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Exploring Big Data and Blockchain Technology for the Assessment of the Impact of Curriculum Deficiency on Labour Market Deliverables

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ABSTRACT

The changing nature of jobs in the workforce necessitates a match between academic programs and the demands of industries. As a result, the paper used a labor market intelligence approach to evaluate how curriculum deficiencies affect labor market outcomes, specifically for HND computer science programs. The study summed up job advertisements derived from a large data set found on Kaggle comprising over 100,000 records that had been analyzed and matched them with employers' required competencies. It used advanced techniques such as TF-IDF vectorization and cosine similarity to establish how much the content of a curriculum aligns with employment requirements. Big Data analytics is a process by which immense amounts of information are processed to identify gaps and trends. While, Blockchain technology ensures that data cannot be altered, thus ensuring trust within evaluation processes. The survey results indicate that there exists major voids in today's curricula, which might hinder graduates from meeting the expectations and demands of companies. This work provides suggestions on how institutions of higher learning can change their teaching approaches besides improving their curriculums where necessary so as to make them more relevant in meeting the the labour market demands. Accordingly, this research adds knowledge into ongoing debates on course design and provides innovative thinking surrounding the impact of emerging technologies.

Keywords: Big Data, Blockchain, curriculum, curriculum-deficiencies labor-market, skill-gap.

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INTRODUCTION

The alignment of educational curricula in Nigeria with labor market demands has become highly significant in the contemporary era, marked by rapid technological advancement and an ever-evolving global economy. The disconnection between the skills imparted through educational systems and those required by employers is a formidable challenge that leads to gaps hindering economic progress and individual career development (Schwab, 2016). The emergence of 'Big Data' and Blockchain technology provides new ways of resolving these challenges, with strong tools for analyzing and mitigating curriculum deficiencies that affect labor market outcomes (Farrugia, 2018).

In the current age, where there are rapid changes in technology alongside a fast-paced global economy, it is important for Nigerian schools to adjust their educational programs to match the demands imposed by the job market (World Bank, 2020). A significant problem arises when graduates possess qualifications that do not meet employers' demands, creating wide gaps between what they know and what they are expected to display in the workplace. Big data and blockchain innovations have opened up fresh paths to address such issues, offering better techniques to determine or mitigate the impacts of curriculum deficiencies on labor markets (Marr, 2019).

The skills institutions of learning provide and the competencies that employers need, as described by Organisation for Economic Co-operation and Development (OECD), lag behind because technology is advancing so quickly and economies are changing (OECD, 2017). This curriculum gap, as described by International Labour Organization (ILO), results in an underemployment condition, where graduates are often not prepared for the needs of modern businesses,

leading to unemployment (ILO, 2021). While advanced technological tools and huge volumes of data are already available, there is no structured means of identifying or filling these gaps (McKinsey and Company, 2021).
The problem lies in the inability to use blockchain technology and big data effectively for assessing, predicting, and validating educational achievements against labor market requirements (Tapscott and Tapscott, 2016). Therefore, a cohesive system that guarantees data integrity while providing actionable intelligence is urgently required to enhance curriculum development and ultimately improve labor market deliverables.
The rise of Big Data, distinguished by its three 'V's – volume, velocity, and variety – has opened up unprecedented possibilities for understanding labor market dynamics and educational outcomes (Gandomi and Haider, 2015). Researchers and policy makers can now use Big Data analytics to draw inferences from a wide range of datasets that were previously inaccessible. For example, data from job postings, employee profiles, industry reports, and academic records can be analyzed to identify emerging skill requirements, assess the effectiveness of current educational programs, and highlight gaps within curricula (OECD, 2021).
Machine learning algorithms, combined with data-mining tools, further enhance these analyses by predicting future skill demands (Sarker, 2021). This is crucial because educational institutions must proactively adjust their curricula, so that graduates can acquire the skills required by the evolving job market. Moreover, Big Data can help to ascertain how changes in curricula impact labor market deliverables, providing empirical support for policy decisions and curriculum design (Li et al., 2020).
The exploration of Big Data in assessing the impact of curriculum deficiencies on labor market outcomes represents a cutting-edge frontier in educational and economic research. By leveraging these technologies, it becomes possible to develop more adaptive and responsive educational systems that are better aligned with the dynamic needs of the labor market (Bhardwaj et al., 2022). This alignment is essential for fostering economic growth, reducing unemployment, and ensuring individuals have the skills necessary to succeed in the modern workforce (WEF, 2023).
The contemporary labor market is characterized by rapid technological advancements and shifting economic paradigms, necessitating a dynamic alignment between educational curricula and industry requirements. The following objectives outline a comprehensive approach to addressing this issue, aiming to create a responsive and adaptive educational system that better prepares individuals for the demands of the modern workforce.
i. Identify curriculum deficiencies in computer science to pinpoint gaps and deficiencies in relation to current and emerging labor market needs.
ii. Assess impact on labor market deliverables by evaluating how curriculum deficiencies influence employment rates, job performance, and career progression of graduates in various industries.
iii. Leverage big data for predictive analysis by utilizing big data analytics to predict future labor market trends and skill requirements, enabling proactive curriculum adjustments to meet these needs.
iv. Develop an integrated framework by creating a comprehensive framework that uses big data to evaluate and enhance educational curricula in alignment with labor market demands.

MATERIALS AND METHOD

Materials

Labor market intelligence refers to the collection, analysis, and dissemination of data and insights regarding the supply and demand for labor. It involves understanding various aspects of the labor market, such as employment trends, wage levels, skill requirements, and demographic shifts.
The study of labor market intelligence (LMI) is a developing multidisciplinary field that is becoming more and more popular in both academia and businesses. LMI is the term that refers to the application and development of Artificial Intelligence (AI) frameworks and algorithms in the analysis of labor market data to facilitate decision-making. The first is the pretense of gleaning information from unstructured materials, such as job openings, curriculum, etc.. This only concentrates on the electronic hiring process by automating the handling of resumes through the matching of candidate profiles with job descriptions. The second is the pressing need to automate tasks in the human resources department.
A comprehensive, transparent, and secure method of comprehending and resolving gaps in education and employment alignment can be achieved through the use of Big Data and Blockchain Technology, which offer transformative potentials in evaluating the effects of curriculum deficiencies on labor market outcomes.
The use of big data analytics has significantly improved curriculum creation and evaluation. Organizations can analyze extensive records of students' achievement to identify specific areas where curricula may be lacking. This data-driven approach ensures that educational materials stay current with shifting market demands and allows for continuous improvement (Daniel, 2017). Additionally, big data-driven personalized learning adapts learning experiences to each student's particular needs and learning preferences, effectively addressing deficiencies (Ifenthaler, 2021). Predictive analytics further enhances this by enabling early detection of students who are at risk, allowing for timely interventions To support their academic success (Panigrahi and

Srivastava, 2020).

Big Data makes skills gap analysis easier in the labor market by helping to uncover the competencies that employers seek and comparing those abilities with what job seekers possess. By aligning curricular modifications with market demands, it becomes possible to close the achievement gap between education and work (Bughin et al., 2018). Monitoring graduates' employment outcomes provides valuable insight into how well educational initiatives are working. Big data-based longitudinal research establishes a connection between professional performance and educational experiences, offering essential insights into how well educational institutions prepare their students for the workforce (OECD, 2021).

Big Data is further enhanced with blockchain technology, which offers an unchangeable, transparent, and secure framework for data administration. Blockchain can be utilized in education to verify credentials, ensuring the authenticity and immutability of academic qualifications (Kouhizadeh et al., 2021). This reduces the risk of fraudulent claims, allowing employers to trust the credentials job seekers present. Additionally, blockchain technology enables the efficient management of student data, providing a secure and comprehensive means of storing and retrieving academic results that can help to identify the strengths and weaknesses of a curriculum (Zhao et al., 2021).

Blockchain-based decentralized learning systems provide an open and responsible way to distribute educational materials. These platforms guarantee that every educational transaction is documented on a blockchain, offering an irreversible record of academic accomplishments and exchanges. In order to preserve responsibility and trust in the delivery of education, this transparency is essential (Chen et al., 2018).

Blockchain technology can be used in the labor market to verify skills and create a trustworthy record of a person's work history and competencies. Based on precise data, this verified record helps companies make well-informed employment decisions (Nofer et al., 2017). Additionally, smart contracts for employment can be implemented using blockchain technology, automating a number of employment agreement components like payment terms and performance reviews. According to Catalini and Gans (2016), automation guarantees that workers receive compensation that appropriately recognizes their abilities and efforts, resulting in a more equitable and productive labor market.

Big Data and Blockchain Technology together provide a potent synergy for evaluating curricular gaps and their effect on deliverables for the labor market. Blockchain protects the security and transparency of this data, while big data analytics provides the means for thorough data collection and analysis. When combined, these technologies offer a strong framework for assessing educational results and matching them to the demands of the labor market.

The first step in this integrated strategy is the collection and analysis of data utilizing Big Data methodologies. Stakeholders in the job market and educational institutions can collect large amounts of data, such as skill evaluations, employment trends, and academic achievement. Chen et al. (2012) concluded that through the analysis of their data, curriculum developers can gain practical insights into the trends, gaps, and connections that exist between educational content and labor market results

Blockchain technology protects data gathered, guaranteeing its accuracy and dependability. Maintaining stakeholders' confidence in the conclusions and suggestions drawn from the data depends on the security of the data which blockchaing technology guarantees (Grech and Camilleri, 2017). Additionally, according to Sharples and Domingue, (2016), blockchain improves accountability and transparency in the assessment process, which facilitates cooperation between educators, employers, and legislators in resolving curricular gaps.

Through the integration of Big Data and Blockchain, academic institutions may guarantee that their curricula are updated often to align with industry requirements. By closing the skills gap, this alignment not only increases the employability of graduates, but also increases the efficiency of the labor market as a whole. To the end, this integrated technology strategy promotes a more responsive and dynamic educational system, better-equipping students to meet the demands of the contemporary labor market.

Method

The study uses a labor market intelligence approach to assess the impact of curriculum deficiency on labor market deliverables. There are three main stages in the research design, which are; data collection and pre-processing of documents, gathering and pre-processing of labor market information and data analysis.

Data collection and pre-processing of documents

Gathering of curriculum materials involves downloading of Higher National Diploma (HND) Computer Science syllabus for course outlines, learning goals, and specific objectives. The curriculum was processed to extract the specific objectives from the syllabus and then make it a double-column table (Table 1) stored in Excel format.

Gathering and pre-processing labor market information

Job advertisements downloaded from Kaggle were analyzed. The job posting downloaded was a very large dataset. It has more than 100,000 rows and 17 columns.

Table 1: Curriculum course and expected skills: showing 12 of 54 rows.

Course	Expected Skills
Introduction to Computers	Basic computer literacy, understanding of computer components, operating systems, and applications
Introduction to Digital Electronics	Knowledge of digital circuits, logic gates, flip-flops, and digital systems design
Introduction to Computer Programming	Fundamental programming concepts, problem-solving, coding, debugging, and algorithm development
Descriptive Statistics	Data collection, analysis, interpretation, and presentation of data using statistical measures
Elementary Probability Theory	Probability concepts, random variables, probability distributions, and statistical inference
Logic and Linear	Logical reasoning, linear equations, matrices, vector spaces, and transformations
Functions and	Understanding mathematical functions, their properties, and applications in computing

The data were filtered to remove any non -computer related skills from the column of the required skills. Table 2 below is a three-column table showing the skills required by the employer from the online job posting downloaded from kaggle .com.

Data analysis

This study employs a multi-faceted approach to data analysis, utilizing feature mapping and Cosine similarity for comparison purposes. The aim is to evaluate the alignment between the Computer science HND curriculum and labor market demands.

Mapping Features

Feature mapping is an essential step in analyzing the alignment between curriculum content and labor market demands in our study. Textual data can be converted into numerical vectors , so that quantitative techniques like Cosine calculations can be used. For this paper, feature mapping process involves two stages: combining text data and TF-IDF vectorization.

Combine Text Data

To analyze the alignment between skills and curriculum content, the text data from both sources was combined. This combined text contained both skill and curriculum data, providing a comprehensive view of the relevant information.

TF-IDF Vectorization

We use the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization technique to transform the textual data into numerical vectors. This method takes into account the frequency of each term in a document and its rarity across all documents.

RESULT AND DISCUSSION

In the methodology section, we detailed the methodology employed to analyze the alignment between the skills taught in the computer science curriculum and the skills required in the labor market.
One of the most common text mapping techniques is term frequency-inverse document frequency (tf-idf), which is a statistical method that measures the importance of a term in a document. The tf-idf score for a term is calculated by multiplying the term frequency (tf) by the inverse document frequency (idf). Term frequency (tf) measures how often a term appears in a document. A higher tf means that the term is more relevant to the document. Inverse document frequency (idf) measures the rarity of a term across all documents. A higher idf means that the term is less common across all documents.
To calculate the tf-idf score, you multiply the term frequency (tf) by the inverse document frequency (idf) using this general formula,

$$\text{tf-idf} = \text{tf} * \log(N/\text{df})$$

Where:

- tf = term frequency: the number of times a term appears in a document
- N = total number of documents in the corpus
- df = document frequency: the number of documents in the corpus containing the term.

The resulting score will be between 0 and 1. A higher score means the term is more important to the document, while a lower score means the term is less important.

Separation of Vectors

After obtaining the TF-IDF matrix, we separated the vectors for skills and specific objectives from the

Table 2: Labor skill: showing 10 of 170 rows.

Job Title	Job Description	Skills
Digital Marketing Specialist	Social Media Managers oversee an organizations social media presence. They create and schedule content, engage with followers, and analyze social media metrics to drive brand awareness and engagement.	Social media platforms (e.g., Facebook, Twitter, Instagram) Content creation and scheduling Social media analytics and insights Community engagement Paid social advertising
Web Developer	Frontend Web Developers design and implement user interfaces for websites, ensuring they are visually appealing and user-friendly. They collaborate with designers and backend developers to create seamless web experiences for users.	HTML, CSS, JavaScript Frontend frameworks (e.g., React, Angular) User experience (UX)
Operations Manager	Quality Control Managers establish and enforce quality standards within an organization. They develop quality control processes, perform inspections, and implement corrective actions to maintain product or service quality.	Quality control processes and methodologies Statistical process control (SPC) Root cause analysis and corrective action Quality management systems (e.g., ISO 9001) Compliance and regulatory knowledge
Network Engineer	Wireless Network Engineers design, implement, and maintain wireless network solutions. They optimize wireless connectivity, troubleshoot issues, and ensure reliable and secure wireless communications.	Wireless network design and architecture Wi-Fi standards and protocols RF (Radio Frequency) planning and optimization Wireless security protocols Troubleshooting wireless network issues
Event Manager	A Conference Manager coordinates and manages conferences, meetings, and events. They plan logistics, handle budgeting, liaise with vendors, and ensure the smooth execution of events, catering to the needs and expectations of attendees.	Event planning Conference logistics Budget management Vendor coordination Marketing and promotion Client relations
Software Tester	A Quality Assurance Analyst tests software and products to ensure they meet quality standards. They identify defects, report issues, and work with development teams to resolve problems.	Quality assurance processes Testing methodologies (e.g., manual, automated) Bug tracking and reporting Test case development Regression testing
Teacher	A Classroom Teacher educates students in a specific subject or grade level. They create lesson plans, deliver instruction, assess student progress, and foster a positive learning environment.	Teaching pedagogy Classroom management Curriculum development Student assessment Differentiated instruction
UX/UI Designer	User Interface Designers focus on the visual and interactive aspects of digital interfaces. They design layouts, buttons, and other elements to ensure a cohesive and visually appealing user interface.	UI design principles and best practices Graphic design tools (e.g., Adobe Photoshop, Illustrator) Typography and color theory Visual design and layout Responsive design
UX/UI Designer	Interaction Designers specialize in designing user interactions within digital interfaces. They create meaningful and engaging user experiences by considering user behaviors and system responses.	Interaction design principles User behavior and psychology Wireframing and prototyping tools Animation and micro-interaction design Collaborative design processes

curriculum content. This enabled us to perform pair wise comparisons between each skill and the curriculum content. Using this python code, the vectors were easily separated.

```
skills_tfidf = tfidf_matrix[:len(skill)]
curriculums_tfidf = tfidf_matrix[len(skill):]
```

By mapping features from the original textual data into numerical vectors, effective analysis of the alignment between the Computer science HND curriculum and the skills from the labor market was done using Cosine Similarity calculations.

Cosine Similarity

A popular metric for comparing two vectors' similarity, cosine similarity, was used to evaluate how well the abilities of the curriculum and the job market data aligned. Each skill receives a similarity score between 0 and 1 based on the algorithm's computation of the cosine of the angle between the two vectors. Lower scores indicate a mismatch or insufficient coverage of a particular ability, whereas scores closer to 1 show a solid alignment between the curriculum content and labor market demands.

By calculating the cosine similarity between these two sets of skills, we identified a number of key areas where the curriculum is currently underperforming in relation to industry needs. Cosine similarity values range from -1 to 1, where 1 indicates perfect similarity, 0 indicates no similarity, and -1 indicates perfect dissimilarity.

Specific Skill Gaps Identified

Our analysis revealed several skills with lower than

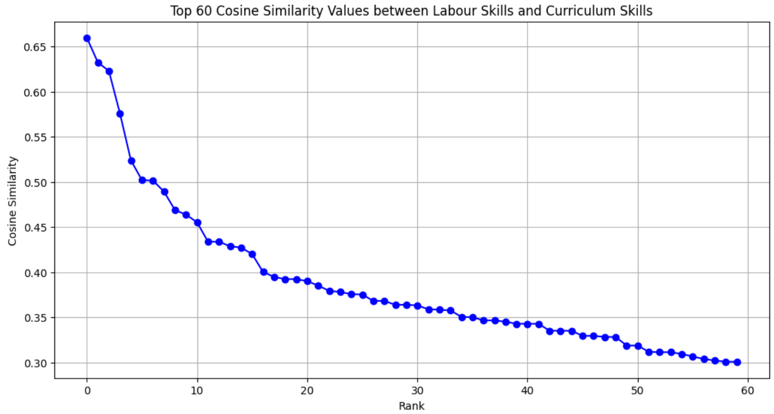

Figure 1: Top 60 cosine similarity values (labor skills vs curriculum skills).

desired cosine similarity values, indicating a misalignment between what is being taught and what is needed in the labor market. These skills include:

- Systems Engineering
- System Architecture
- Integration Testing
- Troubleshooting
- Data Analysis
- Data Analysis Tools (e.g., SQL, Python)
- Data Visualization Tools (e.g., Tableau, Power BI)
- Data Cleansing and Transformation

These skills are crucial for the labor market, particularly in the field of computer science. The lower similarity values suggest that the curriculum currently does not sufficiently address these areas, leading to a gap between educational outcomes and industry expectations.
These under-covered skills are critical for the modern workforce, especially in the field of computer science, and their limited presence in the current curriculum warrants a concern.

Discussion of the Output Graph

The graph presented displays the top 60 cosine similarity values between labor skills and curriculum skills. The x-axis represents the rank (from 1 to 60), while the y-axis represents the cosine similarity values.
The cosine similarity values decrease as the rank increases, starting from around 0.65 at rank 1 and descending to around 0.30 at rank 60. This trend indicates that while some skills taught in the curriculum closely match the requirements of the labor market (as evidenced by higher cosine similarity values), many skills have lower similarity values, highlighting a potential misalignment. The highest similarity values, ranging from 0.65 to approximately 0.50, are concentrated within the top 10 ranks. The top-ranked skills indicate a strong alignment between certain curriculum components and labor market demands. These areas of high similarity represent strengths within the curriculum that effectively prepare students for the labor market.
The graph above (Figure 1) illustrates a clear disparity between certain curriculum skills and labor market demands. By addressing the identified gaps, educational institutions can better prepare their students for successful careers, ensuring that the skills taught are aligned with those required by employers. This alignment will enhance student employability and contribute to a more skilled and adaptable workforce.

Cosine similarity approach performance assessment

Cosine similarity is a powerful and widely-used approach for measuring similarity between vectors, especially in applications involving text and user preferences. Its effectiveness in handling high-dimensional data and its simplicity make it a valuable tool in data analysis and machine learning**.**

Cosine Similarity Distribution Analysis (Mean and Standard Deviation)

To understand the overall similarity distribution between the curriculum and labor skills, there are two performance metrics considered; Mean Cosine Similarity and Standard Deviation.

Mean Cosine Similarity = $\frac{\sum_{i=1}^{n} \text{Cosine Similarity of Skill}}{n}$

Standard Deviation,

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Cosine Similarity of Skilli} - \text{Mean})2}$$

mean_similarity = np.mean (cosine_similarities)

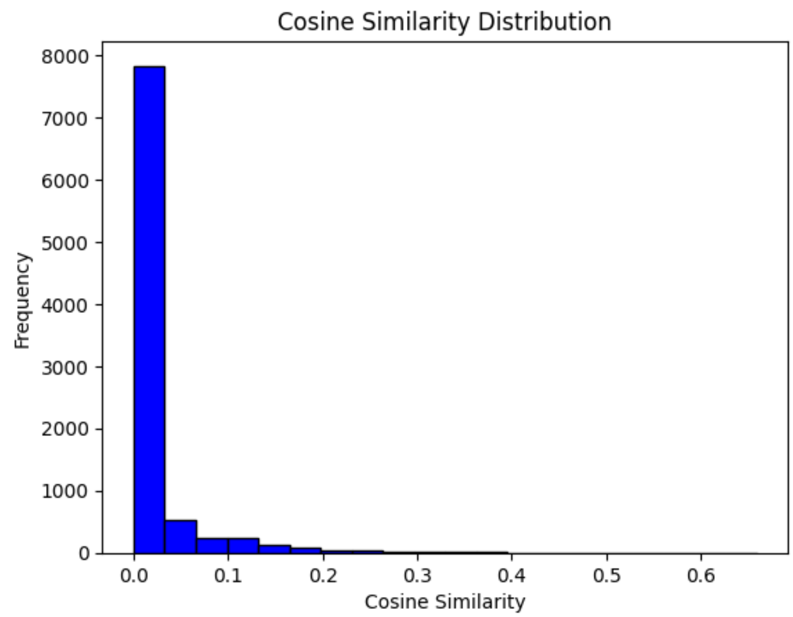

Figure 2: Cosine Similarity Distribution Histogram.

```
std_similarity = np.std(cosine_similarities)
print (f"Mean of Cosine Similarity: {mean_similarity:.4f}")
print (f"Standard Deviation of Cosine Similarity: {std_similarity:.4f}")
```

Using the Python code above, the mean cosine similarity and standard deviation were computed to give,

‘Mean of Cosine Similarity: 0.0180
Standard Deviation of Cosine Similarity: 0.0503’

The significance of the metrics above is that the cosine Similarity Distribution Analysis on the skill-curriculum mapping shows that the mean cosine similarity is 0.0180, and the standard deviation is 0.0503.

Mean Cosine Similarity: 0.0180

The mean cosine similarity of 0.0180 is very low, indicating that, on average, the curriculum skills and the labor market skills have little overlap or alignment. Since cosine similarity values range from -1 (completely dissimilar) to +1 (perfectly similar), a value close to 0 suggests that the skills in the curriculum and the skills required in the labor market are only weakly related.

Standard Deviation of Cosine Similarity: 0.0503

The standard deviation of 0.0503 is relatively small, indicating that the distribution of cosine similarity values does not vary much across different curriculum and labor skills. In other words, the difference between the most and least similar skill pairs is small, and most skill pairings show consistently low levels of similarity (Figure 2).

Mean and standard deviation of cosine can be directly related to the performance metrics of the cosine similarity approach, such as precision, recall, and the F1 score. These metrics provide insight into the quality and accuracy of the mapping between curriculum skills and labor market skills. A low mean cosine similarity score in terms of precision means that the curriculum is identifying only a small number of skills that truly match labor market demands. This suggests that precision in this context would likely be low, as the cosine similarity approach is not finding many highly relevant (i.e., closely matched) pairs of skills.

Recall refers to the proportion of all relevant results that were retrieved by the model. In this case, it would measure how many of the skills that are highly in demand in the labor market are being covered in the curriculum. The low standard deviation suggests that the variation in cosine similarity scores is minimal, meaning that the curriculum is consistently misaligned with labor market skills. A low recall value would imply that the curriculum is failing to cover many of the critical skills required in the job market.

The F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics. It gives a single measure of overall performance for the cosine similarity approach. Since both precision and recall are likely low due to the poor alignment between the curriculum and labor market skills, the F1 score will also be low.

A low F1 score indicates that the curriculum does not provide a sufficient balance between relevant skills being taught (precision) and important labor market skills being covered (recall).

Conclusion

The analysis in the methodology revealed significant gaps between the current curriculum and labor market demands. Addressing these under covered skills through targeted curriculum enhancements will better prepare students for the workforce. By integrating these skills into the curriculum through courses, practical labs, projects, and industry collaborations, educational institutions can ensure that graduates are equipped with the competencies required by employers. This alignment between curriculum and labor market needs can improve employability and career success for students.

For example, Data Analysis is one of the under covered skills in the curriculum. The significance of this skill in the Labor Market involves examining, cleaning, transforming, and modeling data to discover useful information and support decision-making. It is a key skill across many fields, including finance, marketing, healthcare, and technology. So it is suggested that in the curriculum, courses on data analysis should cover statistical methods, data mining, and predictive modeling. Incorporating tools and software used in industries (e.g., Python, R) ensures students are industry-ready.

Besides this, Data Cleansing and Transformation are critical for ensuring data quality and usability. Clean, and well-structured data is essential for accurate and reliable analysis. Courses should cover techniques for identifying and correcting data errors, standardizing data formats, and transforming data for analysis. Practical labs can provide experience with tools and techniques for data preprocessing.

Data modeling involves creating abstract models to represent and organize data, which is crucial for database design and management. Effective data models improve data consistency, integrity, and accessibility. Teaching data modeling can help students understand the principles of database design and management. Courses could include ER diagrams, normalization, and database schema design.

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