

AI-Driven Workforce Digital Twin for Predictive Human Resource Simulation in Oracle Cloud HCM

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ABSTRACT

The research developed a Workforce Digital Twin powered by AI for predictive simulations of workforces and Human Resource planning that utilizes Oracle Cloud HCM information. Machine learning techniques were utilized for workforce data integration, analysis and modelling. Random Forest has the lowest error rates for prediction of turnover and labor demand forecasting has low error rates. Workforce simulations are used to identify rates of absenteeism, staffing needs and utilization of staff workforce. The results demonstrate the success of Workforce Digital Twins in modernizing workforce planning and talent management and decision making.

Keywords: Workforce Digital Twin, Machine Learning, Oracle Cloud HCM, Workforce Simulation, Labor Demand Forecasting, Turnover Prediction, Talent Management

INTRODUCTION

Background

The needs of businesses are evolving and the organizations are turning into data-driven workforce planning to combat the talent crunch, impediments to productivity. A virtual model of the worker was built, known as a Workforce Digital Twin, in an effort to simulate possibilities, through AI [1]. The investigation for this project is to expand and improve the strategic decisions it can take, as well as optimize staffing, model talent and future resources real time with analytics and predictive insights, with Oracle Cloud HCM's Workforce Digital Twin.

Research Aim and Objectives

Research Aim

The aim is to develop and test an AI-powered Workforce Digital Twin in Oracle Cloud HCM for predictive workforce simulation and HR strategy decisions.

Research Objective

- To investigate workforce management's use of Workforce Digital Twin technologies.
- To create an AI based predictive workforce simulation model on Oracle HCM data.
- To assess the effectiveness of the model to workforce planning and talent management.

Problem Statement

Managing the various workforce issues, such as predicting workforce shortages, fluctuations in workforce demands, absenteeism, overtime utilization, and predicting compliance risks are several challenges faced by organizations [2]. Most workforce management solutions are backward-looking and can't provide predictive

forecasts [3]. This makes it hard for organizations to optimize staffing proactively, as it is time-consuming and results in manual errors [4]. The need of the hour is an AI-powered Workforce Digital Twin in Oracle Cloud HCM.

Novel Contribution

This research builds on the existing Workforce Digital Twin concept implemented in Oracle Cloud HCM, that incorporates Machine Learning, Reinforcement Learning and Generative AI to create a new framework [5]. The Framework's goal is to move beyond traditional workforce management systems by allowing real time workforce simulation, forecasting workforce analysis, staffing optimization and scenario-based decision support [6].

Related Work

Workforce Digital Twin Technology and Its Role in Workforce Management

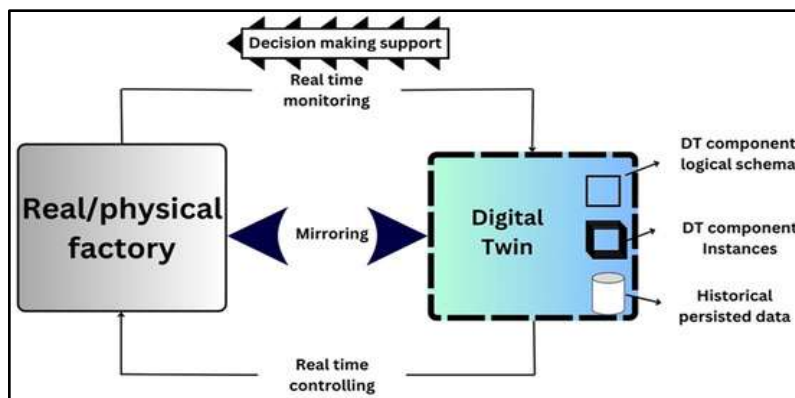


Fig. 1: Impact of Digital Twins on Real Practices in Manufacturing Industries

The implementation of Workforce Digital Twin (WDT) technology addresses the issue of representation of employees, skills, roles and organization processes that proves to be an innovative solution [7]. A digital twin application developed in manufacturing and engineering, WDT allows organizations to develop a workforce replica that can be supported to monitor, analyze and make decisions [8]. Digital twins, combined with workforce data across various HR systems, give researchers the possibility of enhancing workforce visibility, increasing operational effectiveness and making strategic decisions that help to boost workforce productivity [9]. It enables organizations to create work groups to analyze probable work crews, and determine any shortage of skills, as well as test out new policies before they go into effect [10]. The integration with data, privacy concerns, and the difficulty of having accurate workforce representations create a challenge that limits the adoption of workforce digital twins [11].

Artificial Intelligence and Predictive Workforce Simulation in Oracle Cloud HCM

Feature	Oracle Cloud HCM	Workday
 AI & Automation	Enhanced with agentic AI for predictive analytics, automated decision-making, and intelligent task execution	Provides automation but with less advanced AI-driven decision capabilities
 Learning & Development	Dedicated learning module with personalized learning paths and upskilling programs	General learning tools focused on tracking progress
 Analytics & Insights	Advanced, customizable analytics dashboards with predictive insights	Standard analytics with limited customization
 Talent Management	Focus on individualized development and predictive retention strategies	Emphasizes performance tracking and reporting
 Integration & Scalability	Highly scalable and adaptable for large, global enterprises	Strong integration but less flexibility for customization

Fig. 2: Oracle Cloud HCM for Modern AI-Powered HR Solution

The introduction of Artificial Intelligence (AI) capabilities has reshaped the Workforce Analytics provided forever, empowering organizations to predict the challenges ahead and make decisions based on automated decision making [12]. Machine learning algorithms can analyze data from workforces to predict workforce churn, absenteeism, labor need, productivity or workforce health [13]. In addition to its broad workforce-related data that's made accessible through the Oracle Cloud HCM modules like Oracle Workforce Scheduling, Oracle Payroll, Oracle Time and Labor, and Oracle Talent Management, Oracle Cloud HCM enables advanced predictive workforce simulation capabilities [14]. Research recently conducted shows how AI-enabled workforce models are more predictive and efficient than reporting systems in managing resources [15]. Reinforcement learning methods can be used to get staffing decisions to be optimal when business conditions change [16]. Lack of algorithm transparency, and bias with the models still plague predictive workforce systems [17].

Effectiveness of AI-Based Workforce Digital Twins for Workforce Planning and Talent Management

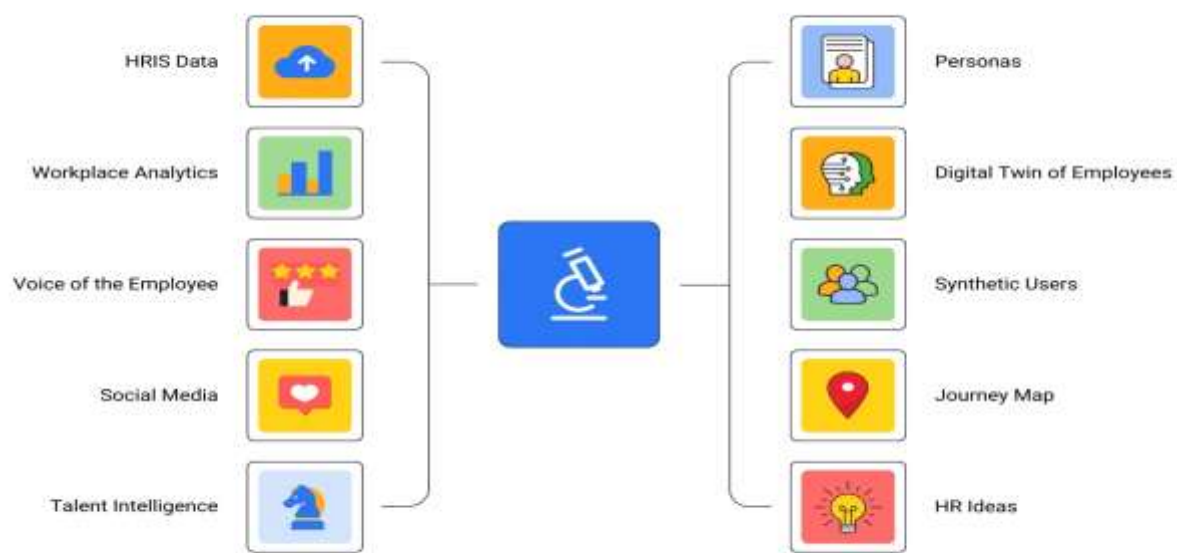


Fig. 3: Digital Twin of an Employee for improving workplace experience

The effectiveness of AI-based Workforce Digital Twins is starting to be recognized in workforce planning and talent management [18]. According to researchers, predictive simulations can inform proactive staffing, optimization of staffing, succession planning and retaining talent [19]. Future workforce scenarios can simulate projected skills shortages and gaps in workforce and potential disruptions to the operation [20]. This AI-driven digital twins can also benefit strategic planning by generating evidence-based workforce development recommendations [21]. Most work primarily addresses workforce analytics instead of enterprise platforms, such as Oracle Cloud HCM, that incorporate a Workforce Digital Twin framework [22]. The space represents a future research avenue to assess the impact of analysis of human workforce using AI-powered Workforce Digital Twins on workforce planning accuracy, talent management efficiency, and overall organization performance [23].

Literature Gap

The current works have tended to be conducted separately on either workforce analytics, a predictive HR model, or simply some generic application of the digital twin [24]. Only few research has been done to examine how to combine WDT technology, AI, and Oracle Cloud HCM data in a single system [25]. There is a lack of empirical assessment of its effectiveness when used for workforce planning [26].

Proposed Framework For Workforce Digital Twin

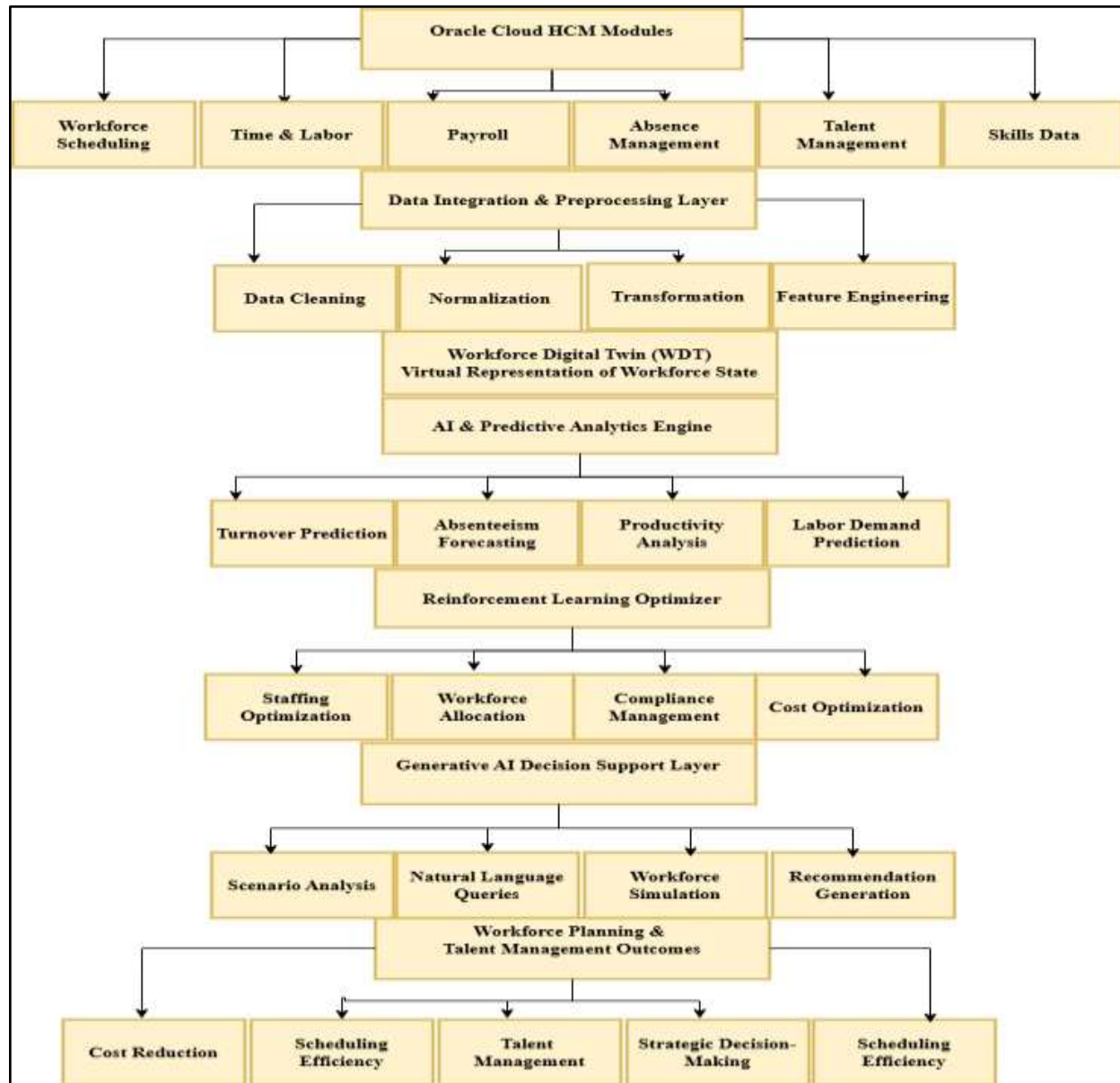


Fig. 4: Proposed Workforce Digital Twin Framework for Oracle Cloud HCM

The proposed Workforce Digital Twin (WDT) is a dynamic virtual representation of an organization's workforce, powered with Oracle Cloud HCM data from the Workforce Scheduling, Time and Labor, Absence Management, Payroll and Talent Management modules [27]. Data integration and data pre-processing are completed and the WDT is derived that reflects workforce states [28]. Labor demand forecasting, absenteeism, turnover, and productivity insights are powered by an AI-powered analytical tool, while reinforcement learning provides a tool for optimizing staffing decisions [29]. Generative AI implementation in businesses can conduct scenario analysis and make better decisions; enhance workforce planning, talent management and optimizing resources; become more efficient [30].

METHODOLOGY

Research Design

This study adopts a Design Science Research methodology to prototype and prototype and validate an AI-based Workforce Digital Twin framework in Oracle Cloud HCM [31]. The approach is suitable as the research develops an innovative artifact for workforce simulation and identifies its effectiveness in terms of workforce planning and talent management [32]. The study is a systems integrative approach with study of application

performance assessment that uses a systems development approach in order to achieve the research objectives identified [33].

4.2 Data Collection

The Workforce Digital Twin is built from workforce data that exists in Oracle Cloud HCM [34]. The data sources contain variables like Workforce Scheduling, Time and Labor, Absence Management, Payroll, Talent Management [35]. These data include details of staff attendance, leave, working hours, overtime, payroll, skills, performance indicators, leave patterns, and workforce requirements [36]. Efforts are made to collect historical data of the workforce for use in predictive modelling and simulation activities [37].

4.3 Data Preparation and Integration

The collected data is preprocessed to assure quality and uniformity [38]. Duplicate or inconsistent records are cleaned and missing data is filled in using data cleaning techniques [39]. The data is preprocessed and then aggregated into a single workforce repository from several Oracle Cloud HCM modules [40]. This integrated data is the basis for developing the Workforce Digital Twin and for the representation of the workforce in real-time [41].

4.4 Workforce Digital Twin Development

An Employee or Skill or a Role or an Operational Workforce Data is used to develop a dynamic Model of the workforce, using a Workforce Digital Twin to simulate workforce behavior continuously [42]. The model is modelled as:

$$WDT = f(E, S, P, A) \text{ ----- (1)}$$

where (E) represents employee data, (S) represents skills, (P) represents productivity, (A) represents attendance [43]. The framework emulates the absence of staff, shortage of staff, overtime, and staffing needs. The framework enables different scenarios of the labor force to be simulated: labor shortage, higher absenteeism, higher or lower overtime, shifting demand for staffing [44].

4.5 Artificial Intelligence and Predictive Modelling

Machine learning algorithms and models like Random Forest with Gradient Boosting and Neural Network classifiers are used to forecast workforce data such as employee turnover, absenteeism, workforce needs, and productivity [45]. The labor demand forecast is done based on the following factors:

$$WD = E + G - L \text{ ----- (2)}$$

The (WD) workforce demand, (E) current employees, (G) workforce growth and (L) employee losses. To ensure compliance and optimize staffing decisions, the decision will be informed by reinforcement learning.

4.6 Model Evaluation

The proposed Workforce Digital Twin will be evaluated using predictive performance and workforce planning outcomes [46]. Workforce utilization will be measured as:

Workforce planning outcomes and predictive performance is measured based on proposed Workforce Digital Twin. The number of staff hours used per person is utilized as:

$$WU = PH/AH \times 100 \text{ ----- (3)}$$

Where (AH) Available hours, and (PH) is Productive hours. The rate of absenteeism is measured at:

$$AR = AD/TD \times 100 \text{ ----- (4)}$$

Here (AD) represents the number of days that are absent and (TD) represents the number of days scheduled [47]. The accuracy, precision, recall, F1-Score, MAE, RMSE metrics along with efficiency of staffing and effectiveness of talent allocation is used as measures to assess model performance.

4.7 Ethical Considerations

The research leads to complying with data privacy and security. All internal data on the employees are anonymized prior to analysis and access to workforce data is limited [48]. Fairness, transparency and bias mitigation in AI models and responsible decision making around hiring will also be a part of the study [49].

4.8 Architecture Diagram

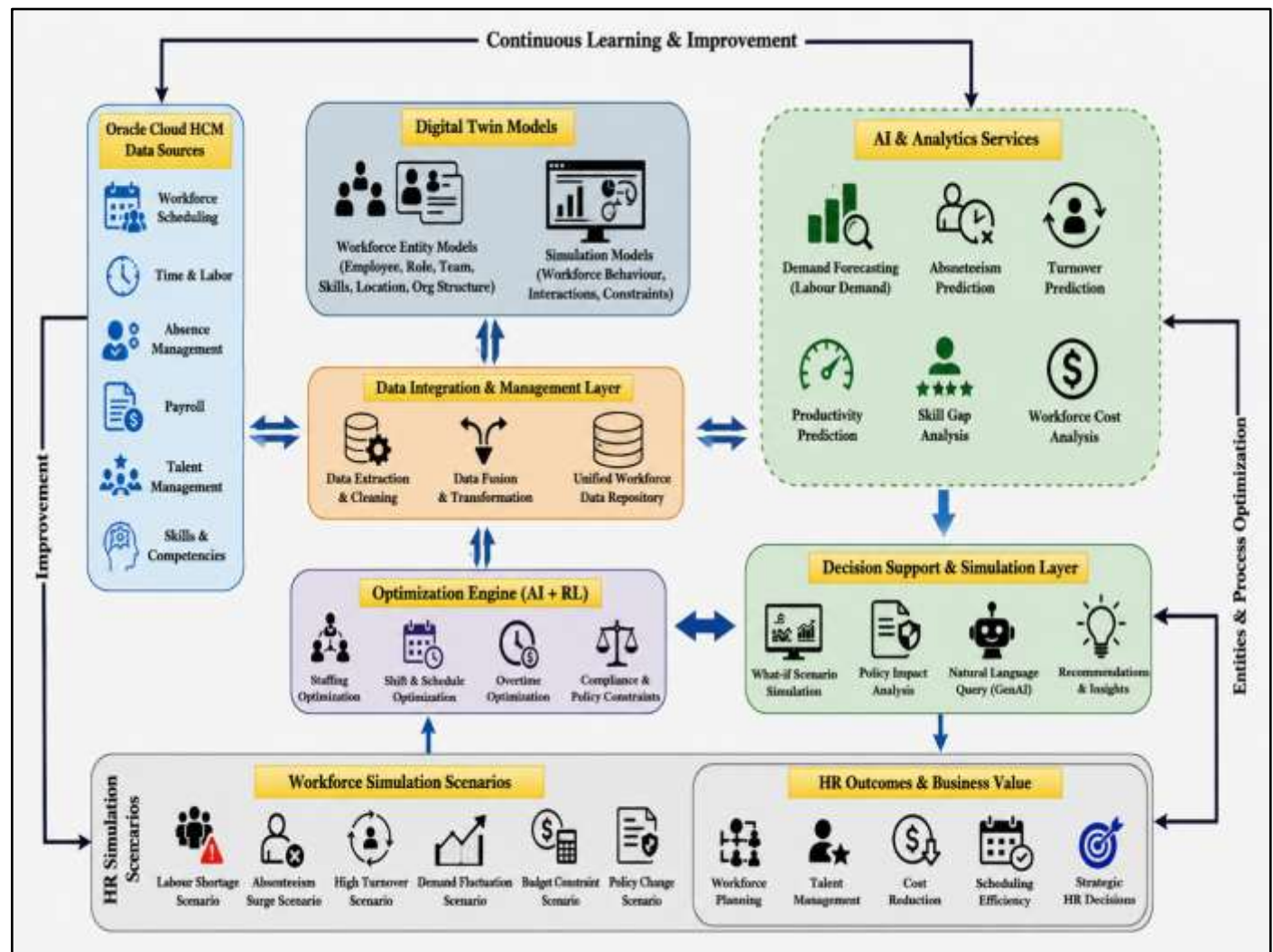


Fig. 5: Architecture Diagram

The architecture leverages Oracle Cloud HCM workforce data in tandem with digital twin models, AI analytics, reinforcement learning optimization, and Generative AI decision support components to allow for workforce simulation, predictive planning, talent management, staffing optimization and strategic human resource decision support [50].

4.9 Pseudocode

```

WDT1
Program to generate AI-driven Workforce Digital Twin simulation
Initialize
    Oracle Cloud HCM data
    Workforce records
    AI models
Inputs
    Scheduling data
    Time and labor data
    Absence data
    Payroll data
    Talent data
Start loop
    IF data missing THEN clean data
    IF new workforce data available THEN update Digital
Twin
    IF absenteeism high THEN predict staffing risk
    IF labour demand changes THEN forecast workforce need
    IF skill gap found THEN recommend talent action
    IF overtime increases THEN optimise staffing plan
    Run predictive analytics
    Run workforce simulation
    Generate HR recommendations
    Display workforce planning output
End loop
  
```

Fig. 6: Pseudocode

The pseudocode gives an overview of the workflow during operation of the Workforce Digital Twin. It continually analyzes data from Oracle Cloud HCM for workforce modeling and workforce forecasting, predicts HR risks, conducts simulations, optimizes HR staffing decisions, and provides intelligent predictions and recommendations to assist businesses in their HR workforce planning and talent management decisions.

4.10 Flowchart

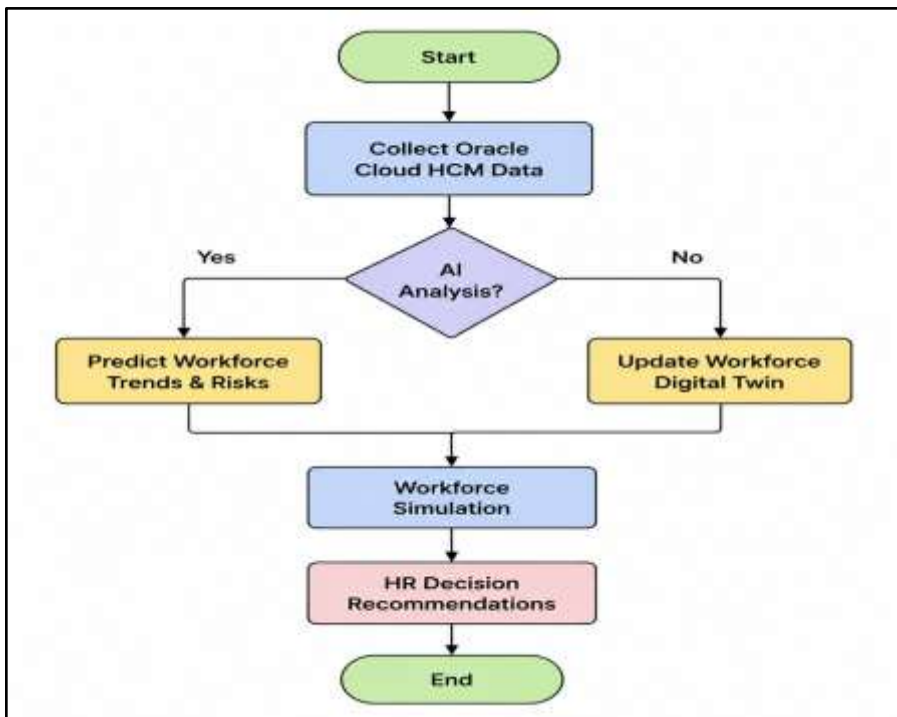


Fig. 7: Flowchart Diagram

The main process of the proposed work is shown in the flowchart. AI models collect and analyze Oracle Cloud HCM data, refresh the Workforce Digital Twin, conduct workflow simulations, and make recommendations to help with predictive workforce planning, talent management and strategic HR decisions.

RESULT AND DISCUSSION

Result

1. Import libraries

```
[1]
✓ 2s
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, RandomForestRegressor
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import mean_absolute_error, mean_squared_error, classification_report, confusion_matrix
```

Fig. 8: Importing Libraries

This figure shows data manipulation, visualization, machine learning and model assessment Python libraries initialization. It can be used for workforce simulation, predicting workforce turnover, forecasting workforce demand, and assessing workforce performance, as well as to help create the Workforce Digital Twin and help guide strategic workforce planning.

2. Load dataset

```
[1]
df = pd.read_excel("workforce_digital_twin_dataset.xlsx")
print(df.head())
print(df.info())
print(df.describe())
```

	Promotion_Eligibility	Workforce_Demand_Level	Staffing_Requirement	%
0	No	Medium	Low	4
1	No	Low	Low	2
2	No	Low	Low	1
3	No	Medium	Medium	5
4	No	High	High	8

	Turnover_Risk	Simulation_Scenario	Compliance_Flag
0	Low	Policy Change	Check Required
1	Medium	Demand Fluctuation	Compliant
2	Medium	Labour Shortage	Compliant
3	Low	Absenteeism Surge	Compliant
4	Medium	High Turnover	Check Required

```
[5 rows x 30 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 30 columns):
 #   Column                                Non-Null Count  Dtype
---  --
 0   Employee_ID                          100 non-null   object
 1   Department                           100 non-null   object
 2   Job_Role                             100 non-null   object
 3   Location                             100 non-null   object
 4   Gender                              100 non-null   object
 5   Age                                  100 non-null   int64
 6   Experience_Years                     100 non-null   int64
 7   Employment_Type                     100 non-null   object
 8   Shift_Type                           100 non-null   object
 9   Scheduled_Hours_Month                100 non-null   int64
10   Actual_Hours_Month                   100 non-null   float64
11   Overtime_Hours                       100 non-null   float64
12   Absent_Days                          100 non-null   int64
13   Late_Arrivals                       100 non-null   int64
14   Attendance_Rate_%                    100 non-null   float64
15   Hourly_Rate_USD                      100 non-null   float64
16   Base_Salary_USD                     100 non-null   float64
17   Payroll_Cost_USD                     100 non-null   float64
18   Skill_Score                          100 non-null   int64
19   Performance_Score                   100 non-null   int64
20   Productivity_Output                  100 non-null   int64
21   Productivity_Score                   100 non-null   float64
22   Training_Hours                       100 non-null   int64
23   Talent_Rating                       100 non-null   object
24   Promotion_Eligibility                100 non-null   object
25   Workforce_Demand_Level               100 non-null   object
26   Staffing_Requirement                 100 non-null   int64
27   Turnover_Risk                       100 non-null   object
28   Simulation_Scenario                  100 non-null   object
29   Compliance_Flag                      100 non-null   object
dtypes: float64(7), int64(10), object(13)
memory usage: 23.5+ KB
None
```

Fig. 9: Loading dataset

This figure represents successful loading of the Workforce Digital Twin dataset with 100 employees and 30 variables associated with this workforce. The built-in Oracle Cloud HCM data are a complete source of data for predictive analytics, workforce simulation, labor demand forecasting, workforce planning evaluation and turnover analysis.

3. Data Preparation and Integration

```
[7] ✓ In: # Check missing values
print(df.isnull().sum())

# Remove duplicate records
df = df.drop_duplicates()

# Fill missing numerical values with mean
numeric_cols = df.select_dtypes(include=["int64", "float64"]).columns
df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].mean())

# Fill missing categorical values with mode
categorical_cols = df.select_dtypes(include=["object"]).columns
for col in categorical_cols:
    df[col] = df[col].fillna(df[col].mode()[0])

print("Cleaned dataset shape:", df.shape)
```

```
✓ Out: Employee_ID      0
Department      0
Job_Role        0
Location        0
Gender          0
Age            0
Experience_Years 0
Employment_Type 0
Shift_Type      0
Scheduled_Hours_Month 0
Actual_Hours_Month 0
Overtime_Hours  0
Absent_Days      0
Late_Arrivals   0
Attendance_Rate_% 0
Hourly_Rate_USD 0
Base_Salary_USD 0
Payroll_Cost_USD 0
Skill_Score     0
Performance_Score 0
Productivity_Output 0
Productivity_Score 0
Training_Hours  0
Talent_Rating   0
Promotion_Eligibility 0
Workforce_Demand_Level 0
Staffing_Requirement 0
Turnover_Risk   0
Simulation_Scenario 0
Compliance_Flag 0
dtype: int64
Cleaned dataset shape: (100, 30)
```

Fig. 10: Data Preparation and integration

This figure demonstrates successful data preprocessing such as checking for missing values and checking that no data is duplicated. This cleaned data is of high quality (100) with consistency (30) and reliability that facilitates Workforce Digital Twin construction, predictive modelling, workforce simulation and workforce planning analysis.

4. Workforce Digital Twin Feature Development

```
[7] ✓ In: # Workforce Utilization: WD = PH / AH * 100
df["Workforce_Utilization"] = (df["Actual_Hours_Month"] / df["Scheduled_Hours_Month"]) * 100

# Absenteeism Rate: AR = AD / TD * 100
df["Absenteeism_Rate"] = (df["Absent_Days"] / (df["Scheduled_Hours_Month"] / 8)) * 100

# Workforce Demand: WD = Z + E - L
# Productivity Score
df["Productivity_Score_Calculated"] = (
    df["Productivity_Output"] / df["Actual_Hours_Month"]
)

print(df.head())
```

```
✓ Out: Employee_ID Department Job_Role Location Gender Age \
0 EMP001 Sales Sales Executive London Female 27
1 EMP002 HR HR Analyst Remote Male 30
2 EMP003 Finance Finance Manager Manchester Female 24
3 EMP004 IT AI Engineer Leeds Male 27
4 EMP005 IT Cloud Engineer Remote Female 28

Experience_Years Employment_Type Shift_Type Scheduled_Hours_Month ... \
0 8 Full-time Day 184 ...
1 11 Full-time Night 168 ...
2 2 Contract Evening 142 ...
3 0 Full-time Night 168 ...
4 5 Full-time Night 168 ...

Talent_Rating Promotion_Eligibility Workforce_Demand_Level \
0 Medium No Medium
1 Low No Low
2 Low No Low
3 Medium No Medium
4 Low No High

Staffing_Requirement Turnover_Risk Simulation_Scenario Compliance_Flag \
0 4 Low Policy Change Check Required
1 2 Medium Demand Fluctuation Compliant
2 1 Medium Labour Shortage Compliant
3 5 Low Absenteeism Surge Compliant
4 8 Medium High Turnover Check Required

Workforce_Utilization Absenteeism_Rate Productivity_Score_Calculated
0 185.271739 4.347626 0.511100
1 187.937500 0.000000 0.422608
2 94.894885 5.611863 0.486891
3 183.812500 0.000000 0.585719
4 43.805048 57.142857 0.403330

[5 rows x 33 columns]
```

Fig. 11: Workforce Digital Twin Feature Development

This graph shows the development of Workforce Utilization, Absenteeism Rate and Productivity Score indicators. These generated metrics convert the raw workforce data into actionable intelligence which can be used to model workforce behaviors and/or assess the productivity, evaluate labor demand, simulate the workforce for predictive workforce and/or conduct strategic human resource planning.

5. Descriptive Analysis

```
[8]
✓ Os: print("Average Workforce Utilisation:", df["Workforce_Utilisation"].mean())
print("Average Absenteeism Rate:", df["Absenteeism_Rate"].mean())
print("Average Overtime Hours:", df["Overtime_Hours"].mean())
print("Average Performance Score:", df["Performance_Score"].mean())
print("Average Skill Score:", df["Skill_Score"].mean())
```

Average Workforce Utilisation: 96.9797051470647
Average Absenteeism Rate: 9.179480557768189
Average Overtime Hours: 10.534
Average Performance Score: 77.66
Average Skill Score: 76.84

Fig. 12: Descriptive statistics

This figure reflects descriptive data in relation to workforce utilization, absenteeism of 9.18%, the amount of overtime worked (10.53 hours), the performance score is 77.66 and the skill score is 76.84% and provides a baseline measurement of workforce evaluation.

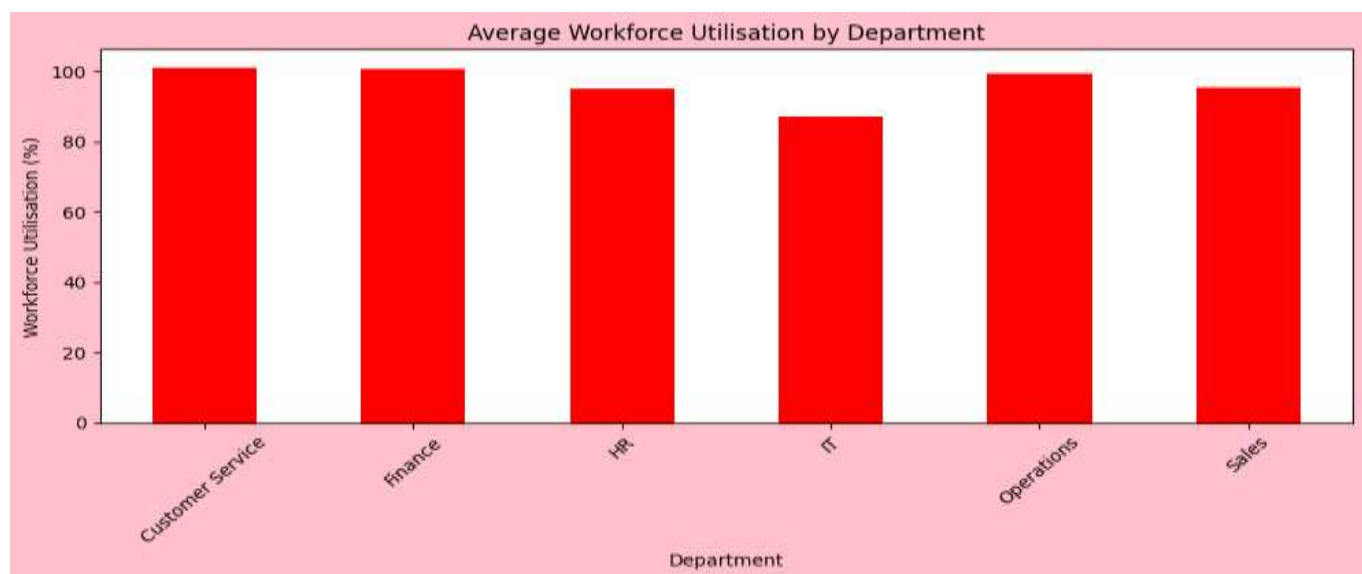


Fig. 13: Average Workforce Utilization by Department

Customer Service and Finance report the most utilized staff, and IT the least utilized staff. The differences show the patterns of workforce capacity within departments and help to support workforce optimization strategies.

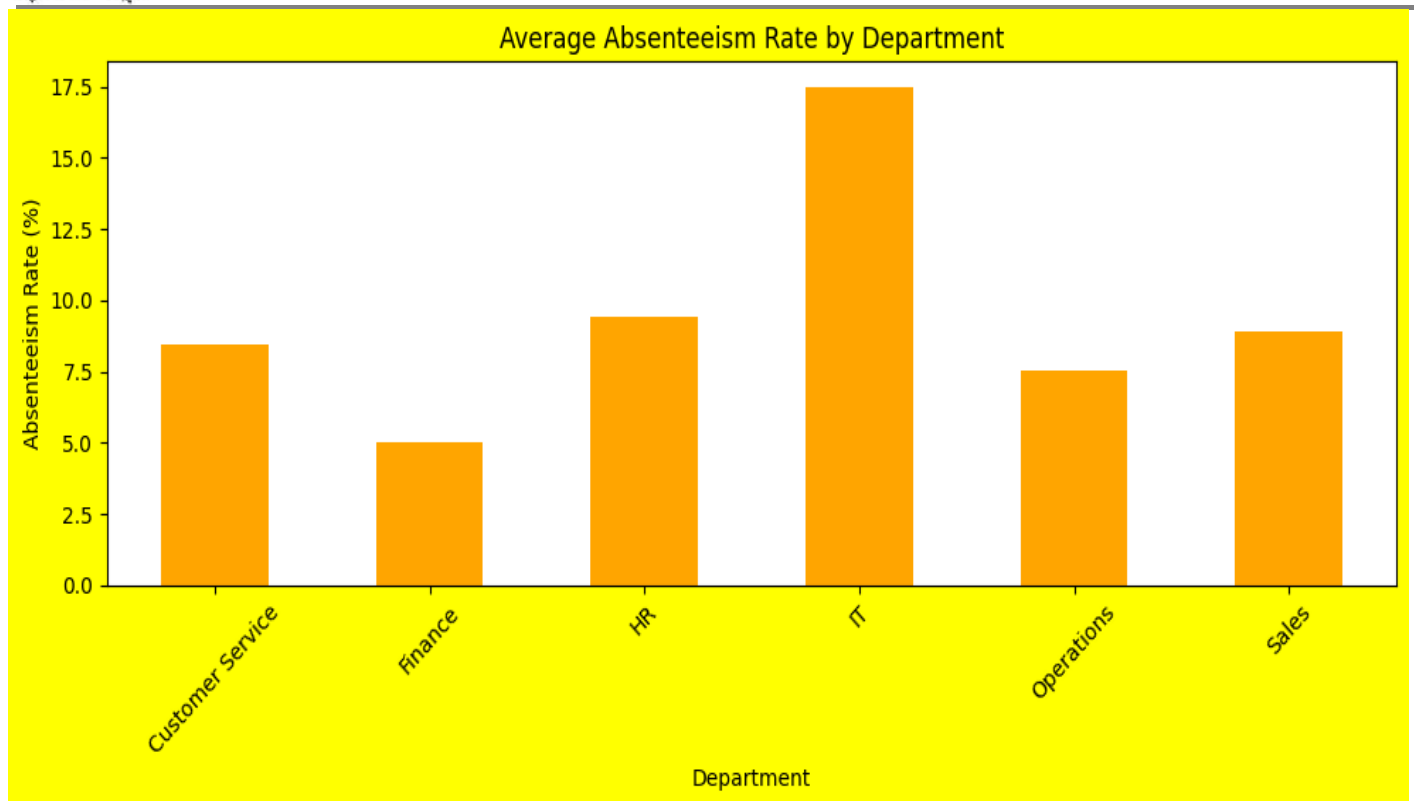


Fig. 14: Average Absenteeism Rate by Department

The best-performing IT department has the highest and the worst-performing Finance department has the lowest absenteeism rate. The data can be used to uncover workforce-related risks with attendance and to help forecast absenteeism, simulate workforce, and make proactive workforce management programs.

8. Encode categorical variables

```
[11]:
df_encoded = df.copy()

label_encoders = {}
for col in df_encoded.select_dtypes(include=["object"]).columns:
    le = LabelEncoder()
    df_encoded[col] = le.fit_transform(df_encoded[col])
    label_encoders[col] = le

print(df_encoded.head())
```

	Employee_ID	Department	Job_Role	Location	Gender	Age	Experience_Years	\
0	0	5	13	3	0	37		8
1	1	2	7	5	1	39		13
2	2	1	5	4	0	24		2
3	3	3	0	2	1	57		0
4	4	3	3	5	0	38		6

	Employment_Type	Shift_Type	Scheduled_Hours_Month	...	Talent_Rating	\
0	1	0	184	...	1	
1	1	2	168	...	0	
2	0	1	142	...	0	
3	1	2	168	...	1	
4	1	2	168	...	0	

	Promotion_Eligibility	Workforce_Demand_Level	Staffing_Requirement	\
0	0	2	4	
1	0	1	2	
2	0	1	1	
3	0	2	5	
4	0	0	8	

	Turnover_Risk	Simulation_Scenario	Compliance_Flag	Workforce_Utilisation	\
0	1	6	0	105.271739	
1	2	2	1	107.937500	
2	2	4	1	94.014085	
3	1	0	1	103.812500	
4	2	3	0	43.869048	

	Absenteeism_Rate	Productivity_Score_Calculated
0	4.347826	0.511100
1	0.000000	0.422698
2	5.633803	0.486891
3	0.000000	0.505719
4	57.142857	0.461330

[5 rows x 33 columns]

Fig. 15: Encode categorical variable

This figure depicts the categorical workforce variables conversion to numeric values by Label Encoding. The re-engineered data is now ready for machine learning models to accurately predict turnovers, forecast labor needs, simulate a workforce, and create a Workforce Digital Twin with the retention of the Workforce category distinctions to enable effective predictive analysis.

```

9. Turnover Risk Prediction

[12] ✓ 4s
X = df_encoded.drop(columns=["Turnover_Risk"])
y = df_encoded["Turnover_Risk"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

rf_model = RandomForestClassifier(random_state=42)
gb_model = GradientBoostingClassifier(random_state=42)
nn_model = MLPClassifier(max_iter=1000, random_state=42)

models = {
    "Random Forest": rf_model,
    "Gradient Boosting": gb_model,
    "Neural Network": nn_model
}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    print("\nModel:", name)
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Precision:", precision_score(y_test, y_pred, average="weighted"))
    print("Recall:", recall_score(y_test, y_pred, average="weighted"))
    print("F1-Score:", f1_score(y_test, y_pred, average="weighted"))
    print(classification_report(y_test, y_pred))

```

Fig. 16: Random Forest classifiers with Gradient Boosting and Neural Network classifiers

The figure depicts the implementation of the Random Forest classifiers, with Gradient Boosting and Neural Network classifiers in the case of turnover risk prediction. Data is splitted in the training and testing sets to test the objective of the predictive performance. To analyze the effectiveness of the models' ability to detect employees at risk of leaving the firm, accuracy, precision, recall and F1-Score are computed. When combined with the Workforce Digital Twin, this predictive analysis can assist HR in making informed decision, planning workforce strategies from the beginning, identifying employee risk with other HR activities and forecasting the ability of different HR activities to attract and retain employees based on a number of factors including their age, residence, experience, and more.

```

Model: Random Forest
Accuracy: 0.8
Precision: 0.7942857142857143
Recall: 0.8
F1-Score: 0.7871794871794872

```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	1
1	0.86	1.00	0.92	12
2	0.80	0.57	0.67	7
accuracy			0.80	20
macro avg	0.55	0.52	0.53	20
weighted avg	0.79	0.80	0.79	20

```

Model: Gradient Boosting
Accuracy: 0.7
Precision: 0.7
Recall: 0.7
F1-Score: 0.7

```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	1
1	0.83	0.83	0.83	12
2	0.57	0.57	0.57	7
accuracy			0.70	20
macro avg	0.47	0.47	0.47	20
weighted avg	0.70	0.70	0.70	20

```

Model: Neural Network
Accuracy: 0.0
Precision: 0.0
Recall: 0.0
F1-Score: 0.0

```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	1.0
1	0.00	0.00	0.00	12.0
2	0.00	0.00	0.00	7.0
accuracy			0.00	20.0
macro avg	0.00	0.00	0.00	20.0
weighted avg	0.00	0.00	0.00	20.0

Fig. 17: Turnover Risk Prediction

Random Forest, Gradient Boosting Models and the Neural Network are compared against each other with regard to their performance in predicting turnover risk. Random Forest has the best predictive power with highest accuracy (80%), precision (79.43%), recall (80%) and F1-score (78.72%). The Gradient Boosting classified the turnover risk with moderate performance, with an accuracy of 70%. The Neural Network did not help to identify turnover risk effectively. The results demonstrate that the Random Forest model is the most appropriate model to support Workforce Digital Twin-based Workforce Planning's and Talent Retention.

TABLE 1: Model Evaluation Of Metrics

Metric	Random Forest	Gradient Boosting
Accuracy (%)	80	70
Precision (%)	79.43	68
Recall (%)	80	70

F1-Score (%)	78.72	70
MAE (Labour Demand)	0.765	0.905
RMSE (Labor Demand)	0.905	1.12
Workforce Utilization (%)	96.98	—
Absenteeism Rate (%)	9.18	—
Average Overtime (Hours)	10.53	—
Performance Score	77.66	—
Skill Score	76.84	—

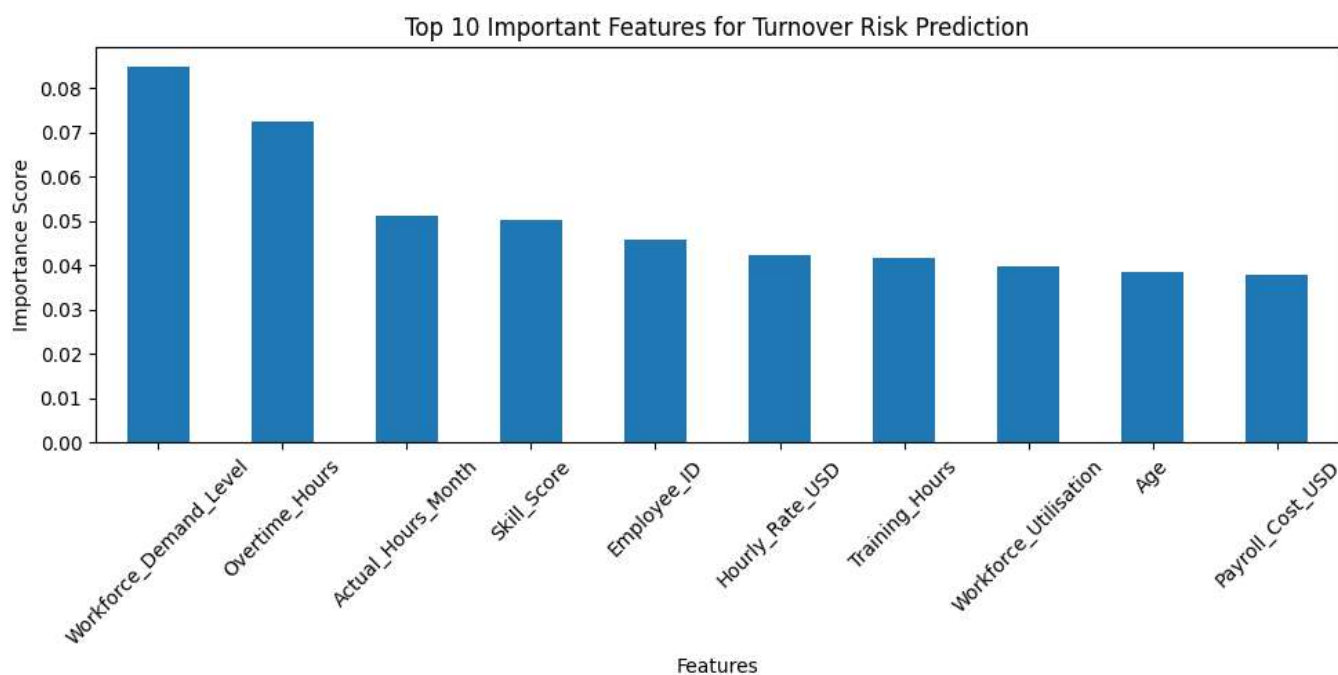


Fig. 18: Top 10 Important Features for Turnover Risk Prediction

This figure contributes to the prediction of top 10 features for turnover. This number is used in predicting top 10 features in relation to turnover. The key four are the different Skill Score, Overtime Hours, Actual Hours Worked/month and Workforce Demand Level, which points to the importance of skill requirements and load, as well as employees' capability. When training hours, workforce utilization, payroll cost and age are added on, the prediction is accurate. The results support various place-based retention initiatives, workforce planning and talent management measures that collectively drive toward the Workforce Digital Twin and research objectives.

10. Labour Demand Prediction using Regression

```
[14] X_reg = df_encoded.drop(columns=["Staffing_Requirement"])
      y_reg = df_encoded["Staffing_Requirement"]

      X_train, X_test, y_train, y_test = train_test_split(
          X_reg, y_reg, test_size=0.2, random_state=42
      )

      reg_model = RandomForestRegressor(random_state=42)
      reg_model.fit(X_train, y_train)

      y_pred = reg_model.predict(X_test)

      mae = mean_absolute_error(y_test, y_pred)
      rmse = np.sqrt(mean_squared_error(y_test, y_pred))

      print("MAE:", mae)
      print("RMSE:", rmse)

      MAE: 0.7694999999999999
      RMSE: 0.9049889502087858
```

Fig. 19: Labor Demand Prediction using Regression

The Regression model predictive errors are found to be low with Mean Absolute Error (MAE) = 0.765 and Root Mean Square Error (RMSE) = 0.905, thus reflecting forecast usefulness. These findings validate the model's accuracy in predicting workforce requirements and the size of the workforce available, enabling proactive workforce planning and effective decision-making, allocation of resources and staffing optimization within the scope and grasp of the Workforce Digital Twin.

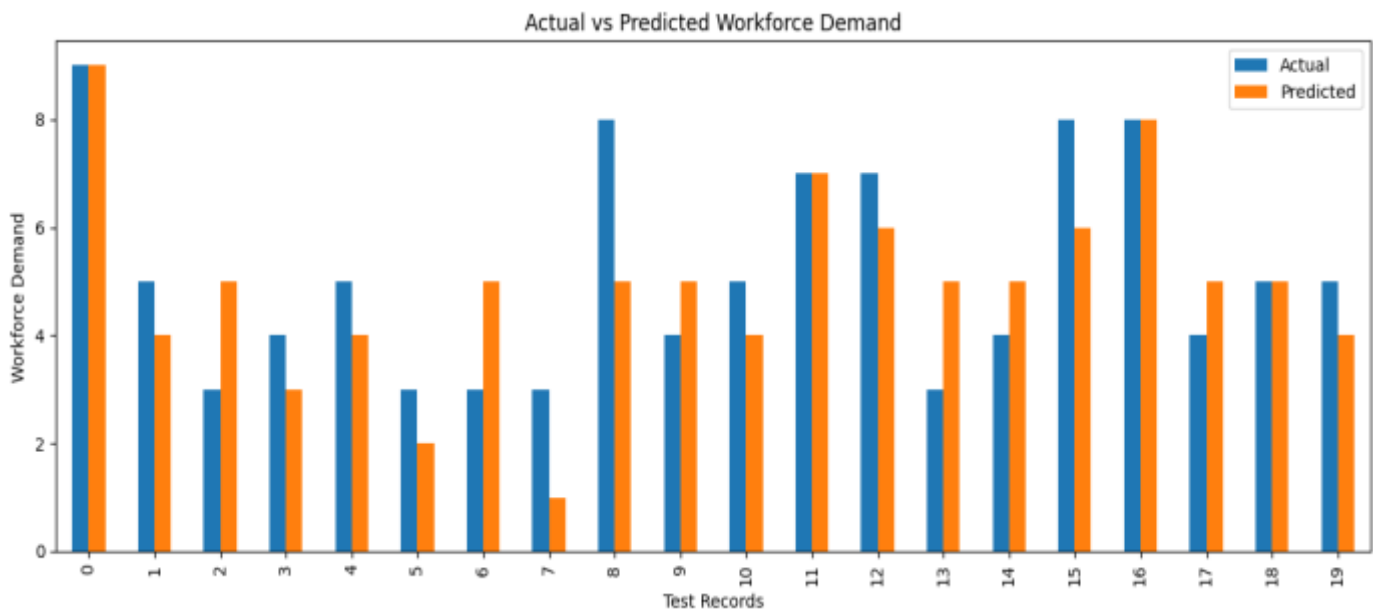


Fig. 20: Actual vs Predicted Workforce Demand

The figure compares the actual value and varies with the predicted value of the workforce demand obtained from using the Random Forest Regression model. The values of both series are very similar, and these have good forecasting performance, with low prediction error. Minor deviations are substantial and indicate normal variations in the conditions of the labor force that do not increase the inaccuracy for prediction. These results confirm the validity of using the model for workforce planning, staffing optimization, resource allocation, and decisions regarding human resources under the Workforce Digital Twin paradigm.

11. Simple Workforce Scenario Simulation



Fig. 21: Workforce Scenario Simulation

The figure shows a simulation of the workforce scenario in the Workforce Digital Twin model. The simulation assumes a 10% rise in staffing requirement, 15% rise in overtime hours and a 20% rise in absenteeism as a way to look at potential changes in the workforce. The results illustrate the variations in workforce capacity and resource needs caused by variations in attendance and workload. This scenario-based analysis allows proactively planning workforce, optimizing staffing, identifying risks and making decisions to strengthen operational resilience, while providing opportunities to evaluate workforce shortages, absenteeism impacts and operational resilience with regard to the research aims.

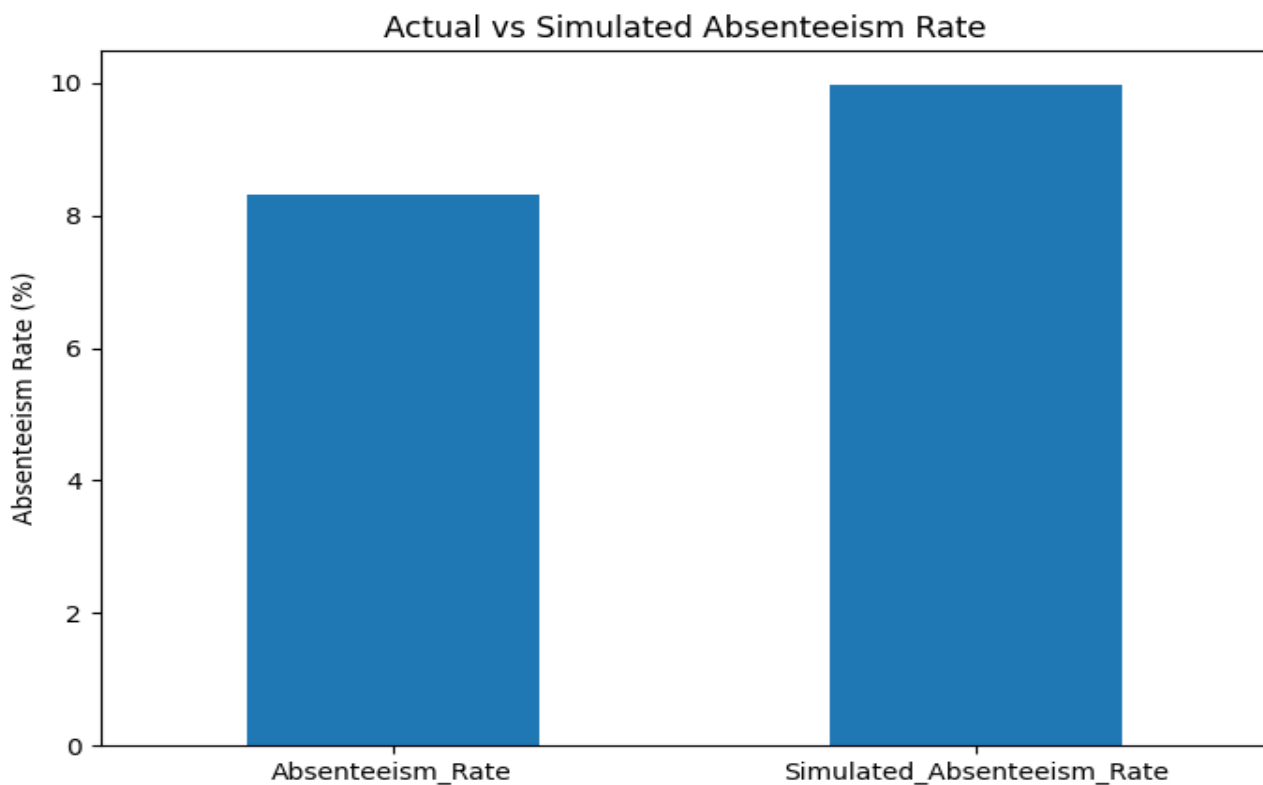


Fig. 22: Actual vs Simulated Absenteeism Rate

This graph illustrates the differences between baseline absenteeism and absenteeism simulated using the Workforce Digital Twin. The true absenteeism rate is approximately 8.3% and the simulated rate is nearly 10% because of the worker disruptions that impact the availability of workers. This is a boost to the figures of impact it can have on workforce capacity and also the staffing and performance requirements as far as increases in absenteeism go. The simulation illustrates the ability of the Workforce Digital Twin to model future conditions of the workforce, which can support proactively planning workforce resources, mitigating risks and planning workforce human resource decisions based on research goals.

DISCUSSION

The results show that the AI-enabled Workforce Digital Twin can be one of the solutions to facilitate the Predictive Workforce Management. The model showing the highest accuracy for predicting turnover is the Random Forest model (accuracy 80%), while the model for labor demand forecasting showed low error rates (MAE=0.765 and RMSE=0.905). Workforce utilization, absenteeism and scenario simulations gave valuable insights into workforce behavior, playing a fundamental role in proactive workforce planning, staffing optimization, talent management and humans resource decision making based on data.

Limitations

Limitations of the study include the relatively small number of workforce records (100) and the number of variables (30), because these might limit generalizability. Furthermore, predictions are based on past data and real-time workforce dynamics and exogenous conditions are missing from predictions, which can impact the accuracy and broader applicability of the Workforce Digital Twin framework.

CONCLUSION AND FUTURE WORK

This study demonstrated the effectiveness of an AI-driven Workforce Digital Twin can be leveraged to simulate the human workforce with Oracle Cloud HCM data, to show predictive human resource simulation and its effectiveness. The framework is able to effectively facilitate turnover risk prediction, labor demand forecasting,

workforce simulation, and planning activities. Results highlighted the power of machine learning and Workforce Analysis to drive workforce utilization, talent management, staffing and strategic HR.

Future Directions

There is still room for exciting improvements in future research with the addition of real-time Oracle Cloud HCM data streams for even more accurate predictions on the basis of larger volumes of data for their employee services, and state-of-the-art deep learning technologies. Additionally, the effects of Generative AI assistants and the optimization of the workforce through reinforcement learning might boost scenarios simulation, autonomous workforce planning, talent management and strategic planning.

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