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AI-Based Skill Gap Analysis for Effective Workforce Development

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ABSTRACT- We are seeing a very quick adoption of digital technologies, automation, and AI which in turn is changing the skills required in today's modern work places. Organizations are reporting it difficult to determine what existing employee skills are gap skills in relation to what is required to achieve organizational goals. Also, very often we see that present skill assessment methods which are mostly manual, based in periodic performance reviews, and very subjective may not be giving us current enough info for workforce development. This paper presents a model which puts forth an AI based approach to identify employee skill gaps and support in the development of the workforce.

The proposed framework includes employee competency profiles, job role requirements, AI assisted skill assessment, gap identification, and personal training recommendations. We see how natural language processing, machine learning, competency mapping, and recommendation techniques play a role in which HR professionals may use to make informed training and development decisions. Also, we see into issues of data quality, privacy, algorithmic bias, transparency, and employee acceptance. Rather than reporting on results of experiments the study puts forth a structured conceptual model which organizations may adapt to fit their workforce needs.

KEYWORDS- Artificial Intelligence, Skill Gap Analysis, Human Resource Management, Employee Competency, Machine Learning, Personalized Training, HR Analytics.

I. INTRODUCTION

Digitalization, automation, cloud computing, data analytics and artificial intelligence are transforming the modern workplace on a rolling basis. As work changes, the demand for technical and professional abilities is changing, too. Employees are increasingly required to update their knowledge and to develop skills that meet changing organizational requirements. Therefore, human resource management has taken on the job of identifying and filling the skill gaps in the workforce.

A skill gap is the gap between the skills the individual currently has and what skills they need to be effective in a given job. These gaps might emerge from technological developments, new company procedures, increasing client expectations, or lack of professional growth opportunities. Skill mismatch is also a broader labor market challenge involving skill shortages, overqualification, underutilization and changing relevance of existing skills [1], [2].

Traditional skill gap analysis which we do perform via employee surveys, interviews, supervisor assessments, performance appraisals, and training needs assessments. While those methods do provide us value, they also may put in a lot of time in to the process and do not always report out on the rapid changes in skill sets. Also, manual evaluations may use inconsistent assessment criteria and play into the hands of individual judgment. AI on the other hand brings to the table different solutions. AI based systems which we may use will look at structured and unstructured info, identify competency trends, compare employee profiles with job requirements, and put forth relevant learning recommendations. Research in AI assisted HRM reports on the growing role of smart tech in the support of HR functions and in the decision-making processes of organizations [3], [4]. However, we should not present the identification of skill gaps as a stand-alone issue. An effective workforce development approach also has to take into account of the present skills of the employee, his career aspirations, job duties, what the organization is trying to achieve and what learning opportunities are available. Also, this paper presents a framework which we put forth for the integration of AI in competency assessment with personal training recommendations.

A. Research Objectives

1. To examine the role of AI in identifying employee skill gaps.
2. To develop a conceptual framework for AI-assisted competency assessment.
3. To present how employee skills may be compared with job role requirements.
4. To study personal training recommendations for workforce development.
5. To report on the ethical, technical, and organizational issues related to AI based skill assessment.

B. Research Contribution

This paper reports our put forth of a structured conceptual framework which presents a connection between employee competency info, job requirements, skill gap identification, and personal training recommendations. We present that AI should support rather than supplant HR professionals and employee input in work force development decisions.

II. LITERATURE REVIEW

McGuinness et al. [1] looked at skill gaps in the workplace which they looked at in terms of measurement,

determinants, and what those skills' impacts are. Their study puts forward the value in that which we see a gap between what employees' current competencies are and what organizations require.

Pouliakas and Redmond [2] expanded on this point by stating that skill mismatch incorporates a number of related ideas, such skill gaps, talent shortages, and skill obsolescence. These distinctions are important because organizations need to identify exactly what kind of problem they have relating to a competency before they can implement successful workforce development initiatives.

Artificial intelligence is increasingly used in human resource management, providing new prospects for the improvement of organizational operations. Jatobá et al. [3] published a systematic literature analysis on intelligent human resources and artificial intelligence adoption, noting the importance of intelligent technology in HR related operations. Verma et al. [4] discussed artificial intelligence-augmented human resource management and offered a layered paradigm for further research. Their work mirrors the growing need for AI to enhance HR tasks and decision making in organizations.

The assessment of skill development and training-needs has long been regarded as critical components of human resource development. Taylor, O'Driscoll and Binning [5] present an integrated methodology for training-needs analysis that considers organizational, task and individual requirements. This approach is important to pinpoint areas where employee talents are missing, and to link training programs to organizational objectives.

The OECD [6] studied skill mismatches using employer survey data and discussed how companies adapt to the mismatches through training, skills anticipation and recruitment. The analysis stresses the significance of comprehending the skills requirements of the workforce at the organizational level. Marler and Boudreau [7] also explored the development of HR analytics as an evidence-based strategy to understand and improve human resource strategies. Their approach lays the groundwork for harnessing worker data to help make better HR decisions.

A systematic literature review on AI based tools and approaches for human resource management was done by Madanchian et al. [8] . Their study explores the use of AI-powered applications in HR tasks and underscores the increasing importance of intelligent technology in domains including recruitment, performance management, employee engagement, and training. These applications highlight the potential of AI to enable more structured and data-informed human resource procedures.

In the field of employee development, Tavakoli et al. [9] developed an AI-based recommender system for individualized labor market driven education. Their work highlights the possibility for skill requirements to be matched with learning materials. Similarly, Wang et al. [10] studied individualized employee training-course recommendations with career development awareness . Their work provides a basis for linking staff development requirements with appropriate learning options.

Wang et al. [11] also presented a Bayesian variational approach to provide interpretable and tailored suggestions of employee training courses. Explainability is especially important in HR applications, since employees and managers should understand why a certain learning advice has been developed. Based on this work, Yang et al. [12] examined contextualized knowledge-graph embeddings for explainable talent training-course recommendation, showing the importance of knowledge linkages in employee learning systems.

Hemmler, Rasch and Ifenthaler [13] explored workplace learning goals in multi-stakeholder recommender systems. Their analysis highlights the need to address individual learning goals and organizational needs in recommendations for workplace learning. This is vital because employee development should benefit the individual and the organization.

The study of AI and human resource development has also focused on the responsible implementation. Ekuma [14] explored the implications of AI and automation on the procedures and outcomes of human resource development. Chen [15] emphasized responsible AI in organizational training and underlined privacy, non-discrimination, interpretability, accountability, and professional duty. These factors are necessary while deploying the AI-based system processing employee data and assisting in development related decisions.

More recently, studies have focused on the link between AI use and the evolution of labor skills. Mhaske et al. [16] explored the digital skill gaps and the factors affecting workforce development, offering a conceptual view on the necessity to meet the shifting skill requirements. Braun et al. [17] proposed a way to identify skill shortages in the sector and to match the demands of the employees with acceptable learning modules. Their work draws attention to linking the identified competency needs with suitable learning options.

Gayathri and Jayaprakash [18] proposed a machine learning-based system for workforce skill-gap analysis and predictive talent development. Their work is closely related to the present study as it explores the application of machine learning to workforce competency assessment and skill-gap identification . However, the present research follows a different conceptual route by developing or experimentally evaluating another predictive model. Instead, it focuses on the HR process that links competency assessment, employee involvement and explainable training recommendations.

Karanth et al. [19] proposed an artificial intelligence-enabled platform for knowledge sharing, student involvement and development of practical skills. Their study, which focuses on student learning rather than staff growth, demonstrates how AI-enabled platforms may improve access to learning opportunities and skill development. The present research contributes to this broader conversation by focusing on employee competency assessment, identification of skill gaps in the workplace and individualized training recommendations in an organizational

A. Research Gap

Existing research has investigated skill mismatch, AI-supported HRM, workplace learning and individualized training recommendations. However, these study fields are generally treated individually. The organization needs a connected process of converting job requirements into observable capabilities, assessing employee skills, prioritizing the gaps and providing relevant learning intervention. This article responds to this conceptual demand via an integrated HR-oriented approach. It also stresses the need for human supervision, employee

participation and ongoing re-evaluation as key elements of the responsible growth of the workforce.

III. RESEARCH METHODOLOGY

The current study is a conceptual and literature-based investigation. It builds on existing research on skill mismatch, training requirements analysis, HR analytics, AI-assisted HRM, workplace learning and employee training recommendation systems.

The framework is developed by decomposing the workforce development process into five related stages: (1) identify organizational and job-role skill requirements, (2) collect and evaluate employee competency information, (3) AI-assisted comparison of required and available competencies, (4) prioritize identified skill gaps, and (5) recommend and evaluate appropriate learning interventions. The approach provided is conceptual and does not claim to have been experimented in an organizational experiment. Its components are designed as a framework for future implementation and empirical evaluation.

IV. PROPOSED AI-BASED SKILL GAP ANALYSIS FRAMEWORK

The objective of the proposed framework is to distinguish between the skills that the position necessitates and the contributions that the employee makes. It employs personal training recommendations, AI-assisted analysis, competency assessment, and HR data.

A. Framework Architecture.

- **Job Requirement Identification:** The organization ascertains the skills and levels of competency that are necessary for each job position. This information is obtained from job descriptions, competency frameworks, departmental objectives, and current industry trends.
- **Employee Skill Profiling:** We create employee competency profiles that we populate with information such as qualifications, work experience, training history, project experience, self-assessments, and input from supervisors.
  This information should be collected in a transparent manner and utilized solely for the purpose of workforce development.
- **AI-Assisted Skill Assessment:** AI tools can play a role in the identification and classification of skills from job descriptions, employee profiles, training records, and other related documents. We see the role of Natural Language Processing (NLP) in the identification of skill related terms and in the organization of these terms into competency categories. Also, we have machine learning which may put forth in the identification of patterns if the system is trained and evaluated on proper data.
- **Skill Gap Identification:** The system will put forward a comparison of the employee's assessed competency level with the required level for the given job role. The out of this comparison is a report of the areas that may require further development.
- **Personalized Training Recommendation:** Based on identified gaps, the system suggests relevant learning activities, such as online courses, mentoring, workshops, practical assignments, certifications, or supervised workplace learning.

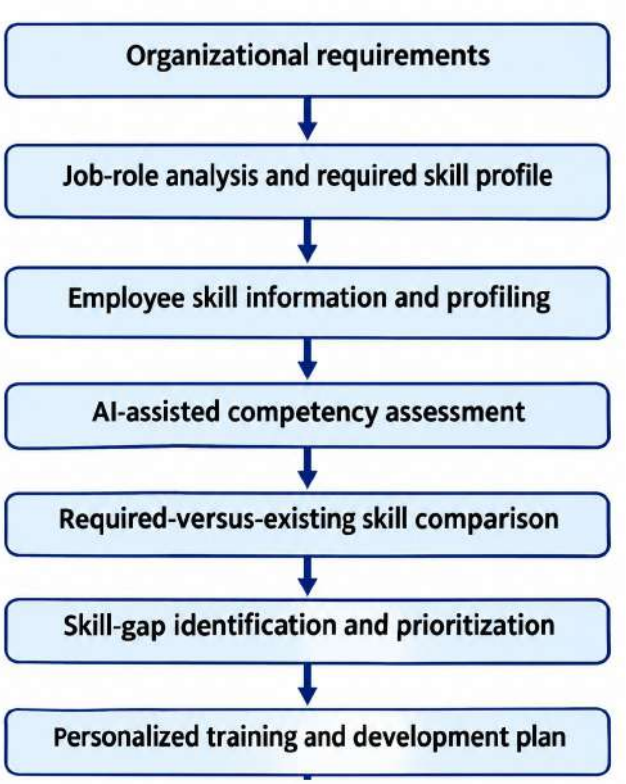

Figure 1: Proposed AI-Based Skill Gap Analysis Framework

In the above Figure 1, it presents the overall architecture of our proposed framework. Firstly, the process begins with identifying organizational requirements and the competencies associated with each job role. Then employee information is collected to establish individual skill profiles. Then AI-assisted assessment compares the available competencies with the required competencies to identify potential gaps. It is based on the results; suitable learning interventions are recommended. Finally, employee progress is reviewed and the competency profile is updated. This feedback mechanism supports continuous workforce development.

B. Skill Categories for Employee Assessment

Table 1: Major Skill Categories for AI-Based Employee Assessment

Skill Category	Examples	Assessment Indicators
Technical Skills	Programming, data analysis, cloud computing	Practical tests, certifications, project experience
Digital Skills	Digital tools, cybersecurity awareness, software applications	Digital competency assessments
Communication Skills	Presentation, writing, teamwork	Structured feedback, communication exercises

Problem-Solving Skills	Critical thinking, decision-making, analytical reasoning	Case studies, task-based assessments
Leadership Skills	Team management, planning, conflict resolution	Supervisor assessment, leadership activities
Adaptability Skills	Learning agility, flexibility, technology adoption	Behavioural assessment, learning progress

Table 1 reports on a classification of which we have put forward six large groups that pertain to what we see in terms of employee competencies. In the case of very technical and digital skills we see that to be very much the focus in roles that are very much in the tech space, while communication, leadership and problem-solving skills are what we see play out in many professional settings. Also, we see that adaptability is a key element as employees must constantly adapt to change in the work place. The assessment indicators we present are put forth as possible sources of information which we do not put forth as the be all and end all in terms of what is a true measure of competence.

C. Skill Gap Calculation

A basic competency analysis can be used to determine the difference between what is required and what is assessed. The skill gap for employee i and skill j can be represented as:

$G_{ij} = \max(0, R_j - A_{ij})$

Where G_{ij} is the skill gap for employee i in skill j; R_j is the required competency level for skill j; and A_{ij} is the assessed competency level of employee i in skill j.

A five-level competency scale may be used, for example: i) Novice; ii) Fundamental; iii) Proficient; iv) Advanced; and v) Expert. A larger gap value indicates a greater difference between the required and assessed competency levels. The scale should be applied uniformly across the organization and tailored to the specific skill which is being evaluated.

Calculation: If a job role requires an advanced data analysis competency level of 4 and an employee's assessed level is 2, the identified gap is $G = \max(0, 4 - 2) = 2$. This indicates that employees may require further development in data analysis. The calculation only demonstrates how the formula operates and does not report data from any organisation.

Because not every skill is equally important for a role, gaps can be prioritised using relevance weights. The priority score for employee i and skill j can be expressed as

$P_{ij} = w_j \times G_{ij}$

where w_j is a weight between 0 and 1 assigned to skill j according to its relevance to the job role and organizational priorities, as agreed by HR professionals and supervisors. Gaps with higher priority scores can be addressed first when training resources are limited. The weights should be reviewed periodically and should not be set by the AI system alone.

The behaviour of the gap measure can be examined by plotting it against the assessed level for different required levels.

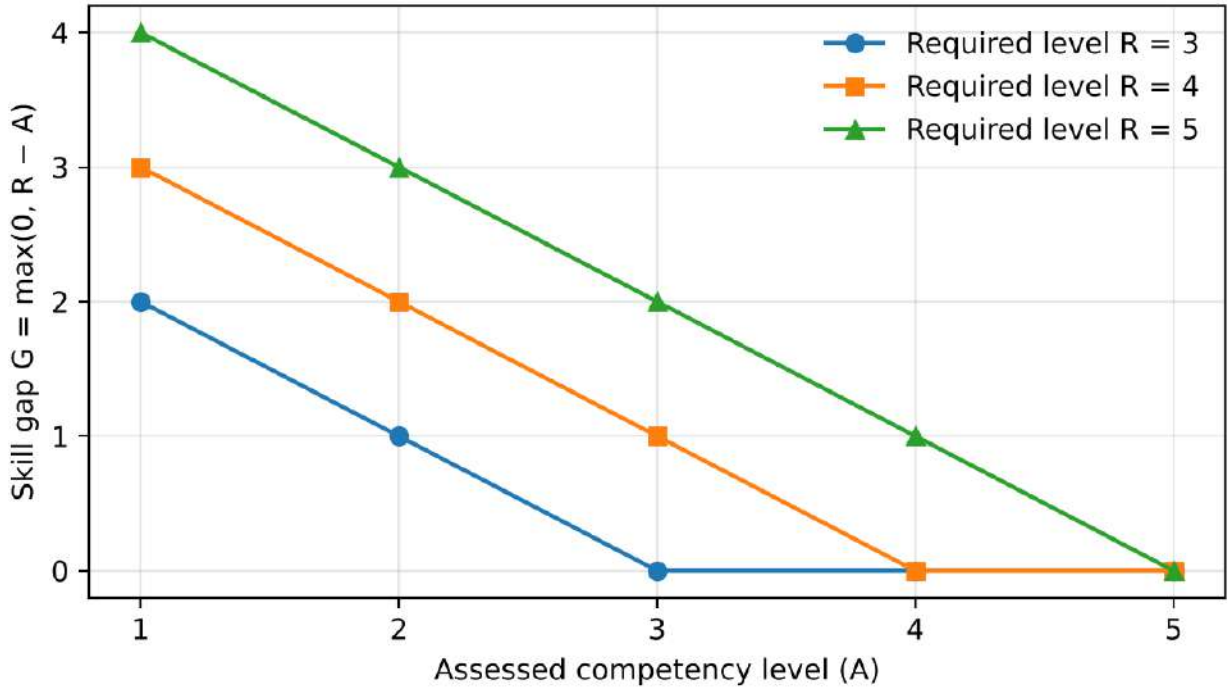

Figure 2: Skill Gap as a Function of Assessed Competency Level

Figure 2 displays the gap G max(0, R A) which we have represented on a five-point scale for required levels of 3, 4, and 5. The gap reduces by one point for every additional level the employee has achieved and goes to zero once the assessed level reaches the required level. It stays at zero thereafter which we did not include as a negative factor in the gap. A higher required level thus results in larger gaps for the same assessed level which is why it is important to careful define role requirements before assessment. The figure is generated from the put forth formula itself and does not report on empirical data. The combined use of the gap and priority measures we have for one job role across the six skill categories in Table 1. The required levels, the levels assessed and the weights shown in Figure 3 are constructed

values chosen merely to demonstrate how the computation is applied, they are not collected from any organization.

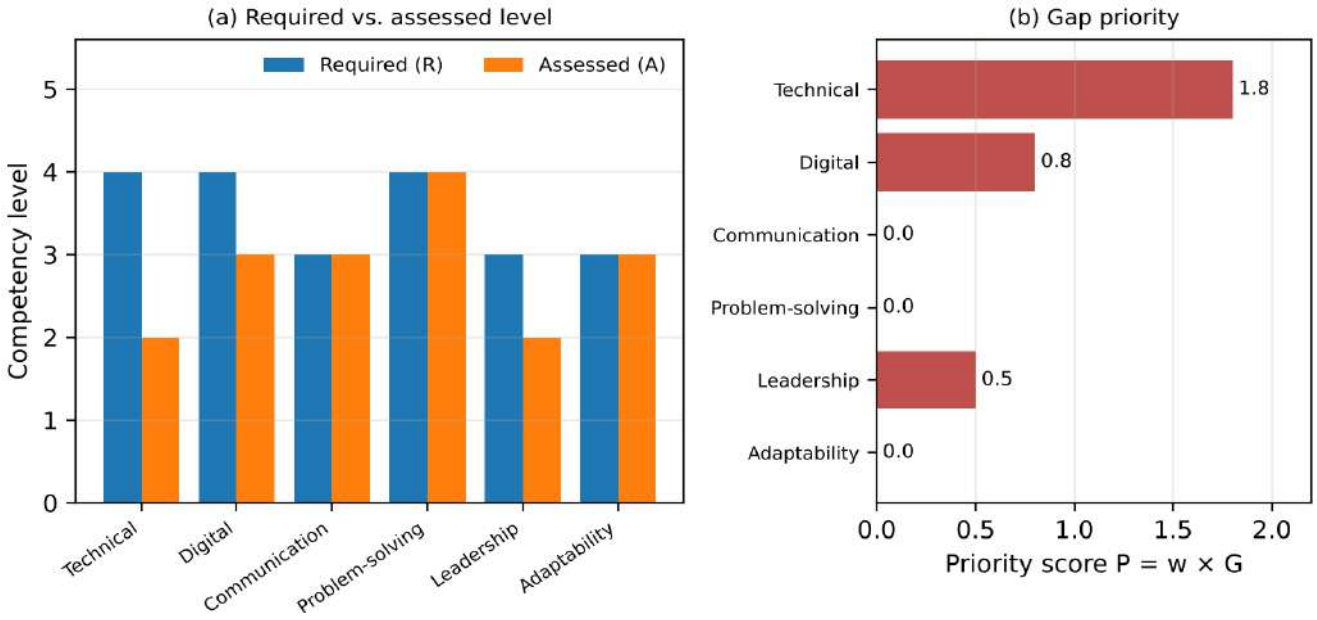

Figure 3: Required vs. Assessed Competency and Gap Priority for a Worked Role Profile

The comparison of the required and assessed levels of competency for the six skill categories of the panel is shown in Figure 3(a) above. The largest gap is in technical abilities (required 4, assessed 2), followed by digital skills and leadership, which are a level apart. Communication, problem solving and flexibility go hand in hand. In Figure 3(b), these gaps are assigned various value according to their significance. The highest score is for technical skills (0.9 x 2 = 1.8), followed by digital skills (0.8 x 1 = 0.8) and leadership (0.5 x 1 = 0.5). The ranking allows HR specialists to see how the framework helps them to select which development needs to address first and why a weighted score delivers more information than the raw gap alone. In reality, the levels and weights would be determined by the organization's own assessments and then validated by HR specialists and management.

D. AI-Based Skill Gap Assessment Process

Artificial intelligence can help HR personnel organize and analyze employee competency information. NLP approaches can be used to extract skill-related information from job descriptions, resumes, training records and personnel profiles. Identified talents can be categorized as technical, digital, managerial and interpersonal abilities. The technology may analyze employee competency profiles against job role criteria, prioritize the gaps by job relevance and corporate priorities and create learning recommendations. The AI-generated assessment should be used as a support to decision making. Before establishing an employee development plan, HR experts and the relevant supervisors should analyze the evidence available to them.

E. Personalized Training Recommendations

Then it suggests suitable learning activities to fill in the skill gaps identified. The recommendations should take into account the employee's present level of proficiency, learning preferences, career aspirations, resources available and organizational needs.

Table 2: Mapping of Identified Skill Gaps to Training Recommendations

Identified Skill Gap	**Recommended Learning Activity**	**Expected Development Outcome**
Programming Skills	Practical coding courses and supervised projects	Improved programming competency
Data Analysis	Data analytics training and practical exercises	Better analytical capabilities
Communication	Presentation and business communication workshops	Improved workplace communication
Leadership	Leadership development and mentoring	Better team-management capabilities
Cybersecurity Awareness	Cybersecurity awareness training	Improved understanding of security practices
Digital Tool Usage	Software training and guided practice	Improved digital proficiency

The links between identified competency gaps and related learning activities are presented in Table 2. For example, an employee lacking data-analysis skills may be given practical analytics training, while an employee needing leadership development may be assigned mentoring and leadership exercises. These are typical alternatives and not rigid rules; the final training plan should reflect the real assessment of the person and the learning needs.

F. Continuous Assessment and Feedback

Skill development should not be considered a one-time activity. After completing the recommended training, employees should be reassessed to determine whether the

intended competency improvement has occurred. Feedback from employees, supervisors, and training providers can help HR professionals evaluate the usefulness of the recommended learning activities.

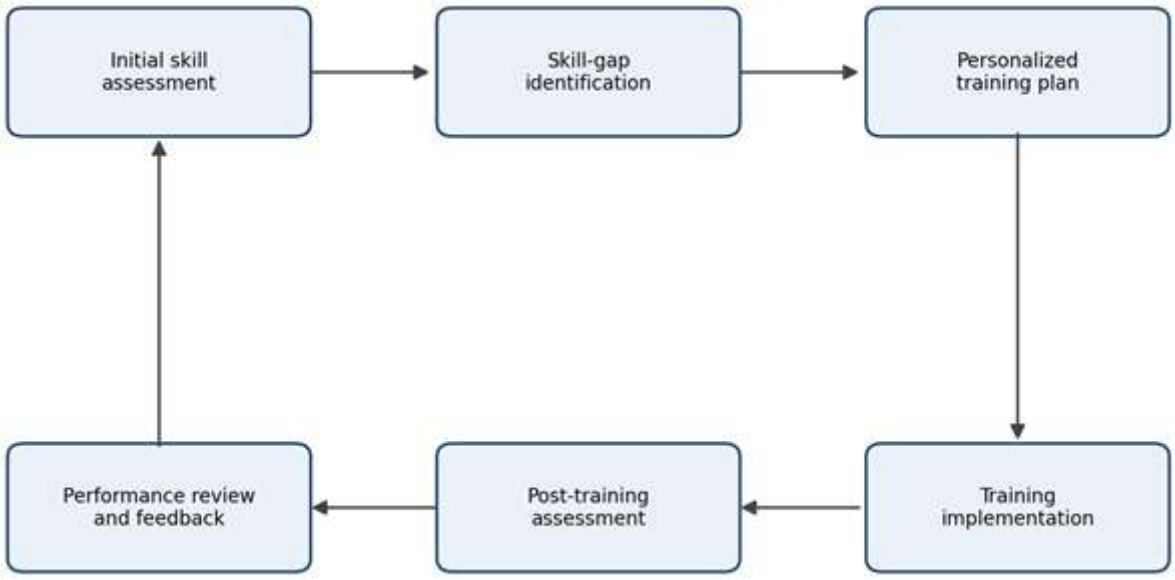

Figure 4: Continuous Skill Development and Feedback Cycle

In above Figure 4 we present a continuous development cycle in which employee competencies are assessed before and after training. The new skill profile enables HR professionals to assess if the training intervention has bridged the stated gap. Additional learning activities may be recommended if the gap exists. This method facilitates the continual growth of employees and helps companies adjust to evolving competency needs.

V. APPLICATIONS AND BENEFITS

A. Strategic Workforce Planning

AI skill assessment allows an organization to learn what competencies they possess in-house. Such knowledge might be used to make decisions regarding the future hiring, employee redeployment, retraining, and succession planning. The HR department can discover those areas where the development of internal competencies would help to eliminate the need for external hiring.

B. Personalized Employee Development

Employees have various professional background, learning styles, and career aspirations. AI-based recommendation system can be useful for HR specialists in determining learning resources which will be appropriate for each individual's needs. Personalized recommendations can increase relevance of the training activity [9]–[13].

C. Optimization of Training Resources

Training activities take time, require financial expenditures and involve employees' participation. Skill gap analysis can help to prioritize training activities based on the real competency needs. Instead of offering uniform training for everyone, organizations can concentrate on those aspects where development is really needed.

D. Employee Career Development

Structured competency profile enables an employee to know about the skills needed in current and future positions. With the inclusion of career development information, the system may offer relevant training opportunities to help with the career mobility.

E. Adaption to Technological Changes

Job requirements evolve and organizations need to keep reviewing their competency framework. With the help of AI-based monitoring of job descriptions, industry news and in-house requirements, HR specialists can determine emerging skills that must be developed by employees.

VI. CHALLENGES AND LIMITATIONS

A. Information Quality

The quality and accuracy of the information provided to the company will determine the dependability and effectiveness of AI generated ideas. Incorrect suggestions may be the result of outdated job descriptions, insufficient personnel profiles, and inconsistent records of assessment. There should be a process for verification and updating of information.

B. Algorithm Bias

AI is able to mimic the bias present in a company's previous personnel statistics. If there were subjective judgments of employees' performance in the past, an AI model based on this data can provide wrong evaluations. "We need to watch for bias, have diverse data, and do human review."

C. Information Security

Employee competency profiles may include personal data, educational background and professional experience. There should be data access control and security mechanism as well as suitable data retention policy and communication with employees on this topic. Data collection should be limited to only what is needed for development purposes.

D. Transparency

Employees and HR specialists should know why a given skill gap is found and why a certain activity is recommended

to enhance it. An explainable recommendation system can create confidence amongst participants [11], [12].

E. Employee Acceptance of AI System

Some employees may see AI-based assessment as a technique to monitor their performance rather than a development tool. The organization should communicate adequately about the objective of the system and also provide opportunity for employees to see their profiles, correct inaccuracies and discuss recommendations with HR.

F. Cost of Implementation and Technical Issues

The implementation of HR systems on the basis of artificial intelligence (AI) technologies will require the necessary software, qualified personnel, data integration and maintenance. This solution may not be available to small companies. With an initial stage of mapping abilities, it can be useful to have a phased introduction.

VII. FUTURE SCOPE

Future work may see the proposed framework extend into practice in a variety of industries, which include information technology, manufacturing, health care, education, and financial services. We see that each industry has its own set of competencies, which may in turn improve the relevance of AI in assessment. Also to be looked at is the issue of which technical models to use which may include NLP, knowledge graphs, machine learning, and explainable recommendation systems. These technical models may in turn help us to see the relationships between job roles, competencies, training resources, and career paths. Also, a very important research direction is the issue of what we may term the evaluation of the bottom line of AI recommended training. We may look at changes in competency levels, training completion rates, employee satisfaction, internal mobility and job performance as a result of the training.

Such as in the case of AI powered skill gap analysis which we may put to use to determine that which improvements if any, we see in workforce development. Also, we may look at what role AI can play in which employees take part in competency evaluation and training choice. Human centered design, transparent recommendations, and employee input into which they learn and how they learn should still be at the fore.

VIII. CONCLUSION

We see that which AI plays a role in skill gap analysis is to put together employee competency assessment with structured workforce development. What we have seen is that traditional assessment methods may not always react quickly to change in job requirements and evolution of tech needs. We have put forth a conceptual framework which addresses this issue by including job-role analysis, employee skill profiling, AI assisted competency assessment, skill gap identification, and personal training recommendations. We also present that which identifying a skill gap is only the first step in workforce development. What organizations also must do is to present learning opportunities, evaluate employee progress, and update competency profiles. AI can help HR professionals in the organization of workforce info and in putting forth relevant recommendations; also at the same time human judgment, transparency, data privacy, and employee input is very much to the fore.

The proposed approach is a theory which requires empirical support before we may determine its success. In the future we will study implementation of this in many different organizational settings. As a whole the framework puts out a structured direction for the use of AI as a decision support tool to promote continuous learning, employee growth, and also organizational preparation for the changing workforce requirements.

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