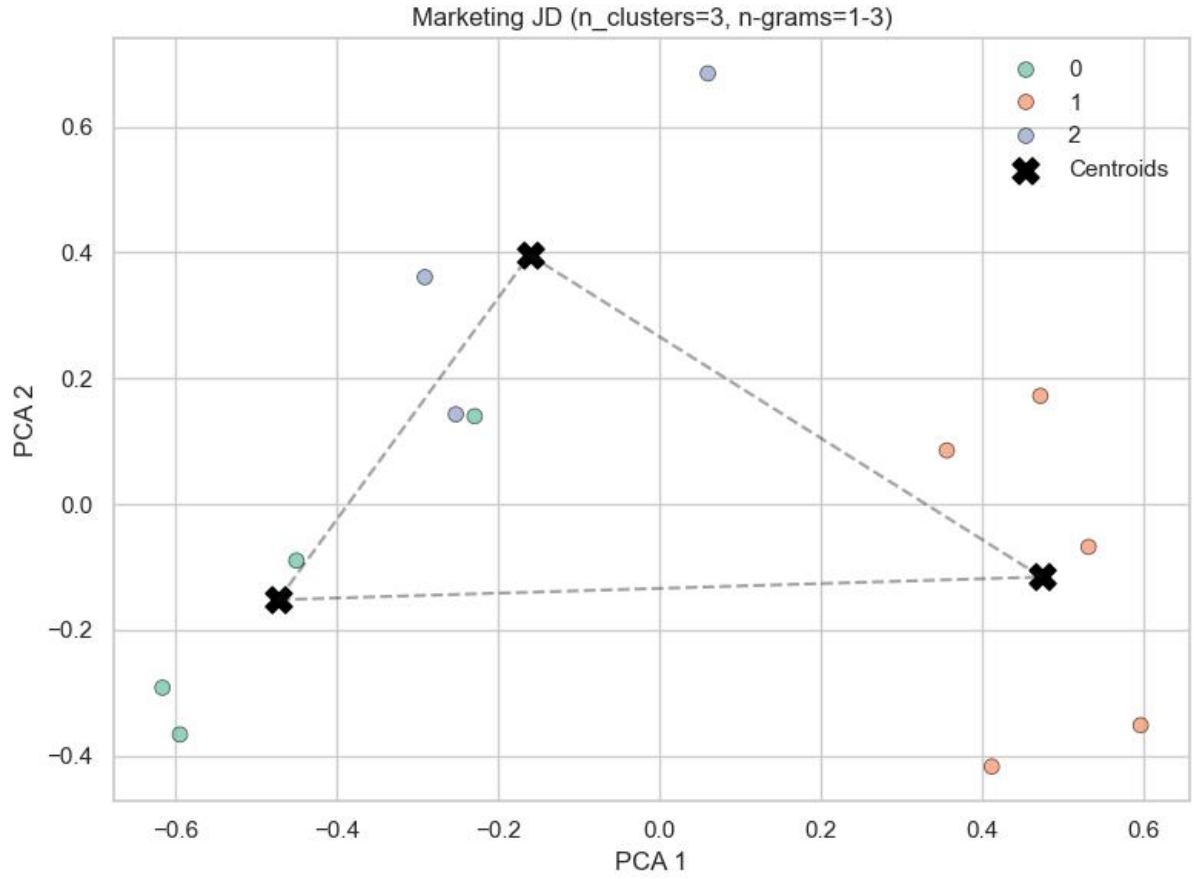


Figure 33 Marketing JD
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

This PCA scatter plot in figure 33 shows that marketing job descriptions have three separate clusters, each color is a different cluster, and X marks in black are centroid.
The extensive distribution and dispersion of clusters imply substantial heterogeneity in the requirements and role profiles described by employers, covering multiple skill sets or priorities in the marketing job market.This chart shows three evident clusters (represented by various colors) in the marketing job description data with the cluster centres identified by black Xs.
The significant division between clusters along the PCA axes indicate that marketing jobs have different sets of necessary skills or qualifications, which point to diverse expectations of employees by their employers.

Finance JD
Cluster 0 → 2 documents
Cluster 1 → 2 documents
Cluster 2 → 1 documents
Cluster 0 keywords: ['communication', 'communication skills', 'finance entry', 'finance entry level', 'mba finance', 'skills', 'years mba finance', 'finance strong', 'mba finance strong', 'strong']
Cluster 1 keywords: ['finance entry', 'finance entry level', 'analyst finance', 'understanding', 'thinking', 'communication', 'communication skills', 'skills', 'analyst', 'management']
Cluster 2 keywords: ['mba finance strong', 'skills', 'strong', 'thinking', 'understanding', 'finance entry', 'finance entry

level', 'mba finance', 'years mba finance', 'financial']
Silhouette Score (quality): 0.135

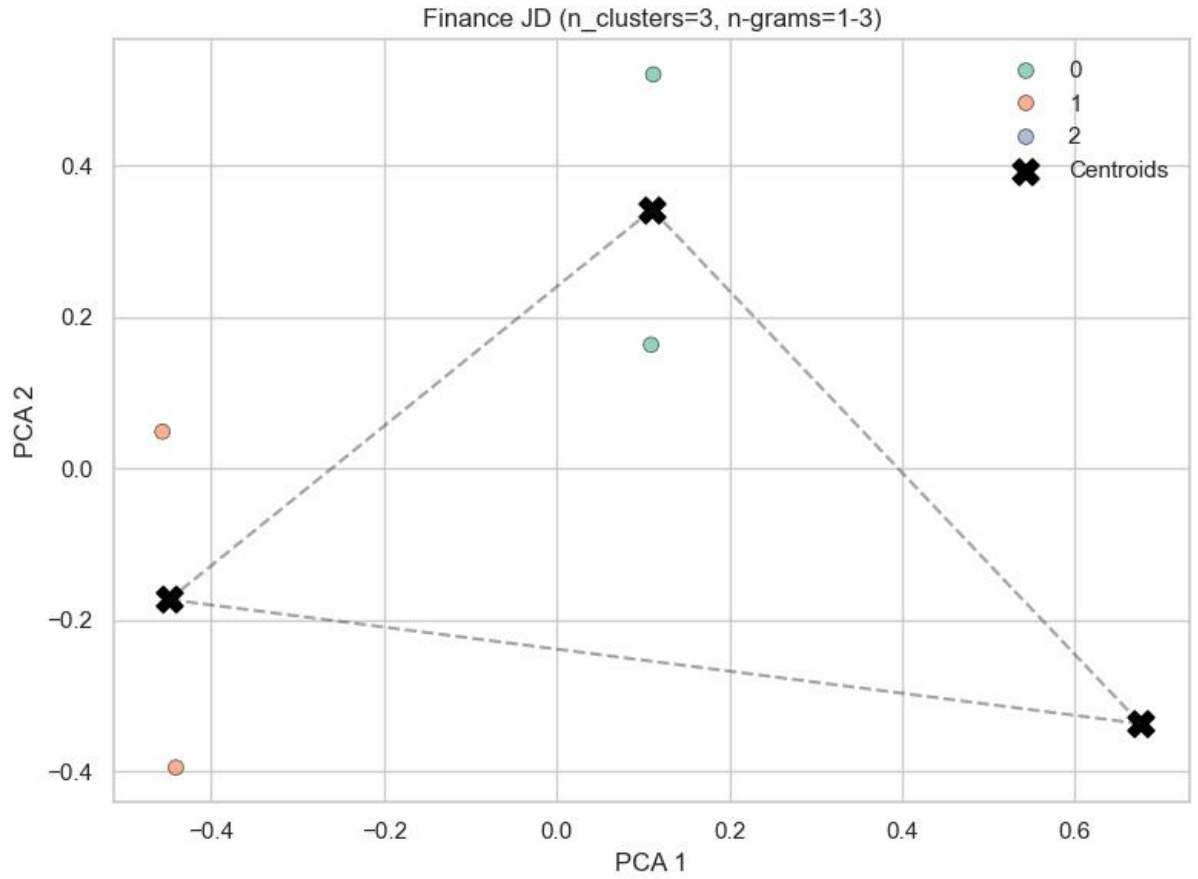


Figure 34 Finance JD
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

In this PCA scatter plot in figure 34 of job descriptions in finance, there are three clusters with clear centres (black Xs).
The layout implies that finance JDs may be assigned to three broad categories and that there are definite disparities in the required skills or job descriptions in the finance industry.

HR JD
Cluster 0 → 5 documents
Cluster 1 → 2 documents
Cluster 2 → 2 documents
Cluster 0 keywords: ['department', 'group head', 'group head department', 'head department', 'welspun group head', 'group', 'technology', 'manufacturing', 'budgeting', 'planning']
Cluster 1 keywords: ['leadership interpersonal', 'quality standards interpersonal', 'knowledge production quality', 'production quality standards', 'quality standards', 'interpersonal skills knowledge', 'relationship conflict management', 'knowledge production', 'technology', 'interpersonal']
Cluster 2 keywords: ['management communication', 'thinking', 'leadership', 'skills', 'proficiency', 'entry', 'entry level yrs', 'entry level', 'communication', 'data']
Silhouette Score (quality): 0.448

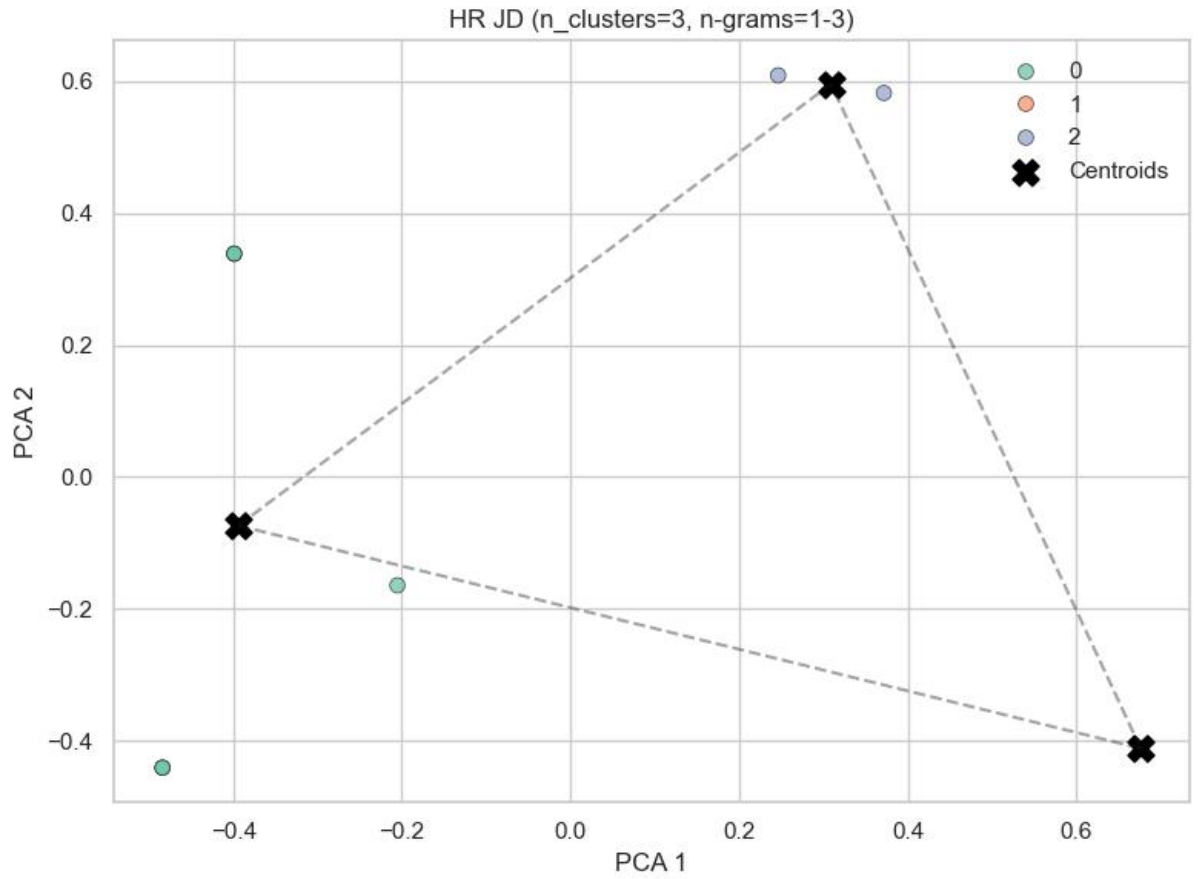


Figure 35 HR JD
Source: Created by authors using python with NumPy, pandas, matplotlib as libraries

Figure 35 shows the HR job description scatter plot on PCA indicates that there are three distinct clusters with a black centroid each. This allocation implies that there are three clearly differentiated HR functions that can be identified (through skill or requirement pattern) and this pattern of diversity indicates the different ways employers expect their HR functions to perform.

5. Conclusion

Does an MBA degree guarantee employability, or does it merely establish academic eligibility? The findings of this study raise a critical question about the preparedness of Indian MBA graduates for an increasingly AI-driven and technology-intensive business environment. The AI-enabled Exploratory Data Analysis (EDA) reveals a notable disconnect between the competencies highlighted by MBA graduates and the skills demanded by contemporary employers. While students frequently emphasise conventional managerial attributes such as leadership, communication, teamwork, and problem-solving, employers increasingly seek advanced analytical capabilities, technical certifications, domain-specific expertise, and demonstrable industry experience. This disparity highlights an emerging paradox in Indian management education: graduates may be academically qualified yet insufficiently equipped to meet the practical expectations of the labour market.

The findings suggest that the employability challenge is not simply a question of whether MBA graduates possess skills, but whether those skills are relevant, demonstrable, and aligned with evolving industry requirements. AI-driven skill mapping further reveals that the nature of this mismatch varies across management disciplines, particularly Marketing, Human Resources, and Finance. Consequently, addressing employability requires more than conventional placement preparation; it demands a systematic transformation of how management institutions develop, assess, and communicate graduate competencies.

First, management education must transition from qualification-oriented learning to competency-driven curriculum development. Universities should periodically evaluate their curricula against emerging industry requirements using AI-enabled labour-market intelligence and skill-gap analytics. Integrating business analytics, AI applications, digital marketing, financial modelling, HR analytics, and business intelligence with industry-recognised certifications can strengthen students' technical capabilities. Experiential learning through internships, live consulting projects, industry case studies, and simulation-based assessments can further bridge the divide between theoretical understanding and practical application. Rather than

treating technological competencies as optional specialisations, business schools should increasingly recognise them as essential components of contemporary managerial education.

Second, institutions must reconsider how MBA graduates communicate their professional value to employers. The comparative analysis of résumés and job descriptions indicates that students often rely on generic descriptions of interpersonal skills without adequately demonstrating measurable achievements, technical proficiency, or practical contributions. AI-powered résumé analysis, automated skill-matching systems, personalised career analytics, and targeted professional development programmes could help students identify missing competencies and present their capabilities more effectively. Universities should complement these technologies with structured career counselling, résumé optimisation workshops, mock interviews, and role-specific employability assessments. Importantly, improving résumé presentation must accompany genuine skill development rather than merely improving the appearance of employability.

Third, stronger industry–academia collaboration is essential to ensure that MBA education remains responsive to changing business realities. Employers should participate actively in curriculum reviews, competency assessments, mentorship programmes, industry-led workshops, and experiential learning initiatives. AI-enabled analysis of recruitment trends and job advertisements can provide institutions with continuous feedback on emerging skill requirements, allowing curricula and training interventions to evolve alongside industry expectations. Such collaboration can also encourage a shift from placement-driven institutional performance indicators towards more meaningful measures of graduate readiness and long-term career progression.

Finally, AI should be viewed not merely as a technological disruption influencing employability, but as a strategic instrument for addressing the employability gap itself. Through NLP, topic modelling, clustering, sentiment analysis, and comparative skill mapping, institutions can systematically identify competency mismatches and develop evidence-based interventions. However, the effectiveness of these approaches depends on the quality and representativeness of the data used. Résumés primarily reflect self-reported and documented competencies, while job descriptions represent stated employer expectations; therefore, the identified gaps should not automatically be interpreted as direct evidence of graduates' actual abilities or job performance.

In conclusion, the central challenge confronting Indian MBA education is no longer simply producing more management graduates, but ensuring that graduates possess the competencies required to succeed in a rapidly transforming professional environment. An MBA qualification may open the door to employment, but industry-relevant skills, practical experience, and technological adaptability increasingly determine whether graduates can walk through it. Bridging this gap requires a coordinated effort among educational institutions, students, employers, and policymakers to build a more responsive, competency-oriented, and AI-enabled management education ecosystem. Ultimately, the future value of an MBA degree will depend not merely on the qualification it represents, but on the professional capabilities it enables graduates to demonstrate.

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