

Ai-Based Android Application For Hr Competency Mapping in Construction Companies: A Machine Learning Approach To Talent Management

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Abstract

Construction is a project-based, labour-intensive and risk-prone industry in which organisational performance depends heavily on the competence of engineers, supervisors, planners and site staff. Traditional competency mapping in construction firms is manual, paper-based and subjective, which leads to inconsistent appraisals, delayed promotion decisions and training that is poorly aligned with real skill gaps. This article presents an AI-based Android application that digitises competency assessment and uses machine learning to predict employee competency, quantify skill gaps, assess promotion eligibility and recommend targeted training. The system follows a three-tier architecture comprising an Android client (Java), a PHP REST API with a MySQL database, and a Python AI/ML engine (Scikit-learn, Pandas) based on a Random Forest model. An illustrative employee profile shows how ten competency factors are converted into a competency score, level, skill gap and training plan. The article concludes that mobile, AI-driven competency mapping can improve the objectivity, speed and strategic value of HR decisions in construction organisations.

Keywords: Competency mapping, Artificial intelligence, Machine learning, Human resource management, Construction industry, Android application, Skill gap analysis, Training recommendation.

1. Introduction

Human capital is the most decisive resource in construction. Project outcomes such as cost, schedule, quality and safety are determined by how well people plan, coordinate and execute work in dynamic, site-based environments. Yet Human Resource (HR) practices in many construction companies, particularly small and medium-sized firms in developing economies, remain administrative rather than strategic. Appraisals are periodic, subjective and recorded on paper or in disconnected spreadsheets, and employees are often promoted for tenure or visible short-term results rather than demonstrated, measurable competence.

Competency mapping is the process of identifying the knowledge, skills, abilities and behaviours required for a role, assessing employees against them, and using the result for selection, development, succession and reward decisions. When done well it links individual capability with organisational strategy; when done poorly it becomes a compliance exercise with little influence on decisions.

Two technological developments make a new approach possible. First, smartphones are now widely available, even among site-level staff, which allows assessments to be captured where the work happens. Second, machine learning (ML) can detect patterns across many employee records and generate predictions more consistently than an individual appraiser. Combining the two yields an AI-based Android application for competency mapping that moves HR from retrospective record-keeping to predictive, data-driven talent management.

The problems addressed by this study are that assessment is manual and dependent on the rater, competency data is scattered across sites, skill gaps are identified late, training is generic rather than individual, and promotion criteria lack transparency. The objectives are: (i) to design a mobile-based competency assessment framework for construction roles; (ii) to develop an architecture integrating an Android app, a REST API, a relational database and an ML engine; (iii) to predict competency, identify skill gaps, assess promotion eligibility and recommend training; and (iv) to examine the managerial implications of AI-based competency mapping. The study is significant because it links competency-based HRM with applied AI in an under-researched sector, and uses open-source tools that can run on a standard Apache/XAMPP server, which suits firms with limited IT budgets.

2. Review of Literature

The competency movement in management is usually traced to McClelland (1973), who argued that measuring competence predicts job performance better than conventional intelligence or aptitude tests. Boyatzis (1982) defined a competency as an underlying characteristic of a person that leads to effective or superior performance in a job, and Spencer and Spencer (1993) offered a widely used model of knowledge, skill, self-concept, trait and motive. Prahalad and Hamel (1990) extended the idea to the organisational level through the concept of core competence. In practice, competency models are applied to recruitment, performance appraisal, training needs analysis, succession planning and compensation.

The Resource-Based View (Barney, 1991) holds that sustained competitive advantage arises from resources that are valuable, rare, inimitable and non-substitutable. Skilled and well-matched human capital fits these criteria, so systematically mapping and developing competence turns the workforce from a cost into a strategic resource. Human capital theory similarly treats training as an investment that raises productivity, but returns are realised only when training addresses actual gaps. This places training needs analysis at the centre of the HR cycle and makes data-driven skill gap analysis valuable.

Research on people analytics shows growing use of algorithms in recruitment, performance prediction, attrition modelling and learning recommendation. Tambe, Cappelli and Yakubovich (2019) note that AI promises better HR decisions but that adoption is constrained by data quality, fairness concerns, employee reactions and the difficulty of measuring HR outcomes. Davenport and Harris (2007) argue that firms which compete on analytics embed data-driven decisions in core processes. On the technology side, the Technology Acceptance Model (Davis, 1989) suggests that perceived usefulness and ease of use drive adoption, which is important for a construction workforce with varied digital literacy.

Existing studies on competency mapping in construction are mostly conceptual or survey-based, and most competency tools are desktop HRIS modules built for corporate offices. There is limited work on a mobile-first, ML-driven system designed for construction roles that links assessment, prediction, skill gap analysis and training recommendation in a single workflow. This article addresses that gap.

3. System Design

The proposed system follows the HR competency cycle enhanced with AI: employee profile and competency scores are the inputs; validation, preprocessing and ML prediction are the processing; competency score and level, skill gap, promotion eligibility and training recommendation are the outputs; and these support decisions on training, promotion, succession and deployment, with re-assessment providing feedback to the model.

The application follows a three-tier client-server architecture, shown in Figure 1. The presentation tier is an Android app written in Java that collects input and displays results, communicating with the server over HTTPS using JSON. The application tier is a PHP REST API that authenticates users, validates and stores assessment data, and brokers communication between the app, the database and the AI engine. The data and intelligence tier consists of a MySQL database, which stores employee, assessment, competency, prediction, training and report records, and a Python AI/ML engine built with Scikit-learn and Pandas.

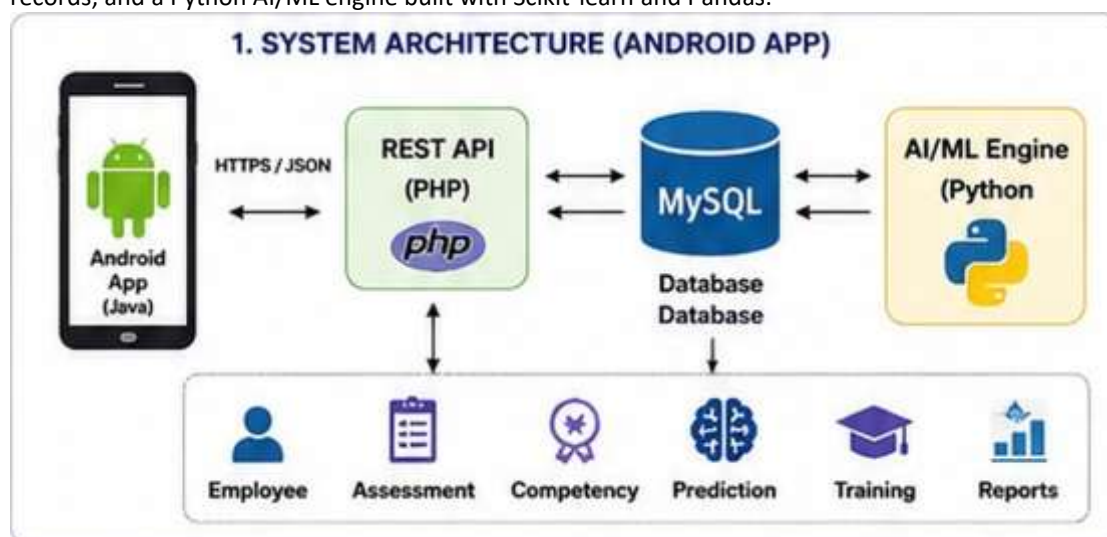


Figure 1: System architecture of the Android application

The Android application is organised into eight modules, shown in Figure 2: Login (role-based authentication), Employee Profile, Competency Assessment, AI Prediction, Skill Gap Analysis, Training Recommendation, Dashboard and Reports.



Figure 2: Android application modules

The process logic is represented by the activity and flow diagrams in Figure 3. The user logs in, selects an employee, fills in the competency assessment, and the data is validated and saved. The data is then sent to the AI model, which predicts competency and branches into three outputs: competency prediction, skill gap analysis and training recommendation. These feed report generation and the dashboard.

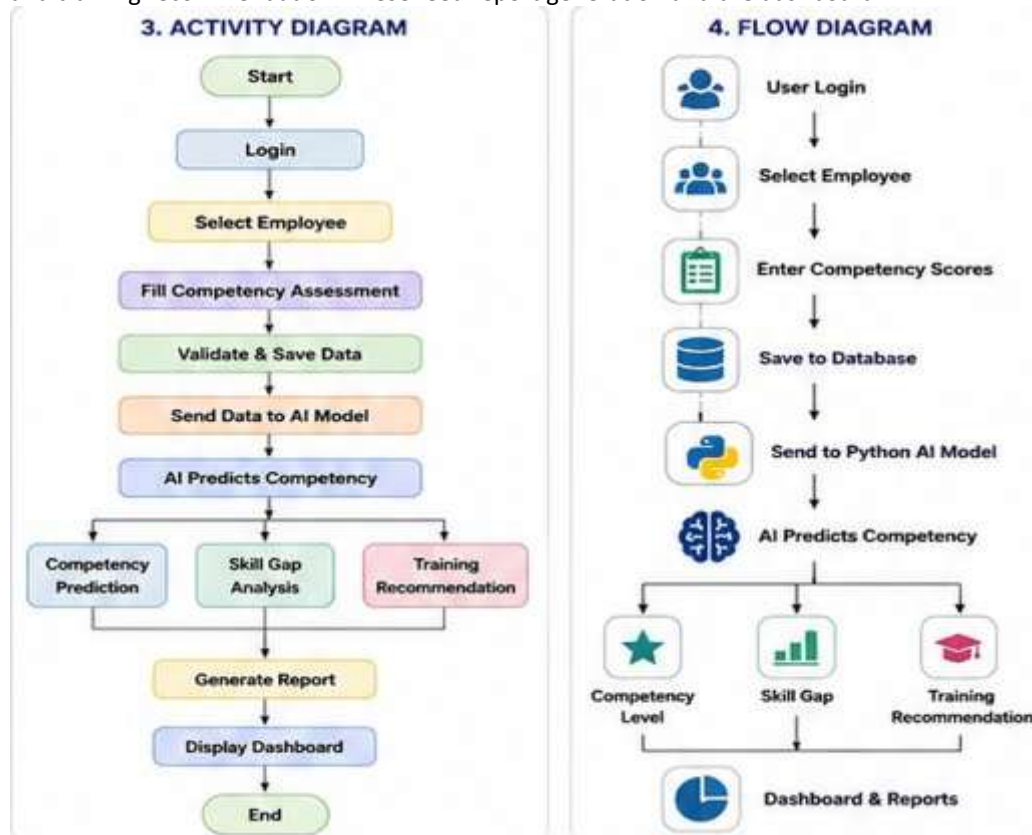


Figure 3: Activity diagram (left) and flow diagram (right)

The interaction between components is shown in the sequence diagram in Figure 4. The app sends a login request, the PHP API validates the user against the MySQL database and returns a login response, and the

assessment is then submitted and saved. The API forwards the data to the Python AI model, and the prediction result is returned to the API and shown on the device.

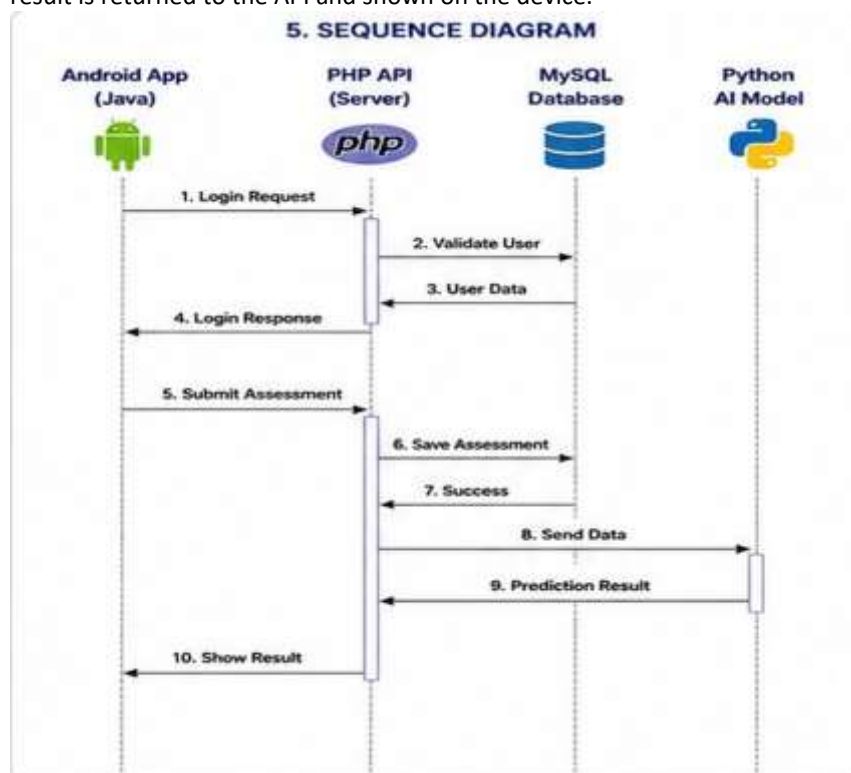


Figure 4: Sequence diagram of the login, assessment and prediction process

4. Implementation

The system is implemented with Java (Android Studio) for the mobile client, PHP for the REST API, MySQL for the database and Python (Scikit-learn, Pandas) for the AI/ML model, hosted on an Apache/XAMPP server with JSON over HTTPS as the communication format (Figure 5).



Figure 5: Technology stack and key benefits

The AI/ML workflow in Python has eight stages, shown in Figure 6. Raw employee scores are collected and preprocessed (cleaning, handling missing values, removing outliers and normalising scales). Feature engineering then selects and combines variables, for example by grouping technical, behavioural and safety scores into composite indices. A Random Forest model (Breiman, 2001) is trained on the data. This algorithm was chosen because it combines many decision trees, handles mixed and non-linear inputs, resists overfitting on modest datasets and provides feature importance measures that support explainability. The trained model predicts the competency score and level, the skill gap is calculated by comparing each factor with the role benchmark, the largest gaps are mapped to a training catalogue, and the result is returned to the app through the API.

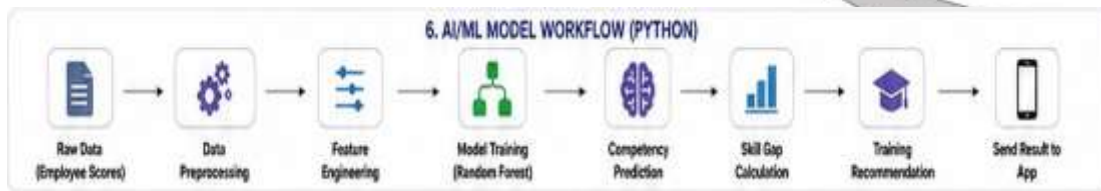


Figure 6: AI/ML model workflow (Python)

The competency assessment uses ten factors scored from 1 to 100, together with experience in years, as listed in Table 1. For model evaluation, the dataset should be split into training and test sets (for example 80:20) with k-fold cross-validation. Classification should be evaluated with accuracy, precision, recall, F1-score and the confusion matrix, and score prediction with RMSE and R-squared, with Random Forest benchmarked against alternatives such as Logistic Regression, Decision Tree, Support Vector Machine and Gradient Boosting.

Table 1: Competency factors used in the assessment

Dimension	Factor	Description
Technical	Technical skill	Core engineering knowledge
Technical	AutoCAD	Drafting and design software
Technical	BIM	Building Information Modelling
Managerial	Project planning	Scheduling and resource planning
Safety	Safety awareness	Site safety and compliance
Behavioural	Leadership	Directing teams and decisions
Behavioural	Communication	Coordination with stakeholders
Behavioural	Team work	Collaboration on site
Cognitive	Problem solving	Handling site problems
Performance	Performance rating	Historical appraisal outcome

5. Result

The following results are drawn from the prototype design and are illustrative; they explain the behaviour of the system and are not empirical findings. The sample employee is a Site Engineer (ID E1005) with 8 years of experience and a BE Civil qualification. The assessment input and the resulting prediction output are shown in Figure 7.



Figure 7: Sample assessment input and AI prediction output

For the sample employee, the model predicted a competency score of 91.35%, a High competency level, promotion eligibility (Yes) and an overall skill gap of 7%, with training recommended. The factor-wise skill gap analysis shows the largest gaps in problem solving (about 22%), leadership (about 18%) and technical skill (about

12%), with smaller gaps in communication and team work. The recommended training programmes are Advanced BIM, Leadership Program, Project Planning, Safety Management and Quality Control. The example shows that an employee can be predicted as highly competent and promotion eligible and still receive targeted development recommendations, which supports both succession planning and continuous improvement. The output screens of the Android application are shown in Figures 8 and 9. The login screen and HR dashboard, the employee profile, the competency assessment form (Figure 8), the AI prediction result and the training recommendation screen (Figure 9) present the workflow from data entry to decision support. At the organisational level, the sample dashboard summarises 850 employees, of whom 310 are high-competency, 420 medium-competency and 120 low-competency, with an average competency of 82%.

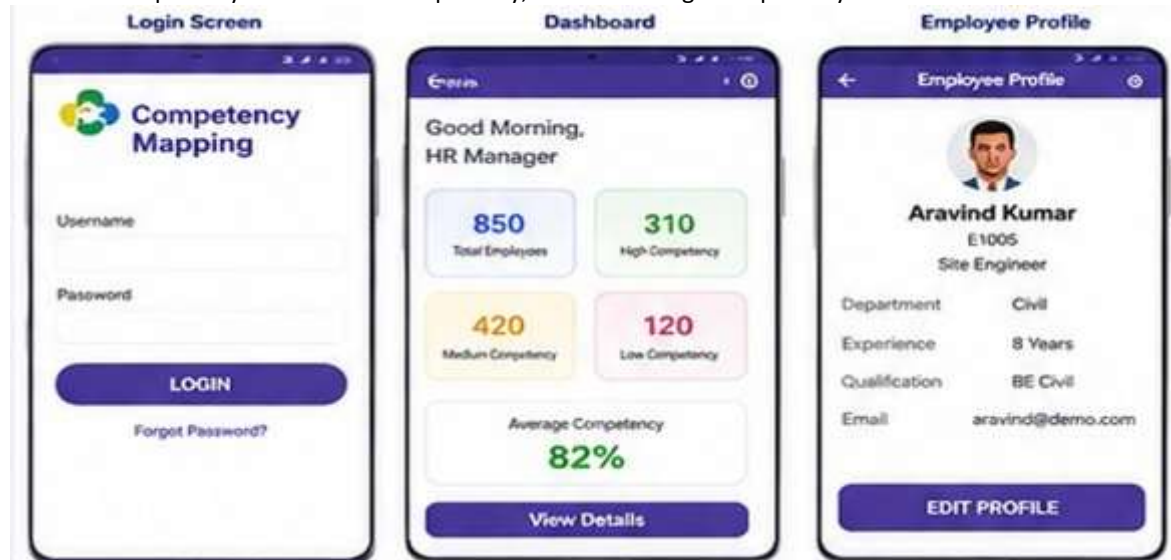


Figure 8: Output screens – login, dashboard and employee profile



Figure 9: Output screens – competency assessment, AI prediction result and training recommendation

The output screens of the implemented prototype are shown in Figures 10 to 19. The application opens with an executive dashboard (Figure 10) and provides an employee directory and an Add Employee form (Figures 11 and 12). Competency is captured on the assessment entry screen (Figure 13), after which the AI prediction screen displays the competency score, predicted level, skill gap percentage, promotion eligibility and model confidence for the selected employee (Figure 14). The training screen lists recommended programmes by priority (Figure 15), the analytics screens summarise competency and skill gaps by department (Figures 16 to 18), and an individual assessment report can be downloaded as a PDF (Figure 19). The sample values on these screens come from the prototype's own demonstration data and therefore differ from the illustrative employee profile discussed above.

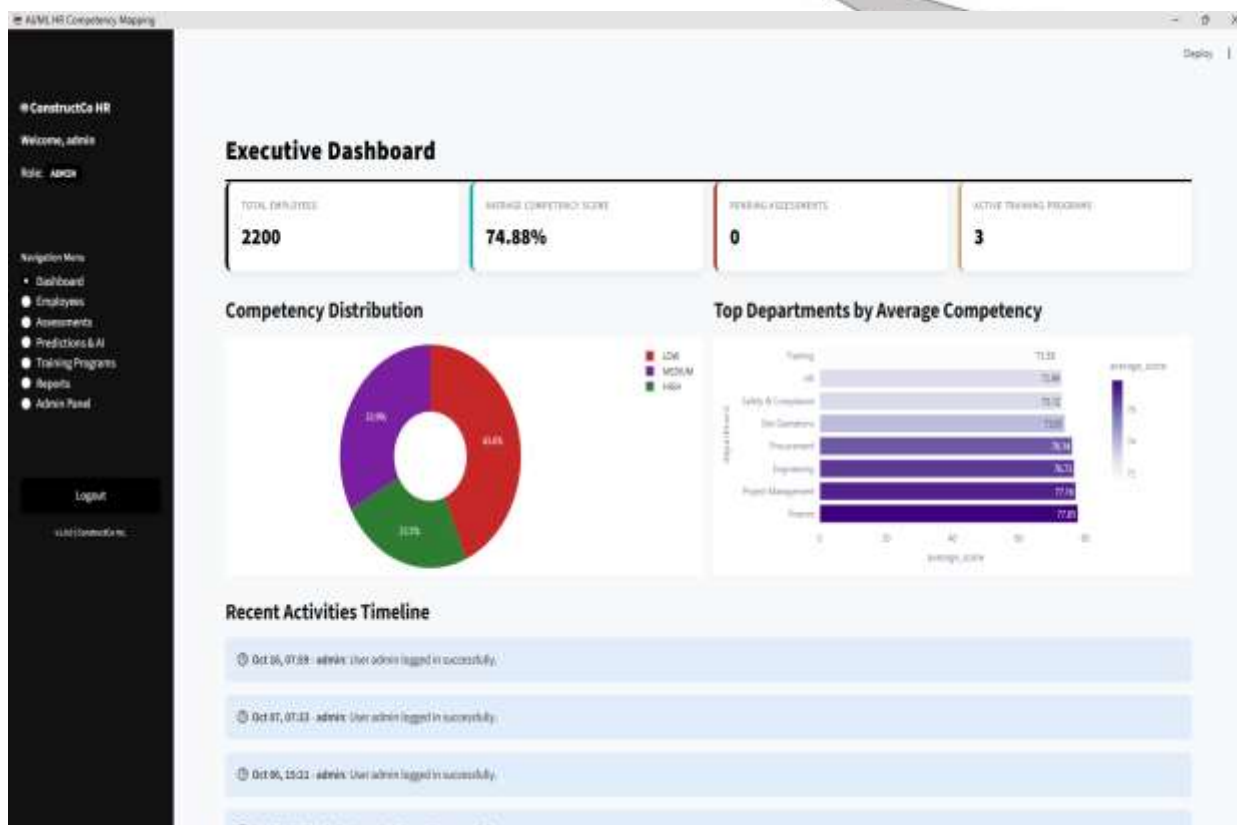


Figure 10: Executive dashboard showing total employees, average competency score, competency distribution and top departments

Employee Directory

Employees List - Add Employee

Search (Name, ID, Email):

Department Filter:

Status Filter:

Showing 50 of 2200 employees.

ID	Name	Department	Designation	Location	Experience	Status
E1001	Amita Kulkarni	Project Management	Project Manager	Ludhiana - Railway Project	5 yrs	Resigned
E1002	Amit Patel	Project Management	Planning Engineer	Jaipur - Corporate Office	3 yrs	On leave
E1003	Rakesh Saxena	Engineering	Chief Engineer	Kolkata - Bridge Construction	1 yrs	Active
E1004	Shruti Gupta	Finance	Accounts Manager	Chennai - Airport Expansion	8 yrs	Active
E1005	Rishika Gupta	Safety & Compliance	Compliance Officer	Ludhiana - Railway Project	3 yrs	Resigned
E1006	Ravi Sharma	Project Management	Assistant PM	Pune - IT Park Development	3 yrs	Active
E1007	Shubh Singh	Procurement	Procurement Manager	Chandigarh - Government Building	6 yrs	On leave
E1008	Shiv Mathur	Project Management	Planning Engineer	Hopur - Industrial Park	2 yrs	Active
E1009	Siba Mathur	Project Management	Planning Engineer	Pune - IT Park Development	18 yrs	Active
E1010	Ronal Chaudhary	Finance	Finance Analyst	Bangalore - Commercial Complex	1 yrs	Active
E1011	Gayatri Desai	Site Operations	Equipment Operator	Kolkata - Bridge Construction	6 yrs	On leave
E1012	Ronal Kumar	Safety & Compliance	Compliance Officer	Hyderabad - Residential Complex	2 yrs	Active

Figure 11: Employee directory with department, designation, location, experience and status filters

Employee Directory

Employee List - 487 Employees

Employee ID (e.g. 01234)

Designation

Full Name

Join Date

2020/12/31

Email Address

Years of Experience

2

Phone Number

Site Location (e.g. Pune - IT Park)

Department

Engineering

Reporting Manager Name

Qualification (e.g. B.Tech Civil)

Save Employee

Figure 12: Add Employee form for entering new employee records

Competency Assessment Entry

Select Employee to Assess

Nisha Reddy (12300)

Assessment Instructions: Evaluate the employee's competency level for each dimension below on a scale of 0 to 100.

Technical Skills	75	Leadership Skills	65
AutoCAD Proficiency	70	Communication	78
3D Knowledge	80	Teamwork	80
Project Planning	70	Problem Solving	75
Safety Management	80	Performance Rating	80

Assessment Comments / Observations

Submit Assessment & Generate AI Predictions

Figure 13: Competency assessment entry form with ten competency sliders



Figure 14: AI-powered competency prediction showing competency gauge, predicted level, skill gap percentage, promotion eligibility and prediction confidence, with the skill gap breakdown against benchmark

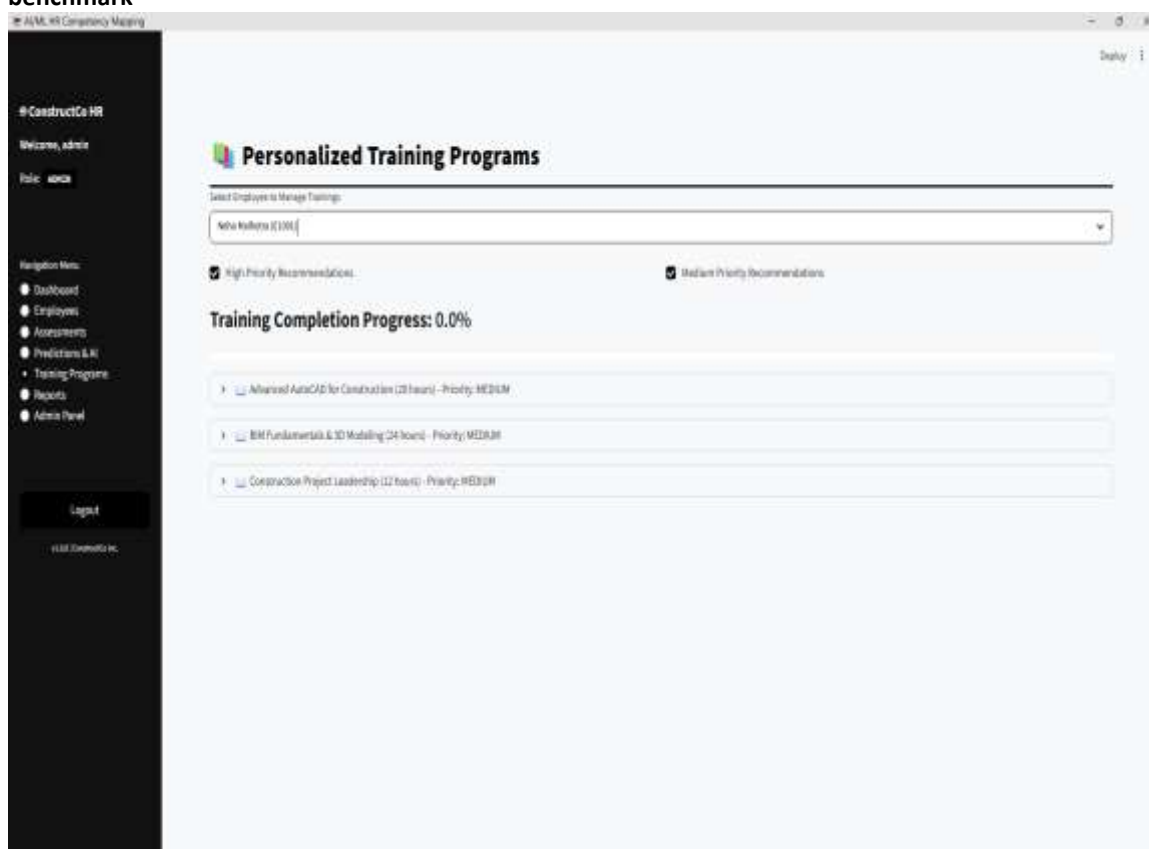


Figure 15: Personalized training programme recommendations with priority filters and completion progress



Figure 16: Analytics reports: average competency score by department

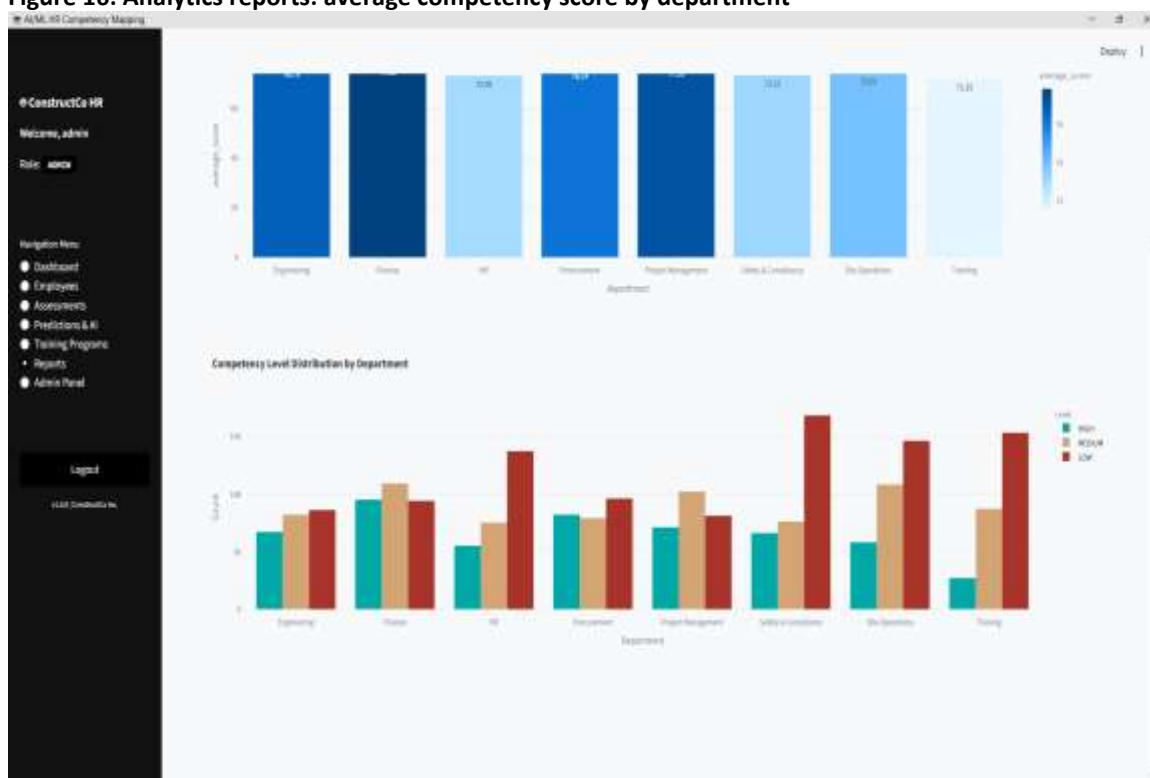


Figure 17: Analytics reports: competency level distribution by department



Figure 18: Analytics reports: average skill gap percentage by department (organisational skill gaps)

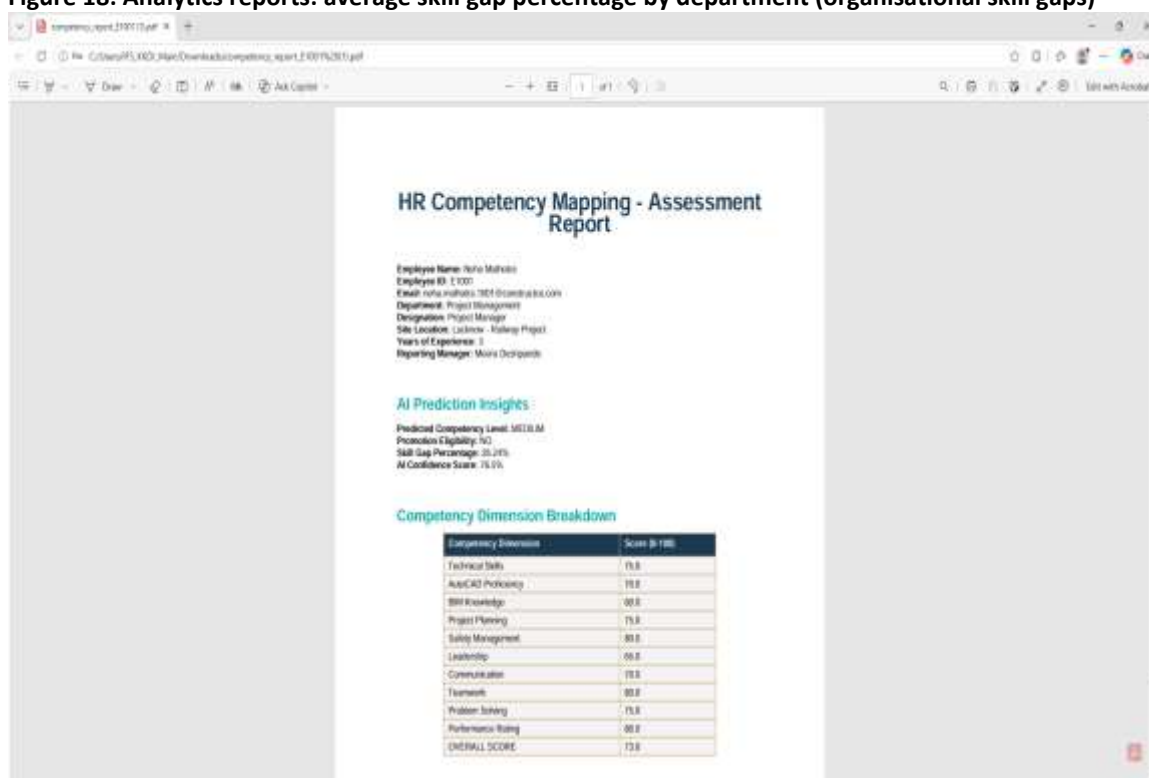


Figure 19: Individual assessment report downloaded as a PDF

The results have several managerial implications. Standardised digital scoring and model-based prediction reduce rater bias and make competency comparable across sites. Promotion eligibility is linked to measurable criteria, improving transparency and perceived fairness. Training budgets can be directed to actual skill gaps, early identification of weakness in safety and quality skills can reduce incidents and rework, and managers can deploy people to projects according to verified competence. Aggregate dashboards give top management a data foundation for workforce planning. Implementation challenges include data quality and rater calibration,

algorithmic bias (sensitive attributes should not be used as predictors and models should be audited), the need for explainability and human oversight, privacy and data protection (for example under India's Digital Personal Data Protection Act, 2023), resistance to change among site staff, poor connectivity on remote sites, and over-reliance on quantitative scores for competencies such as judgement and ethics.

6. Conclusion

Competency mapping is a cornerstone of strategic HRM, yet in construction it is frequently manual, subjective and disconnected from decisions. The AI-based Android application described in this article offers a practical, low-cost approach: it captures assessments on mobile devices, stores them centrally, applies a Random Forest model to predict competency, quantifies skill gaps, evaluates promotion eligibility and recommends tailored training. Grounded in competency theory, the Resource-Based View and human capital theory, the system can make HR decisions more objective, timely and aligned with organisational strategy. Its success, however, depends on data quality, fairness safeguards, human oversight and user acceptance. Construction firms that adopt such tools thoughtfully are likely to build a more capable, safer and more competitive workforce.

7. Future Work

This article presents a system design and an illustrative scenario. Future empirical work should validate the model on real organisational data, compare it with traditional appraisal methods, and test its effect on training effectiveness, promotion quality, safety performance and employee satisfaction. Suggested extensions are:

- A survey-based study using the Technology Acceptance Model to examine adoption among construction HR managers and employees.
- Role-specific competency libraries for site engineers, project managers, safety officers, quantity surveyors and skilled trades.
- Integration with learning management systems and attendance, payroll and project management data.
- Explainable AI techniques such as SHAP or LIME for transparent predictions.
- Longitudinal studies of competency growth after training interventions.
- An offline-first mobile architecture and multilingual interfaces for diverse site workforces.

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