



Generative AI -Based Employee Skill Gap Analysis and Personalized Upskilling Recommendations

Dr.M.Sangeetha¹, Dr.Banoth Rajendranath²

¹(Assistant Professor

Commerce

Shri Shankarlal Sundarbai Shasun Jain College for Women, CHENNAI

sangeethamohanraj.m@gmail.com)

²(Assistant Professor

Department of Management

TKR College of Engineering and Technology,

Medbowli, Meerpet Rn Reddy Rr Dist,Tg

drbrajendranath@gmail.com

Abstract. Rapid integration of generative artificial intelligence (AI) into enterprise processes highlights critical gaps in workforce readiness in terms of skills required for successful implementation of new technologies. This paper introduces a framework which will enable use of generative AI for conducting dynamic skill gap analysis and providing personalized recommendations for upskilling. The framework includes mapping of competencies according to shifting role demands, individual performance assessment through AI and adaptation of learning path for each individual based on results. Using the information obtained from surveys about AI adoption in enterprises and competency maps developed in recent research, this paper will show how generative AI can be used for making static learning programs adaptive and relevant to the current needs of learners. The problem discussed in the paper is related to not only technical AI literacy, but also to human skills, such as critical thinking, ethical decision-making and change management. Comparative analysis of methods shows that personalized training offered by generative AI is more engaging and relevant than generic models of training programs.

Keywords: Generative AI, Skill Gap Analysis, Personalized Learning, Workforce Upskilling, Human-AI Collaboration, Competency Mapping, Enterprise Training

I. Introduction

The proliferation of generative artificial intelligence technology has resulted in a pressing need for workforce transformation that has never been more evident before. The reason is that the latest wave of automation technology, unlike all previous waves, enters the areas traditionally attributed exclusively to human skills—such as knowledge work, creative processes, and analytic reasoning. As a result, an ironic situation has emerged wherein technologies designed to enhance human capabilities find themselves in workforces whose personnel does not have necessary skills to implement those technologies effectively. According to surveys conducted in the industry, the majority of companies consider skill shortages to be the main factor preventing their organization from extracting value from AI investments [1] [3].

However, the magnitude of the challenge cannot be overstated. In the coming years up to 2027, generative AI is anticipated to require a large proportion of the engineering labor force to develop new capabilities such as prompt engineering, retrieval-



augmented generation, and human-AI collaboration [1]. Apart from technical roles, general workers now require basic AI literacy skills, data analysis capabilities, and the critical skills necessary to critique AI-based results. The skills that are most desirable in an AI-augmented world do not lie in technical knowledge alone; rather, analytical skills, resilience, adaptability, leadership, and social influence are perennially high on the list of desirable skills [5].

Current methods of training in business tend to use a standardized curriculum on set schedules, which does not allow for the identification of specific skill deficiencies, nor is the training customized based on roles. This leads to a disconnect between training availability and training needs. Employees state that there is a lack of support from their organization to acquire the necessary skills to work with generative AI technologies, whereas leaders note that training investments need to be made alongside AI investments if the latter is expected to succeed at all [2][4][7].

However, generative AI technology provides a promising solution to this problem by being able to diagnose the competency level of the person, assess their skill gaps in relation to the new role requirement, and suggest learning activities to help individuals build their skills accordingly. Recent studies have been conducted into how artificial intelligence can be used to create a tutoring system and adapt learning process based on the learner's needs. Some findings show that learners who receive personalized guidance tend to achieve better results in skill acquisition and performance compared to those taught uniformly [8].

But then, application of generative AI for skill gap assessment and upskilling suggestions poses various technical and ethical challenges. Validity of competency identification, ethics and bias in recommendations generation, protection of personal data of employees, and possible amplification of biases need to be considered. Besides, the proposed framework should also take into account the fact that a lot of employees approach AI with anxiety and distrust; trust needs to be established by demonstrating the benefits [2][5][7].

The purpose of this paper is to develop a systematic methodology for skill gap analysis using AI-based methods and recommendations of personal upskilling. Competency mapping, AI-based assessment, and pathways adaptation have been integrated into the methodology. The paper analyzes results of comparative performance of training methods and discusses possible implementation implications of the process. Structure of this paper includes: Literature Survey which provides a review of existing research on workforce skill gaps, AI-based skill assessment, and human-AI collaboration; Methodology which describes proposed framework and its operation; Analysis of results and comparative evaluation of proposed framework and finally Conclusion.

II. Literature Survey

The research related to the skills gap problem in the field of generative AI has developed very fast since 2023, leading to an extensive number of publications devoted to competence-based approaches, assessment techniques, and upskilling opportunities. The review of existing studies proves some recurring trends concerning the nature of the issue and solutions to it.

For example, Salem et al. performed a wide-ranging study of the usage of generative AI by Dubai government employees who were interviewed and answered questionnaires. They concluded that even though the majority of users appreciated the positive aspects of using generative AI like time saving and better-quality work, there was no proper training for those who wanted to use it despite the willingness. The authors also noted such problems as mistakes in output, violation of data privacy and biases in results [2].

The third annual Wharton-GBK AI Adoption Report was produced by Puntoni, Tambe, and Korst and surveyed roughly 800 high-level executives from U.S. companies. Their research revealed a trend of transition from the experimental stage to full-scale adoption as 82 percent of executives said they employed generative AI on a weekly basis and three out of four expressed satisfaction with their ROI. Importantly, the authors stressed that human capital was one of the main levers of success as 43 percent of executives mentioned skill atrophy as a threat and 49 percent listed recruitment of Gen AI as their primary problem [3].



Capgemini Research Institute conducted a study of 1,500 leaders/managers together with 1,000 employees in 15 countries to understand how the implementation of generative AI will change the structure of responsibilities and roles. It was found that employees believed that in a year, one-third of entry-level jobs will be accomplished with the help of generative AI and, hence, transformed from creative to evaluative. Authors have stated that 97 percent of leaders have tried generative AI applications but only 15 percent of them use them regularly, pointing out the existing gap between trials and usage. They concluded that organizations need to reconsider career paths, change the structure of collaboration between humans and AI and develop appropriate competencies [4].

Business at OECD (BIAC) reviewed the changing skill requirements in AI-impacted occupations relying on the information provided by WEF and OECD. Authors separated three levels of AI competencies: technical skills in AI necessary for specialists; general AI literacy which is needed by most people who work with AI technologies; and ethical AI. Authors highlighted that although analytical thinking is highly valued now, soft skills like resilience, flexibility and leadership become more and more important [5].

Maiti, Rafalson, and the Coursera Skills Research Team examined nearly six million enterprise learners from more than 7,000 institutional customers for their Job Skills Report 2026. Their findings showed that enrolments in generative AI increased by 234 percent on a yearly basis, while enrolments in critical thinking increased by 185 percent for GenAI learners. They noted that among skills that learners were most interested in for Generative AI was the content creation skill, suggesting that proficiency in Generative AI is becoming important even for non-technical jobs. In addition, the authors described the closing gender gap in technical training and a 91 percent increase in professional certificate enrolments [6].

Oliver Wyman Forum conducted a survey of 25,000 respondents in 16 countries on the impact of generative AI on businesses and societies. The authors concluded that 55 percent of employees were using Generative AI at least once a week, but 61 percent did not consider the technology very reliable. The authors noted that 80 percent of white-collar workers wanted to get better AI training, but only 64 percent got it. The authors proposed a "people first" strategy requiring massive training and support, communication, and job-specific reskilling [7].

In this regard, Google Cloud has created an informative course with the name of "Unleash Team Potential: Assess Learning Needs Using GenAI," which explains how managers can use generative AI in order to assess the skills of their teams as well as provide them with career development recommendations. In the course material, it has been elaborated upon how one can create an AI-based survey, analyze its findings and accordingly devise a learning plan [8].

In addition, Tambe and Puntoni, together with their industry partner Korst, have explored more deeply the dimensions of human capital related to the adoption of generative AI technology in their 2025 study. They have discovered that with increased usage, 43 percent of respondents have reported potential risks of skills proficiency loss. The authors have stressed that the issue is not about substitution but about readiness, and companies that will put efforts in training, culture, and controls will find themselves better prepared to take advantage [10].

However, despite the growing number of research papers on this topic, there are still three significant gaps in this scientific area. Firstly, most of the frameworks provide information about the required competencies but do not give enough details about how generative AI can assess the proficiency level of the individual. Secondly, only a few research works combine the processes of assessment, gap identification, and recommendations generation in one continuous process. Lastly, there are very few studies addressing how to prevent the issues of algorithmic bias and employee data protection in upskilling processes using AI technology. The methodology described in the next section is aimed at closing these gaps.

III. Proposed Methodology

The suggested approach for generative AI-enabled skill gap analysis and personalized upskilling recommendations includes five interrelated elements: competency modeling, multi-source assessment, skill gap analysis, recommendations generation, and refinement. The framework is intended to be applied on three different levels – individual, group, and organizational – and adapt to the level of analysis.

Competency Modeling

This framework starts with a dynamic competency model that captures the competencies needed to perform effectively in augmented roles. Unlike traditional job descriptions, the competency model will be regularly reviewed and updated to incorporate changing requirements, new tools, and organizational priorities. The competency model has three competency domains: technical AI competencies (such as prompt engineering, evaluation, and competence with specific tools), general AI literacy (knowledge of AI capabilities and limitations, interpretation of data, ethical considerations), and human skills that remain important no matter what.

The architecture of the competency model is presented in Figure 1, which shows the three competency domains as well as their connections to the role archetypes. The use of competency domains by different role families is demonstrated in the figure.

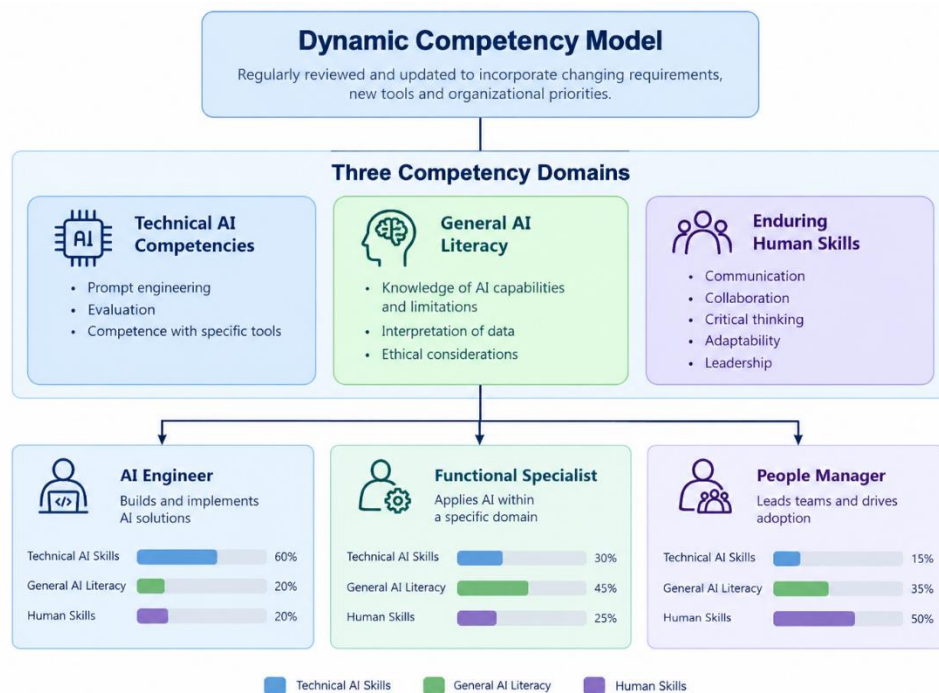


Figure 1: Competency Model Architecture

Multi-Source Assessment

Competency assessment utilizes various sources of data to create a complete overview of individual competence. The main method of competency assessment is conversation: the generative AI agent interacts with the employee in role-appropriate scenarios testing their comprehension, problem-solving skills, and ability to make judgments. Contrary to multiple choice tests, a conversation allows for clarifying the answers of the individual and presenting new situations that require using various competencies. Additional sources of data for assessment could include self-reflection questions, comments of the managers about the performance of the employee, and analysis of work results if possible and appropriate.

The conversation agent is set up to use role-specific scenarios and scoring criteria. For instance, an employee working in marketing might receive a scenario when some of the content created by AI is factually incorrect, and the employee is required to detect the problems, suggest corrections, and provide explanations of the reasoning.

Gap Analysis

The gap analysis section measures the proficiency levels of an individual against the competencies described in the competency model for both the present job and the future ones. The gaps are identified based on two parameters: first is the level of

proficiency and the other two being criticality and urgency, which is how important the competency is and the time frame within which it is required.

Generative AI model employs the assessment information to come up with gap profile for the individual and point out those areas which require development. Gap Profiles are aggregated to give an overview of gaps at the team and organizational level which gives an idea about what areas are weak in the organization. Figure 2 depicts the flow of Gap Analysis.

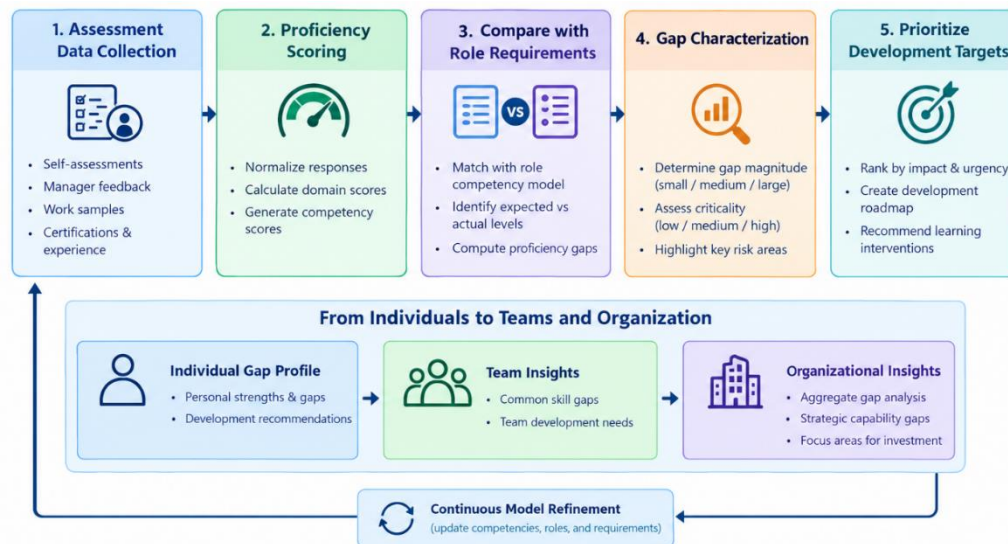


Figure 2: Gap Analysis Workflow

Recommendation Generation

The recommendation engine produces upskilling paths tailored to the user's gap profile, learning style, amount of time available, and the organization's learning materials. Recommendations take different forms depending on the needs of the learner such as courses, micro-learning sessions, practice questions, project assignments, mentoring relationships, and peer learning situations. The AI engine will then build upskilling paths that make sense and have realistic timeframes.

The key difference about the recommendation system is the integration of learning into the workflow of the person. Instead of creating separate learning experiences, the system finds ways for the learner to practice and reflect in their existing tasks. If a worker has a gap in prompt engineering, then they will get a recommendation to employ certain prompt techniques in their next task along with a quick instruction video and a reflection question.

Continuous Refinement

The system includes continual learning and improvement process. The results of assessments, recommendations accepted by user, completion of learning and subsequent results of reassessments are used in the competency model and recommendation engine to increase the quality and relevance of results. It forms a positive loop, when the system starts to become more and more familiar with the context.

IV. Analysis

Analysis of the framework's likely effects on potential uses is based on available information from surveys, implementation cases of AI-powered training, and comparison of different training formats. There are three aspects that need to be taken into consideration: the extent of the skill gaps and their nature, the efficiency of personalized versus standardized training, and implementation aspects.

The Skills Gap Landscape

Data from various surveys show a clear trend: majorities within organizations have identified significant skill gaps that hinder the implementation of AI technology, while individuals have cited a lack of training as the biggest obstacle. According to enterprise surveys, most companies offer some training related to AI technology, but training practices are inconsistent and lack depth. While the two most popular ways to train people on AI technology are general courses and tools, certification programs and institutional partnerships could be more beneficial in developing the necessary skills.

Figure 3 depicts the relative training expenditure in different functional departments using data from a business survey. The figure indicates the distribution of various types of training and the disparity in tool availability and skill development.

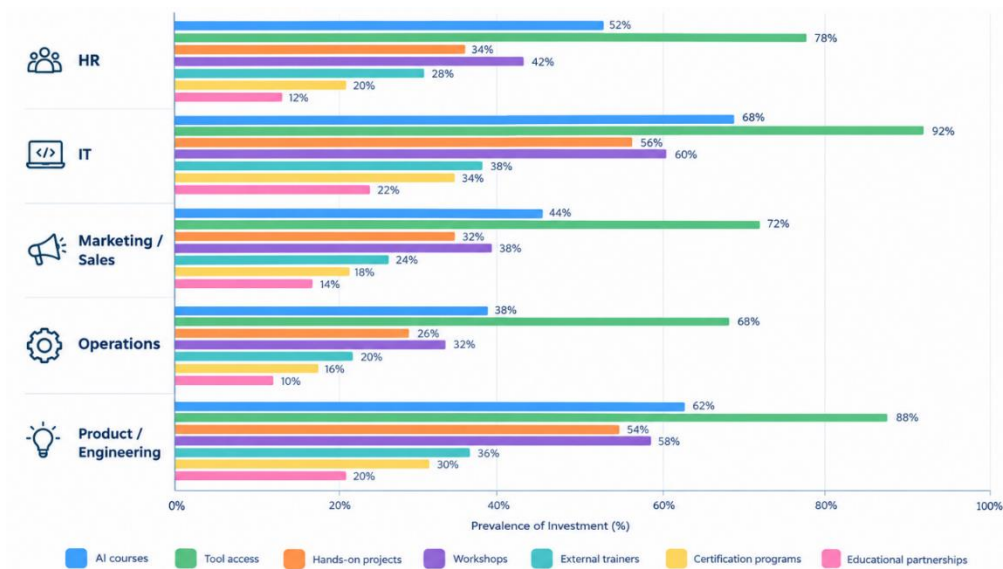


Figure 3: Training Modality Prevalence by Function

Based on the information, whereas the availability of tools and courses is extensive, there are relatively few opportunities for more intensive learning approaches that would have higher potential for competence development. These include certification programs, external training, and educational alliances, which are less common than exposure approaches that do not necessarily help in gaining skills needed for AI application.

Comparative Effectiveness of Training Approaches

Comparisons have shown that customized, participatory, and practical trainings result in much more positive results when compared to traditional trainings. There are numerous studies conducted on AI-based tutoring and adaptive learning systems that show significant benefits for upskilling and retaining knowledge. Companies that apply customized learning paths report higher engagement levels than companies using traditional training programs.

Figure 4 offers a comparative analysis of training methodologies from the perspectives of personalization, scalability, engagement, practical application, and cost-effectiveness. This is done through the use of a comparative framework in the figure below.



Figure 4: Comparative Evaluation of Training Approaches

From the above comparative analysis, it is evident that AI-based personalization presents the best blend of personalization and scalability but involves initial investments in the form of development of the system and data infrastructure. The blended approach which combines the best of both worlds (AI-based personalization and human coach) might be the optimal choice.

Comparative Analysis Table

Table 1 below provides a detailed comparison between the suggested model and traditional training methodologies on various criteria.

Table 1: Comparative Analysis of Skill Gap Analysis and Training Approaches

Dimension	Conventional Training	Generative AI-Based Framework
Assessment method	Self-report, periodic evaluation	Conversational, continuous, role-contextualized
Gap identification	Aggregate, lagging	Individual, granular, real-time
Personalization	Limited, cohort-based	High, individual pathway generation
Content adaptation	Static curriculum	Dynamic, responsive to progress
Scalability	Moderate, constrained by trainers	High, AI-mediated
Feedback loops	Delayed, summative	Immediate, formative
Workflow integration	Separated from work	Embedded in tasks
Cost structure	High fixed cost, low marginal	High development, low marginal
Data requirements	Minimal	Substantial (competency data, learning history)
Bias risk	Human trainer bias	Algorithmic bias, training data bias



This comparison points out the main strength of the generative AI approach, which is its ability for continual, personalized, and contextualized assessment and recommendation, as well as the main limitations, such as the need for data and potential for bias. Traditional training is simple and cheap but cannot cope with fast-changing skills.

Discussion of Implementation Considerations

The successful implementation of this framework should take into account certain aspects of implementation. One of the most important is data privacy and security. The information about employees' competencies is personal data, and therefore, the employees should believe that their data will be used not for punishment but for their development. Clear explanation of how this system works, which data it uses, and how the recommendations are formed makes this trust possible.

Algorithmic fairness is one of the key aspects of implementation. The algorithm can reproduce historical data on competencies and thus perpetuate the previous biases in the training process or evaluation. Auditing recommendation outputs for different impacts on different demographics is crucial in this regard. Certain measures should be taken to increase equitable access.

The smooth integration of the framework into current learning infrastructure is essential for its successful implementation. The framework does not need to change the existing learning management systems, human coach relations, and organizational development programs. The human review of recommendations generated by AI algorithms is critical.

V. Conclusion

The above research has provided an organized framework for generative AI-based employee skill gap analysis and upskilling suggestions. The framework caters to an important problem faced by organizations today – namely, the increasing disparity between the skills required to utilize generative AI effectively and the skills of the existing workforces. Through dynamic competency modeling, conversational assessment, detailed gap analysis, and personalized recommendation generation, the approach promises to provide a more flexible solution than traditional approaches to training.

There are many takeaways from the literature and analyses performed. First of all, there are many components of the skills gap in question, which include not just technical skills but also literacy and human skills. Only training programs that cover all three components are able to provide necessary skills to work together with AI effectively. Second of all, personalization counts. The curriculum that includes all required courses but follows the standardized schedule won't be able to keep up with the rapid development of AI tools and roles they require. Generative AI allows for personalized learning experience. Third of all, it is important to pay attention to trust, equity and integration with workflows.

The suggested model does have its limitations, since it requires competency models to be available and of adequate quality, the availability of enough assessment data and the organization's commitment to developing the employees. For those organizations that do not consider training an important part of their strategy, but use it merely to comply with legal requirements, the potential of the model will go unfulfilled.

There should be more studies conducted in order to empirically prove the efficiency of the framework in real organizational settings, to refine the assessment processes in terms of validity and reliability, as well as to examine the long-term consequences of such learning for individuals and organizations. The inclusion of agentic learning with AI-augmented decision-making can be viewed as a valuable direction in this case.

The underlying premise in this writing is the recognition that the generative AI technology is not just something that replaces capabilities but also a great vehicle through which such capabilities can be built. Those who take advantage of the ability of the technology to personalize, scale and adapt will be more likely to tap into the promise of productivity and innovation offered by AI technology. It is not an either/or decision between AI or capability because it could end up being a neither/nor scenario where companies will end up failing in their investments because of using powerful tools in inadequately prepared workforces.



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