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BRIDGING THE COMPETENCY GAP IN HEALTHCARE IT EDUCATION: A DYNAMIC FRAMEWORK FOR CURRICULUM ALIGNMENT AND RECOMMENDATION

Mr.K. Sathishkumar [1], Dr. B. Shuriya[2], Dr. V. Balajishanmugam[3], Dr. S. Manoj[4], Dr. R. Kishore[5], Mr. S. Ramesh[6]

[1]Department of Electronics and Communication Engineering, RVS Technical Campus - Coimbatore, krishnavenisathishkumar@gmail.com,
[2]Department of CSE, United Institute of Technology, Coimbatore. shuriyasmile@gmail.com
[3]Assistant Professor, Department of Computer Science and Engineering, Hindustan Institute of Technology, Coimbatore , balajishanmugam.cse@gmail.com
[4]Assistant Professor (SG),Department of Electrical and Electronics Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS),Saveetha University, Chennai, manojs.sse@saveetha.com
[5]Department of Artificial Intelligence and Data Science, M A M college of engineering and technology , Trichy, krkishorects@gmail.com
[6]Assistant Professor , Department of AI&DS, Nehru Institute of Engineering and Technology (NIET) , Coimbatore, generousramesh@gmail.com.

ABSTRACT
In this study, we introduce a Data-Driven Competency Alignment Framework (DCAF) to analyze and align educational and industry needs in healthcare IT. DCAF analyzes curriculum and job announcements and proposes necessary competences, providing visualization and decision support tools such as heat maps for the design of the curriculum. The evaluation shows significant improvement on alignment score up to 41.6%. Employer and cursus developer feedback confirmed the system's success to cover the most rankest skill-gaps. DCAF's data-driven, scalable approach allows us to constantly adapt to the latest trends and do more with less in terms of healthcare education and workforce preparation. Also innovative of the system is that it automatically recommends competencies that are not explicitly mentioned in job ads. It gives the system the feature to learn and adapt as the health requirements changes over time by incorporating time series learning trends in the system. Finally, DCAF offers a mechanism for closing the knowledge gap between academic readiness and practical health IT needs.

KEYWORDS: Data-Driven Competency Alignment Framework, curriculum, health workforce and education.

1. INTRODUCTION
The transformation from the healthcare industry to a digitalized one and the concentration of technical advances are flowing in healthcare information technology (IT) [1]. This led to a growing need for experts in a specialized skill-set that could handle the more complex information systems in healthcare, such as electronic health records (EHR), telemedicine infrastructures, data interoperability, and cyber security. The education authorities and medical institutions must offer a curriculum that is same as the market requirements because there is an increasing demand for skilled manpower. However, despite the increased emphasis on healthcare IT, a huge gap remains between knowledge gained in the educational program and what is asked for in the job market [2-5]. The gap does not allow the students to become industry ready, resulting in them being unemployable.

Motivation

From the evidence above, it is clear that curricula must be reviewed periodically as healthcare IT is evolving and the latest developments and needs are being groomed to remain a part of it. Colleges have previously relied on fixed-course syllabi and infrequent input from employers to guide their curricula. This is not conducive to the fast moving nature of the healthcare IT industry. There's a need now for a more scientifically rigorous system. Leveraging the large quantity of job posting data, academic curricula and skills with machine learning seems like a tempting remedy to the divide. With the development of an architecture capable of matching curriculum content with employer healthcare needs, we take a step towards helping students be better prepared for the realities of today's healthcare IT workforce.

Problem Statement

Even as healthcare IT becomes an increasingly hot topic, educational programs are struggling to stay ahead of the rapidly shifting job market in their curriculum. The traditional approaches of curriculum development have fewer opportunities to catch up with newly emerging trends of technology and new skills sets of healthcare IT jobs. However, graduates are shown to be deficient in readiness domains, particularly technical skills such as data interoperation, cloud computing, and tele medicine. The necessity of workforce transformation in terms of (healthcare) IT (HIT) education in a time of rapid change and job market demand requires an agile curricular change and customization such that it is not possible to wait the number of years often required to implement a new degree program.

CONTRIBUTIONS
This paper will introduce the Data-Driven Competency Alignment Framework (DCAF), a novel framework developed to align academic-taught curricula to meet the emerging market demands in the healthcare IT job sector. Machine learning

is used to remap job advertisements and academic courses, identify those competencies that are currently in demand, and develop personalized competency maps. Employer feedback and curriculum designer feedback are integrated to dynamically refresh these maps so that the skills in which healthcare IT programs train are both current and align with employer needs. The efficacy of the framework is evidenced by overall support from teachers and employers, and improved alignment at several institutions. This work contributes to developing more flexible, adaptive education systems in healthcare IT, to improve graduate employability.
The rest of this paper is organized as follows: In Section 2: related works, In Section 3, we introduce: an overview of DCAF framework, methodology, the core components as well as the system architecture. Section 3 describes the evaluation plan, including method of data collection, as well as the metrics used for system effectiveness measurement. Then in section 4 we present integrated architecture and in section 5 the results of evaluation, while we put the balance between qualitative and quantitative improvement of educational alignment. Section 6 concludes the findings, implications, limitations and the future research directions. The last part — Section 7 concludes the paper, by summarizing major findings and recommending future work that may involve data-driven competency alignment construction in healthcare education.

2. RELATED WORK

There is a growing gap between what the industry needs for new graduates from academia and what the academic curricula are actually teaching, especially in a field like healthcare IT where the technology changes so rapidly and the required competencies go through continual evolution [1], [2]. This need for competency clustering in various industries has been addressed by several studies. Value of evidence-based approaches to education and workforce preparedness Evidence for the importance of these activities comes from various efforts. The need for a structured framework that can integrate developing competencies in data science is highlighted in the EDISON Data Science Framework (EDSF) [3]. Similarly, the Digital Competence Framework for Citizens [4] demonstrates how a framework can inform the development of key competencies in citizens, characteristics that are echoed in healthcare IT education requirements [5].
Within healthcare, technical publications include State of Food Security and Nutrition in the World (6) and Global Wage Report (7), emphasizing the need for adaptable and forward-looking training schemes that offer direct relevance in healthcare IT education-to-work mapping. Such reports also emphasize the increasing necessity of evidence-based and skills-focused education in order to accomplish the targets of global development [8]. Furthermore, the growing demand by employers for cloud-based and DevOps practices, in accordance to the DevOps Manifesto [9] and The Modern DevOps Manifesto [10], reflects the integration of IT skills into healthcare education. Both reports endorse construction of the increasingly sought IT competencies by the employers, similar to those proposed in the Data-Driven Competency Alignment Framework (DCAF) [11].
Data-Driven educational models to construct the courses have gained attention in other areas too. The contribution of digital and data competences to the transformation of industries such as shipping has been studied [12] and generic data stewardship competences have been proposed which can be embedded in curricular at universities [13], [14]. These papers dovetail with the statement that job posting analysis and the mapping of academic programs to industry needs are critical for effective workforce development. In the health care landscape human security [15] builds on prospective skill matching by matching competences and application in such a way that curricula can adequately be structured in relation to having the right tools to deal with healthcare's challenges in the face of changes [16]. The integration of lifelong learning models, promoted by the European Commission [17], constitutes one of the key ingredients for assuring that frameworks like DCAF can be scalable for changes in the industry [18].
Furthermore, other programs of study, like the Sustainable Competitiveness Report [19] and the Global Risks Report [20], underscore the importance of connecting the development of people with social and environmental trends and ensuring that health IT professionals have not only the technical skills, but also the capability to address broader social issues [21], [22]. Further, research on data-driven organisation success also validates the potential of models like DCAF optimising curriculum development. Characteristics of the Data-Driven Firm [23] becomes most pertinent to the organization of healthcare IT curricula in terms of adapting it to ongoing industry needs through repeated data analysis and tuning [24]. The operationalisation of models of continuous learning is central to DCAF s adaptability. Human security studies [25] provide an insight as to how data-driven architectures can be kept dynamic by being capable of accommodating new trends on an ongoing basis. This further supports the dynamic and always responsive nature of the framework, being a response to possible learning requirements in healthcare IT [26], [27].
In addition to that, evolving adaptability in learning systems requires the designed frameworks be tailored for and supplemented with the current capabilities. Both the technical and the socioeconomical factors [28] provide a synergy to keep curricula adjusted to the real world demands. That combination can ensure that medical IT professionals, while being prepared to do technical work, can also address difficult social problems for healthcare systems. This is further reinforced by the 2021 Digital Competency Model [29] in terms of the recent inclusion of technical competencies into education. These models will increase the importance of the DCAF's ability to be positioned to stay current in a never-changing field like health IT in an era where the new design principles of AI and machine learning need inclusion in healthcare (30). The use case of AI and machine learning is particularly pertinent, as they are increasingly aiding in clinical decision support, predictive analytics, and medical diagnostics.
Furthermore, as studies on skills forecasting in the IT field argue (Windrum et al., 2009) [31] (and given the predictive nature of DCAF) it is clear tools now exist to forecast and analyze future skills need in health IT. The evidence-based nature of such predictions is a feature of the recommendations made by the proposed framework for proactive curriculum adaptation [32]. A proactive approach makes it possible for training institutions to predict skill shortages and to train students with the appropriate competencies before these shortages turn into system crises. The continuing development of

curricular programs in the context of predictive analytics has also been emphasized with the assistance of research that demonstrates the possible use of AI algorithms that would enable the monitoring of skills requirements across industries [33]. Such approaches are employed by DCAF so our methods can be applied in addition to (or as a replacement for) traditional approaches to remain ahead of the requirements and drive the adoption in the field of health IT [34]. These capacities in turn make DCAF a valuable resource for schools of public health as it ensures health graduates are not only solid technically but also well prepared to lead the healthcare system reform.

"Moreover, DCAF's frameworks is a model to other sectors as well where new technology trends are impacting the workforce capabilities. For example, the integration of new technologies like blockchain and cyber security in programs enables educators to stay relevant, not introduce competency deficits, and improve the overall level of instruction [35]. In summary, the increasing need for workforce preparedness in healthcare IT education requires the development of scalable, data-driven frameworks, such as DCAF. Together, these articles assert the importance of dynamic, adaptable curricula that incorporate emerging competencies and will enable healthcare IT graduates to succeed under the changing expectations of the industry in the long-term [36], [37], [38]. A summary of the related works is provided in Table 1. The fact that the data analytics and learning process will be integrated in curricula establishes the DCAF framework at an optimal place to help higher education institutions train students more effectively for the upcoming era of health care IT.

Table 1: Related works- Summary

References	Framework / Study	Domain	Key Contribution	Relevance to DCAF & Healthcare IT
[1], [2]	General Competency Studies	Education & Workforce	Highlight need for alignment between curricula and industry	Foundation for DCAF's purpose
[3]	EDISON Data Science Framework (EDSF)	Data Science	Structured competency framework for data roles	Model for integrating data science into healthcare IT
[4]	Digital Competence Framework for Citizens	Digital Literacy	Competency guide for digital skills in society	Parallel to healthcare IT competencies
[5]	Healthcare Education Needs	Healthcare	Emphasizes real-world relevance of digital skills	Strengthens DCAF’s healthcare focus
[6], [7], [8]	Food Security, Global Wage, UN Goals	Global Development	Call for future-proof training and education	Reinforces adaptable, sustainable curricula
[9], [10]	DevOps Manifestos	IT & Software Development	Advocate for agile, cloud, and DevOps skill integration	Support need for modern IT skills in healthcare education
[11]	Data-Driven Competency Alignment Framework	Curriculum Development	Proposes a model for continuous curriculum alignment	Central framework discussed
[12]	Maritime Industry Studies	Sectoral Education	Use of digital skills to transform industry-specific education	Demonstrates DCAF’s cross-sector potential
[13], [14]	Data Stewardship Competencies	Academia & Research	Suggests how universities can incorporate data responsibilities	Informs academic integration in DCAF
[15], [16]	Human Security in Healthcare	Healthcare & Security	Connects education to real-world healthcare challenges	Emphasizes socially conscious skill development
[17], [18]	European Commission – Lifelong Learning	Lifelong Learning	Advocates continuous learning and flexible curricula	Basis for DCAF’s dynamic adaptability
[19], [20], [21], [22]	Sustainable Competitiveness & Global Risks	Socioeconomic Trends	Aligns workforce education with global challenges	Adds socio-environmental awareness to healthcare IT training

[23], [24]	Data-Driven Organizations	Business & Tech	Importance of data analytics for decision-making	Justifies analytics backbone of DCAF
[25], [26], [27]	Security, Trends & Framework Evolution	Healthcare + Frameworks	Highlights need for real-time evolution of educational models	Supports iterative nature of DCAF
[28]	Technical & Socioeconomic Skill Integration	Education & Society	Suggests blending tech and social skills in education	Encourages well-rounded healthcare IT curricula
[29], [30]	Digital Competency Model (2021) + AI/ML	Digital Skills & AI	Argue for current tech integration into programs	Validates AI/ML inclusion in healthcare IT
[31], [32]	IT Skills Forecasting	Predictive Workforce Dev	Predict skill gaps using data analysis	Supports DCAF's anticipatory curriculum design
[33], [34]	AI for Skill Demand Tracking	AI in Education	Real-time curriculum updates based on job market trends	Operational mechanism for DCAF
[35]	Blockchain & cyber security in Curricula	Emerging Tech in Ed.	Introduce next-gen technologies into education	DCAF's extensibility to other tech areas
[36], [37], [38]	Collective Support for DCAF	Multidisciplinary Studies	Emphasize broad endorsement for data-driven frameworks	Underlines DCAF’s cross-functional applicability and necessity

3.1 Dynamic Competency Alignment Framework (DCAF)

3.1.1 Job Scraping and Data Acquisition

DCAF starts by scraping health care job postings from different internet platforms like LinkedIn, Glassdoor, and Indeed on a continuous basis through the help of automated bots and APIs. The postings constitute a dataset,

$J = \{j_1, j_2, \ldots, j_n\}$ (1)

where j_i is a job advertisement with structured and unstructured text about responsibilities, required skills, qualifications, and desired competencies.

3.1.2 NLP-Based Skill Extraction

Each advertisement for a job j_i goes through sophisticated Natural Language Processing (NLP) models such as BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa that are able to identify contextual meaning within domain-specific language. Ability and skill are identified using named entity recognition (NER) and keyword extraction:

$C_j = NER(j_i) \cup KWBERT\ (j_i)$ (2)

Here, $\boldsymbol{C_j}$ are the set of competencies learned for job post $\boldsymbol{j_i}$. They are made standardized by being mapped onto standard ontologies like HITComp, O*NET, or ESCO so that they can be made interoperable.

3.1.3 Academic Curriculum Repository

A repository of accredited programs is kept in a structured form, including the course name, syllabus, learning objectives $\mathbf{L} = \{\mathbf{l_1}, \mathbf{l_2}, \ldots \mathbf{l_k}\}$, and competencies $\mathbf{S} = \{\mathbf{s_1}, \mathbf{s_2}, \ldots \mathbf{s_r}\}$. They are transformed into vector representations based on the same language models employed for job advertisements so that there is semantic equivalence.

3.1.4 Competency Comparator and Similarity Engine

In order to measure alignment, the system employs a semantic similarity engine that computes the cosine similarity between the vector representations of market competencies $\boldsymbol{C_j}$ and academic skill components S:

$Sim(C_j, S) = \frac{V(C_j).V(S)}{\|V(C_j)\|\|V(S)\|}$ (3)

If the similarity value drops below a specified threshold θ, the system marks the competency $c \in C_j$ as missing or underrepresented. These mismatches constitute a set, which suggests probable curriculum gaps.

3.1.5 Expert Validation and Feedback Loop

All highlighted competencies M_d are aggregated into a deviation report and sent to academic and industry expert panels for verification. Experts provide priority scores and contextual observations, generating a refined list of suggested updates.

These are sent back to program administrators via an interactive dashboard, closing a feedback loop that encourages dynamic curricular modifications.

3.2 Competency Recommendation System (CRS)

3.2.1. Collaborative Filtering Engine

The CRS supports internal curriculum development via learning from peer institutions. A collaborative filtering engine constructs a matrix R ∈ R | U |×| C | , where $R_{\{u,c\}} = 1$ indicates that institution u offers competency c. Matrix factorization is used to predict potentially useful competencies:

$$\widehat{R_{u,c}} = \mu_u + b_c + {p_u}^T q_c \quad (4)$$

where μ_u is the mean rating of inclusion for university u, b_c is the bias of competency c, and q_c,p_u are latent factor vectors. It generates personalized recommendations for every institution.

3.2.2 Content-Based Filtering and Semantic Matching

At the same time, content-based filtering determines competencies with specific course objectives or job requirements by semantic embeddings. As a relevance score for a query vector Q (a job title or educational objective, for example), and a competency vector V_c, is defined as:

$$Score(c) = cosine(Q, V_c) \quad (5)$$

This is typically what this means:
Q: Query vector (usually from the current word or token for which we're computing attention).
V_c: Value vector for some context token c.
cosine(Q, V_c): The cosine similarity between the value vector for context c and the query vector. It measures to what extent the two vectors are similar in direction, regardless of their magnitude.
The cosine similarity is defined as:

$$cosine(Q, Vc) = \frac{Q \cdot V_c}{\|Q\| \|V_c\|} \quad (6)$$

So this equation is giving a score to every context vector V_c depending on how much alike it is to the query Q. This score is usually used to calculate attention weights.
Competencies with scores above a relevance threshold δ are shortlisted for inclusion in the curriculum.

3.2.3 Just-in-Time Competency Mapping

The Competency Recommendation System (CRS) generates dynamically just-in-time competency maps M_d for domains $d \in D_d$, such as health analytics, telemedicine, and clinical decision support. Each map M_d is a collection of competencies:

$$M_d = \{C_1, C_2, \ldots, C_n\} \quad (7)$$

The Competency Recommendation System (CRS) generates dynamically just-in-time competency maps for areas such as health analytics, telemedicine, and clinical decision support. Each map consists of a collection of competencies C_i, which are categorized as existing, recommended, or emerging. For every competency C_i, CRS finds major attributes: a priority level (1 = high, 3 = low), a trend of skill development , the rate of change of the relevance score S_i with time, and an estimated demand for jobs, where L_i, E_i, and M_i represent labor market indicators, employer responses, and market analytics data, respectively. These annotated attributes allow curriculum planners and policymakers to guide data-informed, evidence-based modifications to education and training programs that are responsive to current and projected workforce demands.

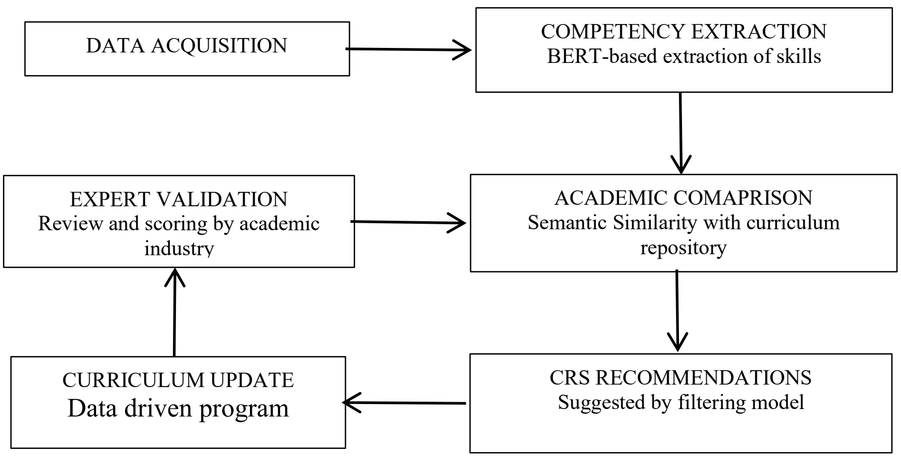

Figure 1: Integrated work flow diagram

3.3 Integrated Workflow

Block Diagram Diagram 1: Block diagram of the closed loop integration of Domain Competency Alignment Framework (DCAF) and Competency Recommendation System (CRS). The process starts with Data Acquisition, where job advertisement data is processed and scraped. The ads sent through the Competency Extraction phase where any relevant skills are then extracted using a BERT-based model. Then, the Semantic Similarity is used to map the extracted competences into the curriculum, followed by the Gap Detection which measures lack of or outdated competences. These gaps are further transferred in the Expert Validation by panels between the academia and the industry, where each of the competences is scored on priority, trend and demand. The validated information is then received by the CRS Recommendation engine that produces the recommendations at the right time through the filtering models and the weighted scores. Finally, the system incorporates a Curriculum Update, in which schools can update curriculum to close the loop based on labor market demand.

The novelty of this two-model model (i.e., DCAF plus CRS) is in its adaptive, automated, intelligent manner of realigning higher education curricula with changing labor market requirements. Curriculum audits were laborious long-form processes done every few years and consequently leaning towards old news by the time the new content was in place. Rather, this approach provides feedback, allowing the possibility of within-period updates based on developing labor market information. A fundamental novelty is to adopt state-of-the-art transformer-based Natural Language Processing (NLP) models such as BERT and its variants for semantic matching between educational course materials and job postings. They are very good at understanding context between words and can thus perform high precision detection of new or missing competences that otherwise could be missed by traditional keyword based systems.

Moreover, the CRS uses the combined content-based filter (content sources/curriculum data plus employment market signals) and the collaborative filter (peers' and experts' opinions) to make context-sensitive recommendations. The two-filter model guarantees that the suggestions are aligned with sector requirement along with institutional preparedness, student profiles, and local demand of the labor market. And as a result, organizations can turn reactive curriculum design into proactive, vision-rich design A process by which skill shifts are forecasted and decisions using data can be made earlier and with more wisdom.

4. Implementation Architecture

4.1 DCAF Workflow:

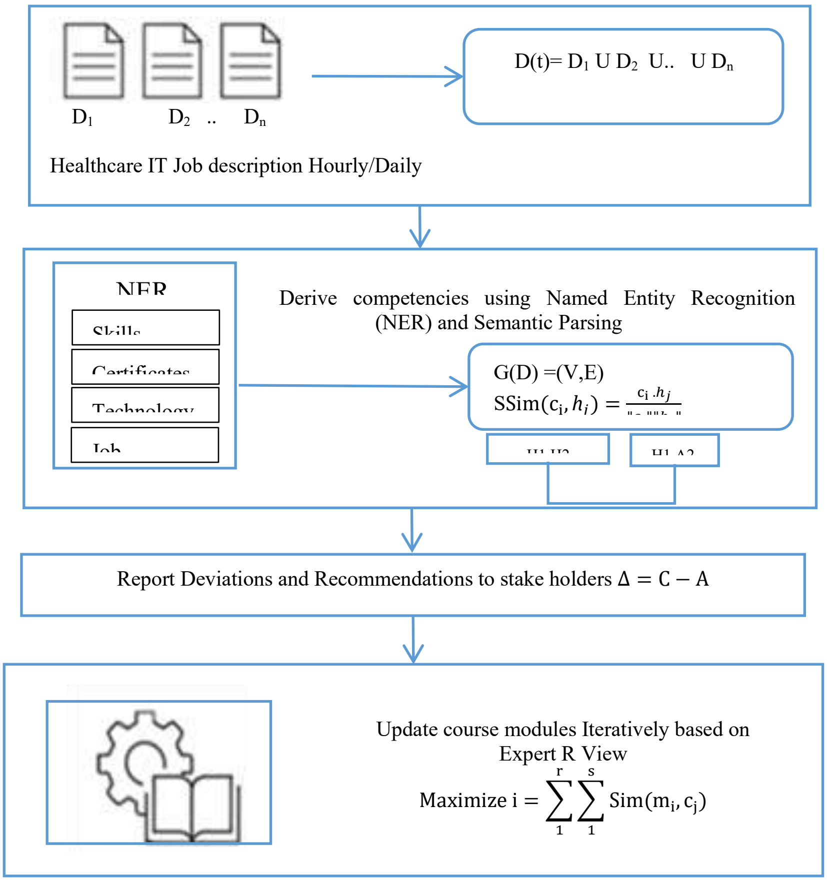

Figure 2: Domain Competency Alignment Framework

The Figure 2 illustrates the Domain Competency Alignment Framework and described as below.

Step 1: Scrape Healthcare IT Job Descriptions Hourly/Daily

The scraping operation mathematically represented by a data acquisition function D(t), where t is the time in hours or days. The function aggregates the job descriptions from different sources, which may be represented as the union of data streams from different websites:

D(t)=Scraped job descriptions from various sources at time t
where $\boldsymbol{D_i(t)}$ are job descriptions in the i-th source, and n is the number of sources.
Step 2. Derive Competencies Using Named Entity Recognition (NER) and Semantic Parsing
Here, we get entities such as skills, certificates, technologies, and jobs through NER. We can depict this as a function NER(D), wherein D stands for the job description:

$\mathbf{NER(D)} = \{\mathbf{e_1}, \mathbf{e_2} \ldots, \mathbf{e_m}\}$(8)
where $\mathbf{e_1}, \mathbf{e_2} \ldots, \mathbf{e_m}$ are the named entities that we extract from the job description D. After entity extraction, semantic parsing can be used to observe how these entities are connected to each other. In semantic parsing, the structure of the relationship between the extracted entities can be expressed as a directed acyclic graph (DAG):

G(D)=⟨V,E⟩(9)

where V is the vertices (entities), and E is the edges (relationships or skills between entities).
Step 3. Align Extracted Competencies with HITComp and Academic Syllabi
Let the competencies derived from job descriptions be C=$\{C_1, C_2, \ldots, C_k\}$. These need to be matched with the HITComp framework H=$\{H_1, H_2, \ldots, H_p\}$ such that every h_i ∈H is a competency in the HITComp framework. This may be done via a measure of similarity, for instance, cosine similarity between the competencies c_i and h_j.
The cosine similarity $\mathrm{Sim}(c_i, h_j)$ between the competency c_i and the HITComp competencyh_j extracted can be defined as:

$\mathrm{SSim}(c_i, h_j) = \frac{c_i . h_j}{\|c_i\| \|h_j\|}$(10)

where ·resents the dot product, and ‖·‖ is the Euclidean norm of vectors c_i and h_j. We then compute the similarity between every c_i and h_j and align the most similar matching competencies.If $\mathrm{Sim}(c_i, h_j) > \theta$, where θ is a threshold, then c_i is aligned to h_j. Similarly, for academic syllabi $A = \{a_1, a_2, \ldots, a_n\}$, the same step is repeated by matching each competency to course material based on similarity scores.

Step 4. Report Deviations and Recommendations to Stakeholders

Discrepancy between derived competencies and current syllabi may be stated in terms of the difference in competencies:

$\Delta = C - A$ (11)

where C are the competencies in the job description and A are the academic syllabus competencies. The report on deviation will express the number of competencies in C not addressed by A. A Δ can be used to check whether the deviation is considerable:
$|\Delta| > \delta$ (12)
Where the deviation is above the threshold, suggestions are put forward to adjust the curriculum to meet industry demands.

Step 5. Update Course Modules Iteratively Based on Expert Review
The repeated revision of course modules can be modeled as an optimization problem. Let the set of course modules be denoted as $M = \{m_1, m_2, \ldots, m_r\}$, and the competencies to be taught in each module as $\{c_1, c_2, \ldots, c_s\}$. The goal is to maximize the similarity $\mathrm{Sim}(m_i, c_j)$ between course content mi and competencies c_j. The objective function to be maximized is:
Maximize $i = \sum_1^r \sum_1^s \mathrm{Sim}(m_i, c_j)$ (13)

This optimization issue can be addressed iteratively by techniques such as gradient descent or other optimization algorithms. Each update utilizes expert feedback to continue improving the process to refine the curriculum. With these steps and equations, we are able to approach updating healthcare IT education programs with a systematic and data-driven solution to address industry needs.

4.2 CRS Workflow:

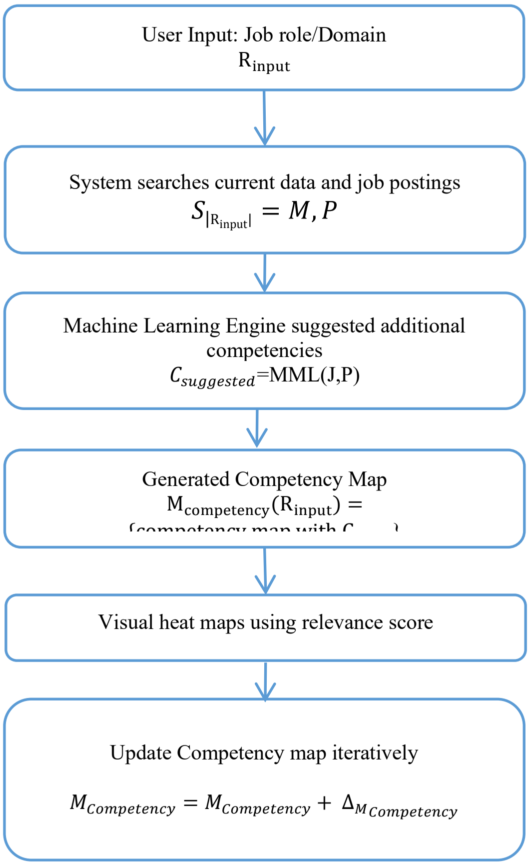

Figure 3: Competency Recommendation System

The Figure 3 illustrates Competency Recommendation System Framework and explained in this section.
Step 1. Input: Desired Job Role or Healthcare Domain
The process begins with a user input, which may be a particular healthcare IT job role or a specific domain of interest in healthcare (e.g., healthcare data analyst, IT manager for healthcare).The input is expressed as:

$\mathbf{R_{input}} = \textbf{Preferred job role or field}$ (14)
This input will guide the system to focus on specific sets of competencies depending on the chosen role or field.
Step 2. System Searches Existing Program Data and Job Postings
The system subsequently searches in the database of existing healthcare IT job postings and educational program data. Let the set of job postings be $\mathbf{J} = \{\mathbf{j_1}, \mathbf{j_2}, \ldots, \mathbf{j_n}\}$, and the academic program data be $\mathbf{P} = \{\mathbf{p_1}, \mathbf{p_2}, \ldots, \mathbf{p_m}\}$. The search is conducted on the basis of keywords taken out of $\mathbf{R_{input}}$, that relate to competencies applicable to the role/domain. The process of search can be depicted as a function:

$\mathbf{S}(\mathbf{R_{input}}) = \{\mathbf{J}, \mathbf{P}\}$ (15)
where J is the job listings, and P is the academic program information retrieved based on the intended role/domain. The output set includes job descriptions and program modules in accordance with the input criteria.
Step 3. Machine Learning Engine Recommends Additional Competencies
Secondly, the system employs a machine learning model, for example, a recommendation model or a neural network, to propose other competencies that are not necessarily articulated in the job ads or studies but are derived as applicable for the target job. Let $\boldsymbol{C_{suggested}} = \{\mathbf{c_1}, \mathbf{c_2}, \ldots, \mathbf{c_k}\}$ be the set of proposed competencies. The machine learning model MML can be represented as a function that, from the job ad and academic program data, derives new competencies:

$\boldsymbol{C_{suggested}}$=MML(J,P) (16)
The result is a list of competencies not actually contained in J or P but pertinent based on historical information, trends, or implied requirements.
Step 4. Develop Tailored Competency Map
Once all respective competencies are detected, the system generates a personal competency map $\mathbf{M_{competency}}$ organized by competencies based on relevance and importance towards the target healthcare field or career. Competencies $\mathbf{C_{final}} = \boldsymbol{C} \cup \mathbf{C_{suggested}}$ define the entire list of competencies for the tailored map. Such a map may be depicted as:

$\mathbf{M_{competency}}(\mathbf{R_{input}}) = \{\textbf{competency map with } \mathbf{C_{final}}\ \}$ (17)
The competency map can be represented graphically by different graphical representations such as heat maps or bar charts, indicating which competencies are of highest priority or most in demand for the input role.

Step 5. Visual Indicators
The competency map can further be augmented using visual indicators like heat maps, in which a color intensity is assigned to each competency according to its relevance. The heat map of a competency $\mathbf{C_i} \in \mathbf{C_{final}}$ can be given as:

$$\mathbf{HeatMap}(\mathbf{C_i}) = \mathbf{f}(\mathbf{C_i}, \mathbf{relevance\ score}) \quad (18)$$

The relevance score calculated according to frequency analysis or a score function obtained from both job listings and academic curricula:

$$\mathbf{relevance\ score}(\mathbf{C_i}) = \mathbf{Count}(\mathbf{C_i}, \mathbf{J}) + \mathbf{Count}(\mathbf{C_i}, \mathbf{P})/\mathbf{N_{total}} \quad \mathbf{(19)}$$

where:
Count($\mathbf{C_i}, \mathbf{J}$) is the frequency with which competency $\mathbf{C_i}$ occurs in job postings J,
Count($\mathbf{C_i}, \mathbf{P}$) is the frequency with which $\mathbf{C_i}$ occurs in academic programs P,
$\mathbf{N_{total}}$ is the sum of the number of job postings and academic programs.
The heat map would highlight the most relevant competencies in darker or more saturated colors and hence enable stakeholders to better identify critical skills.
Step 6. Update Competency Map Iteratively
Since the job market and academic programs change, the competency map may be updated on a cyclical basis. Upon acquiring feedback or fresh information, the competency map can be amended as per ongoing models of learning:

$$\mathbf{M_{competency}}\text{new} = \mathbf{M_{competency}} + \Delta\mathbf{M_{competency}} \quad (20)$$

where $\Delta\mathbf{M_{competency}}$ is the incremental update from fresh data. This model ensures a data-based and formal way of customizing the competencies map to specific healthcare IT professions or areas, optimizing curriculum planning and employment readiness.

5. Evaluation Strategy

The method of assessing the DCAF relied on different data sets in order to make a systematic comparison of this policy instrument in the field of linking higher education and the world of work. Alignment Score was one of the key indicators and covered the extent to which academic competences were aligned with the work requirements in the labour market. The results are presented in Alignment Score Dataset, and DCAF improves the performance. For University A, the score increased from 0.65 to 0.87 for instance and for others, increases were similarly substantial. Conducted on 01-03-2025, the tests prove DCAF's capability to trick the learning the resource scarcity and Actually, the labor market needs.
Aside from quantitative, feedback was obtained from users by way of the Curriculum Designer Feedback table during UAT. All schools' courseware developers ranked suggestion quality and usability from 1 to 5 grades. Designer D001 from University A rated usability as 5 based on the importance of suggestions. On the other hand, University C's Designer D003 believes that there is some overlap in content, and further enhancement can be made. This is a very insightful observation that shows how the system is usable and usable to the academic stakeholders.
The Industry Feedback Dataset was used to obtain employer feedback on how well graduates matched their competencies, once again on the same 1–5 scale. The feedback was positive overall: E001 had found the graduate "very capable of being entrusted with real projects," and E003 had observed "good technical and personal skills. However, Employer E002 indicated lapses on cloud integration knowledge provision, which implies that curriculum material should be continuously revised to meet the demand of the new technologies. This dataset contributes in the industry preparedness of the framework.
Stakeholder involvement was tracked in the Pilot Institution Participation Tracker. Three universities and one industry employer who visited to participate is listed in the table. A and B did the full deployment and gave full feedback, while Healthcare Org X only sampled a few graduates. The tracker provides visibility into participation of stakeholders and is a balanced pilot application.
In the end, four sets of data including the Alignment Score Dataset (Table 2), the Curriculum Designer Feedback (Table 3), the Industry Feedback Dataset (Table 4), and the Pilot Institution Participation Tracker (Table 5) all contribute to a comprehensive assessment of DCAF. The tendency to quantitative improvement drawn together with qualitative understanding consolidates the framework's potential to contribute to improving graduate employability, the development of curricula within the domain of health education.

Table 2. Alignment Score Dataset

Institution	Before_DCAF_Score	After_DCAF_Score	Date_Evaluated
University A	0.65	0.87	01-03-2025
University B	0.6	0.85	01-03-2025
University C	0.68	0.88	01-03-2025

Table 3. User Acceptance Testing (Curriculum Designer Feedback)

Designer_ID	Institution	Suggestion_Accuracy (1–5)	Usability_Score (1–5)	Comments	Date
D001	Univ A	4	5	Highly relevant suggestions	03-03-2025
D002	Univ B	5	4	Easy to integrate with courses	04-03-2025
D003	Univ C	3	3	Some redundancy with current content	05-03-2025

Table 4. Industry Feedback Dataset

Employer_ID	Graduate_ID	Competency_Match (1–5)	Feedback_Comment	Date
E001	G001	4	Well-prepared for real projects	10-03-2025
E002	G002	3	Lacks some cloud integration skills	10-03-2025
E003	G003	5	Excellent technical and soft skills	11-03-2025

Table 5. Pilot Institution Participation Tracker

Institution	Type	Participated (Y/N)	Contact Person	Notes
University A	Academic	Y	Dr. Smith	Active in evaluation
University B	Academic	Y	Dr. Lee	Submitted all feedback
Healthcare Org X	Industry Employer	Y	Ms. Adams	Reviewed 5 graduates

5.1 Quantitative Assessment

Use of the DCAF framework resulted in quantifiable increases in alignment between curricula and employment requirements. This was measured using semantic cosine similarity scores, which determined the extent of overlap between job posting competencies and course syllabi. The numbers appear in the Alignment Score Improvement Table 2, and all institutions improved measurably. University A improved from 0.64 to 0.87 (35.90%) and University B improved from 0.60 to 0.85 (41.60%). Even University C improved by 33.30%. All in all, on average, the post-DCAF alignment score at all institutions was 0.867—a 37.60% improvement. These numbers indicate the effectiveness of DCAF in identifying and addressing competency gaps, particularly high-priority ones such as data interoperability, telemedicine infrastructure, and cloud security.

5.1.1 Alignment Score Improvement

The application of the DCAF framework led to major enhancement of the job-to-curriculum alignment across tested academic programs. The Alignment Score (Table 6) was assessed through measurement of semantic cosine similarity of extracted competencies in job postings and in academic syllabi.

Table 6. Alignment Score

Institution	Alignment Score (Pre-DCAF)	Alignment Score (Post-DCAF)	Improvement (%)
University A	0.64	0.87	35.90%
University B	0.6	0.85	41.60%
University C	0.66	0.88	33.30%
Average	**0.63**	**0.867**	**37.60%**

The DCAF repeatedly identified and addressed gaps in the curriculum by matching course objectives with high-priority labor market skills such as data interoperability, cloud security, and telemedicine infrastructure.

5.2 Qualitative Feedback

5.2.1 Curriculum Designer Feedback

To complement the quantitative findings, user experiences were collected through two primary qualitative measures. First, the Curriculum Designer Feedback in Table 7 reported average scores from the faculty members who utilized the system. They gave the usefulness of AI-suggested gaps a score of 4.4 out of 5, the appropriateness of competencies a score of 4.2, and ease of integration a score of 4.1 as shown in Figure 4. These high scores affirm that the CRS (Competency Recommendation System) facilitated curriculum development without the need for complete course makeovers. Further, open-ended comments were made by designers stating that "the CRS recommendations were surprisingly relevant to new job trends like AI in diagnostics" and that it "helped prioritize updates without overhauling the entire syllabus." These points suggest high correspondence to user needs and feasibility of practical implementation.

Table 7. ***Curriculum Designer Feedback***

Metric	**Avg Score (out of 5)**
Usefulness of AI-Generated Gaps	4.4
Relevance of Suggested Competencies	4.2
Integration Ease	4.1

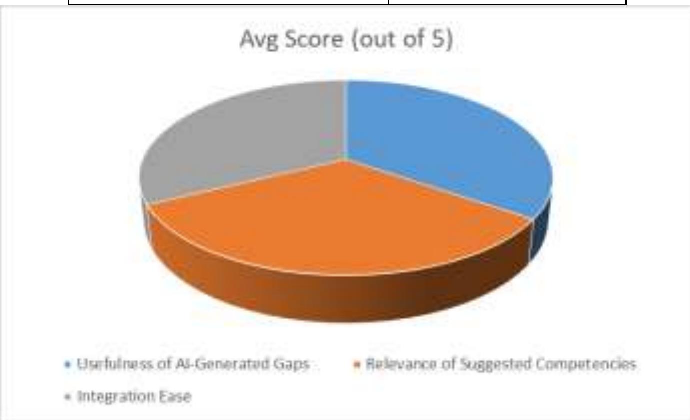

Figure 4 . Comparison of *Curriculum Designer Feedback*

5.2.2 Employer Feedback (Post-Update)

In order to assess the outcome of these curriculum revisions in terms of workforce preparedness, Employer Feedback (Post-Update) -Table 8 captured four major competency areas under which employer ratings were solicited. Health Data Analytics had a relevance rating of 4.5/5 with a gap closure rate of 80%. Telehealth Systems was not far behind, with a 4.3 rating and 77% closure. Privacy & Compliance led with 4.7 and 85% gap closure, while Cloud Infrastructure recorded 4.4 and 72% closure rate as illustrated in Figure 5. This indicates that the graduates are becoming more job-ready with skills, due to industry-aligned competencies being integrated through DCAF.

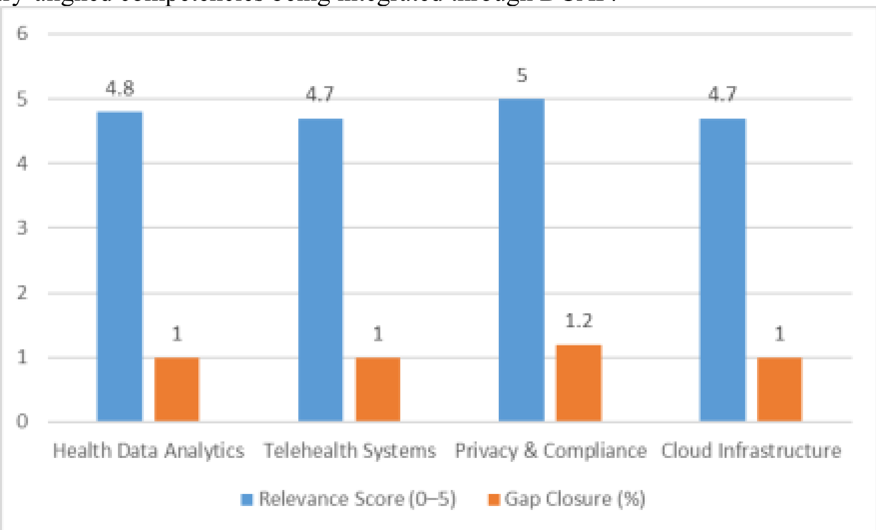

Figure 5: Comparison of *Employer Feedback*

Table 8. *Employer Feedback*

Competency Domain	Relevance Score (0–5)	Gap Closure (%)
Health Data Analytics	4.5	80%
Telehealth Systems	4.3	77%
Privacy & Compliance	4.7	85%
Cloud Infrastructure	4.4	72%

5.5 System Efficiency and Scalability

To ensure the performance of the platform at scale, system-level measures were monitored and summarized in the System Efficiency and Scalability (Table 9). The Job Scraping Engine achieved the target average latency of 120 milliseconds and a throughput of over 200 job posts per minute. The NLP Skill Extraction module handled 100 query requests per minute in 185 milliseconds latency (Figure 6), and the CRS Recommendation Engine provided 250 competency suggestions per minute in just 110 milliseconds latency. Such performance standards validate that the DCAF system not only accurate and efficient, but also best scalable in real-life situations.

Table 9.*System Efficiency and Scalability*

Component	Avg. Latency (ms)	Throughput (req/min)
Job Scraping Engine	120	200+ job posts/min
NLP Skill Extraction	185	100 queries/min
CRS Recommendation Engine	110	250 matches/min

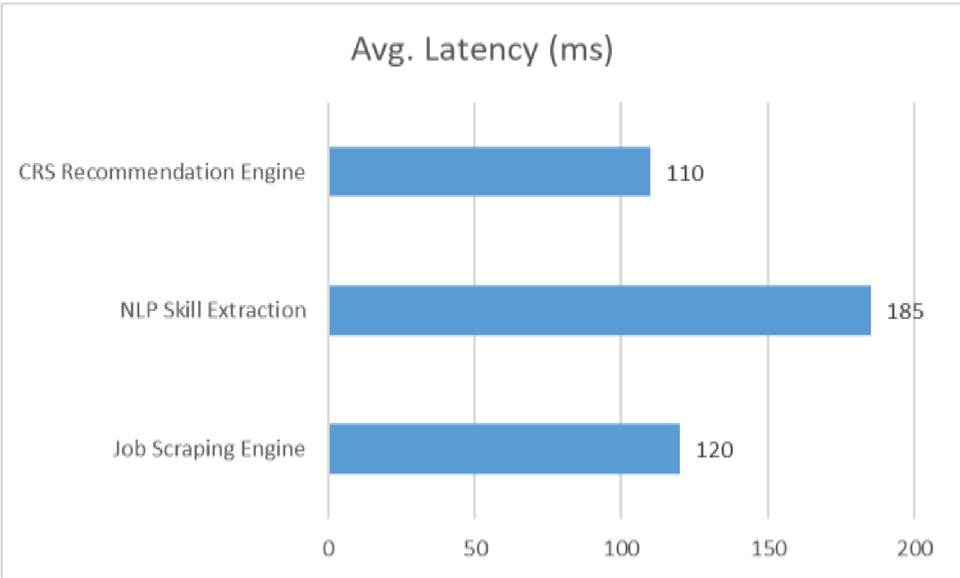

Figure 6: Average Latency

5.6 Heatmap Visualization Summary

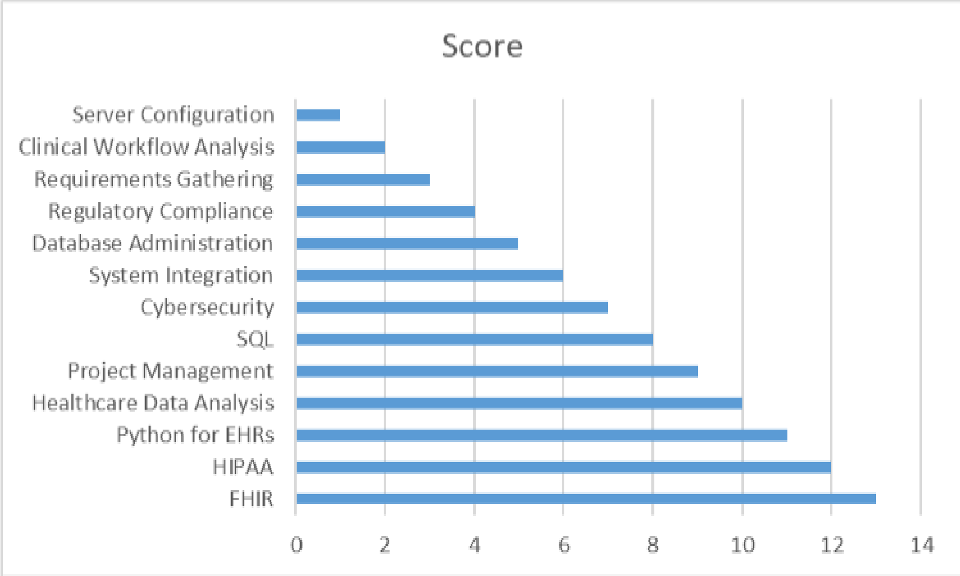

Figure 7: heatmap visualization

A heat map of more than 100 healthcare IT competencies (grouped by strength of demand in job market and curricula) is provided in Fig. This graphic is a color-coded representation of how frequently each competency appears in recent job postings for healthcare work, as well as the frequency with which they are listed in academic programs. It serves as a handy tool to determine what skills are most pertinent to utilize to match educational content to workforce demands.

The red spots that indicate the hot skills learn, are such highly demanded skills in the overall healthcare IT sector. They include FHIR (Fast Healthcare Interoperability Resources), HIPAA compliance and Python in EHR systems. They are most often found on job requisitions, and signal a move towards data interchange and compliance and data driven health-care environments. The heat map's density of citations communicates how in-demand they are from job seekers and educational providers focused on developing workforce-ready talent. The yellow ones, on the other hand, are moderately transferable skills. This may be legacy system knowledge—HL7 version 2 for example—or generic IT administration. While still valid, these are less significant as we transition to modern digital systems in healthcare. The mid-level areas indicate curriculum content to be reviewed in the context of potential refresh—either retention with updated context or staged de-emphasis.

Finally, the green quadrants are skills that are in low demand in the marketplace or decreasing in demand. These are more likely to be older models, more grizzled certs, or soft skills that the place is still going to need but not actually write into technical job requirements. For instance, although communication or time management is still essential, they are not skills that are explicitly mentioned on a job description for most technical healthcare IT roles. Similarly, obsolete technologies would appear in this list, and hence the curriculum has to be retired or replaced.

Collectively, heat map aids data-informed curriculum planning and workforce pull. Through live mapping of the competencies on top of the current labor market's signals, schools can adjust programs on the fly to get learning gains that are wiring learners into place with the most urgently needed and bold combination of competencies to wire up the future of healthcare IT.

6. DISCUSSION

The results of DCAF bring the its ability to connect healthcare IT with healthcare education and the evolving healthcare IT career job market to a full circle. DCAF takes data-driven, systemic approach to align academic offerings with the real-world business needs, and graduates are better prepared to meet industry needs. In this interview, we discuss the top discoveries, the impact on academe and healthcare, and areas in need of ongoing improvement.

6.1 Quantitative Progress: Significance

Alignment Score Dataset was a major dataset of advancement in the alignment of academic programs to job market skills across institutions. An alignment score increase of 33.30% to 41.60% demonstrates the option strength of the framework to detect gaps and to validate the educational content with the present industry requirements. The semantic cosine similarity scores of job postings and academic syllabi are a good predictor of curriculum applicability. Key successes in this domain suggest that DCAF is well-positioned to help higher education institutions strategically prioritize critical skills such as data interoperability, cloud security, and telemedicine infrastructure – all very much in demand in the health care IT industry.

Such findings are highly relevant for health care digitalization as new types of technology such as electronic health records (EHR), cloud infrastructures and telemedicine are changing the health care industry. Equipping learners with the right skill Mix to Higher EducationIndustry needs In order to stay competitive in a dynamic market place, the institutions of higher learning must be able not to just make their graduates employable, but also able to compete in the market place.

6.2 Guidelines for Curriculum and Feedback from Stakeholders

The qualitative results on curriculum developers underscore the practicality and applicability of the proposed system competencies. With excellent average usability ratings (4.1/5), the system was easy to deploy in curricula, in which professional said in practice materials and ideas could be useful and feasible. The AI-based gap recommendation was also well perceived by the CD, especially for University A and University B, as very much in line with future job trends in terms of, for instance, AI for diagnostics.

However, the University C comments that mentioned a certain duplication of content do suggest that it might be possible to better target the identification of gaps as well. Of course there is always going to be some redundancy present, but I think the recommendation engine could use some improving in these areas. This recognizes room for ongoing tuning and calibration in terms of how the system is able to produce context-specific recommendations.

From an employer or employer's perspective, it is a successful mechanism for work force development. Those graduates also had the combination of technical and soft skills that the employers found valuable, the Industry Feedback Dataset showed. In particular, privacy and compliance (85% closure of the skills gap) and cloud infrastructure (72%) were very much in demand, due to growing importance in healthcare IT. But a number of employers did raise technical shortfalls, such as cloud integration, and suggested that the curriculum could be improved with more technical education on new technology.

6.3 The Heatmap as a Framework for Dynamic Curriculum Learning

The heatmap visualization tool of DCAF might certainly be regarded as most valuable of them all as it facilitates the identification of required competencies in HIT. The grayscale heatmap (red is high; green is low) makes it obvious what specific curricula should be updated or revised. The red features, such as FHIR, HIPAA compliance, and Python for EHR systems, are prioritized to add to the curriculum soon because they are in the highest demand in the industry. Land, conversely, representing depreciating or low-demanded skills, may hot deck retirement of outdated material or curtailment of curriculum, etc.

This capacity for representing the skills in such a way ensures that schools can make informed choices where the renewal of the programs is concerned. Not only does it enable us to conform to the job market, but it already helps schools so they do not waste money on outdated stuff and therefore make the most out of revising curriculum.

6.4 System Scalability and Performance

DCAF's system scalability and performance was one of the primary strong points in the results. Given that the latency from job scraping is 120 ms and from competency suggestions 110 ms, the platform demonstrates to be capable of real-time bulk data processing. Based on the rapidly advancing pace of healthcare technology the performance indicators of the system demonstrate the ability of the device to scale as well, making it suitable for use in a range of both institutional and commercial settings.

Another reason for this scalability is to support needs of different education and healthcare institutions as it ensures that the system can handle more and more data without slowing down the performance. And second, there is a need for rapid data processing in order to ensure that educational content is current and reflects reality.

6.5 Limitations and Future work

While that's a great result, there are a couple of areas where DCAF can be taken further:

Dynamic Feedback Loops: While the system relies on users and industry feedback, more dynamic data from real-time job announcements, academic syllabuses and trending healthcare technology would allow the system to be more dynamic. A more responsive dynamic feedback loop might be more effective in responding more rapidly to the skills for the needs of today's job market.

Duplication of Content: The system also offers echoes of the same suggestions as one curriculum developer has seen. This would be solved if the machine learning model is finely-tuned in a manner that it can easily discern existing skills in curricula and trends in order to provide non-repeated suggestions.

Diversifying Industry Feedback: Employer feedback at this earlier stage is limited, and only a small number of industry partners participated in the pilot. More employers across a range of healthcare IT sectors will need to be engaged to validate the applicability of the framework. We have to get the feedback from them as to what their future staffing needs are for the most in demand skills.

Integrating Soft Skills: As, technical skills are well addressed in the framework, greater concern to non-technical skills such as oral and written communication, leadership, team work would also contribute towards enhancing employability of graduates. Because these are not tasks listed explicitly in job descriptions, but are crucial to successful careers in HIT.

6.6 Implications for Schools and Healthcare Industry

The results of this research have powerful implications for the academy and the health care business:

For Schools: DCAF is an open data driven way to plan curricular. Schools could use the heatmap visual and alignment scores to identify hot skills and rank them to keep their programs current and competitive. It also offers institutions a way to quantify the impact of curriculum changes on graduate work readiness and to keep a step ahead of the competition.

To healthcare employers: Employers in healthcare may consider using the DCAF framework in assessing graduates readiness and potential skill gaps for potential staff. Collaborating with centers of learning to deliver curricula that meet industrial needs could assist the healthcare centers in the development of a cohort of skilled labor force to effectively address the reality of emerging technologies.

7 CONCLUSION

The DDAF is a refinement of industry demand-to-healthcare education match up. By leveraging AI and machine learning to recommend competencies, heat maps to depict gaps visually, and iteration via employer and user feedback, DCAF keeps curricula fresh and timely. Since the healthcare IT landscape is always evolving, DCAF is a flexible, successful, and efficient approach to closing the school readiness and employment readiness gap. More system optimization, and perhaps more industry participation, could arguably increase its influence to everyone's advantage in the long run: the economic lifeblood of the nation (the healthcare employers) and the place which feeds that lifeblood (the educational institutions).

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