

AI-Based Manpower Demand-Supply Analysis in Udaipur's Hotel Industry

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ABSTRACT

Manpower mismatches within the hospitality industry in Udaipur, Rajasthan are caused by seasonality in tourism activities, lack of adequate skills pipelines and lack of utilization of data analysis for recruitment purposes. In this study, the dynamics of manpower demands and supplies in the hotel industry of Udaipur are assessed through a survey among 120 professionals working within the hotel industry, and an artificial intelligence framework for forecasting and optimizing manpower planning is recommended. The highest challenges included employee turnover (27.5%), followed by high recruitment costs (24.2%). 49.2% of respondents were aware of AI for forecasting, and 34.2% expect its use in HR to increase over the next five years. The study recommends an integrated AI model including time series prediction using LSTM, job description sentiment analysis, and an LMI dashboard to help balance manpower supply and demand in real time. Contributions made include the rare empirical literature on the use of AI models for workforce prediction in regional Indian hospitality organizations.

Keywords: Artificial Intelligence (AI), Manpower Forecasting, Hospitality Industry, Hotel Sector, Demand–Supply Analysis, Human Resource Management, Udaipur Region, LSTM Neural Network, Workforce Planning, Recruitment Analytics, Skill Gap Analysis, Labour Market Information (LMI), AI-Based Recruitment, Tourism Industry, Hospitality Workforce Optimization.

1. INTRODUCTION

The hotel and tourism industry is considered the most labour-intensive in terms of global economic performance, with human capital being its largest expense and key to differentiation (Kevin, 2007). Hence, the role of manpower planning, or staffing properly with an optimal amount of labour and the correct skill set, is crucial for survival and competitiveness in the business (Wong et al., 2012). Nevertheless, in emerging economies like India, labour market information (LMI) is limited for the service sector, which creates an information gap between employer and worker (Khare, 2014).

Udaipur, popularly known by its name 'City of Lakes', acts as a major tourist destination in the state of Rajasthan, India. In Udaipur, there are more than 400 hotels, including boutique heritage hotels and luxury 5-star hotels managed by renowned international hospitality companies. Although there have been developments in the domain of tourism in the state of Rajasthan, with 53 million domestic tourists and 1.5 million foreign tourists traveling to the state in the year 2022-23, the hotels suffer from certain challenges in terms of recruitment and retention of qualified manpower UCCI, 2023. It becomes challenging to attract new recruits because of the lack of skills; however, the mid-level managers leave the hotel due to high attrition rates.

HR data internally available, and macroeconomic conditions, it will be possible to make more accurate predictions compared to regression models Yurtsever, 2023; Agarwal et al., 2013. Unfortunately, there is no research related to the use of such techniques in tourism-oriented cities like Udaipur in India.

This paper proceeds as follows: in section two the relevant literature review has been provided, methodology is discussed in section three, section four describes and discusses the obtained results, section five proposes the AI-based forecast model, and section six concludes.

2. RESEARCH METHODOLOGY

Research Design

The current study used a descriptive cross-sectional survey methodology as is conventionally used in studies on the area of hospitality human resource management (Kevin, 2007; Wong et al., 2012). A self-administered, structured questionnaire was developed after reviewing relevant literature. This questionnaire underwent expert validation through two senior professors of hospitality management and one Human Resource Manager in the industry. The questionnaire contained 40 questions divided into eight sections: (1) demographic characteristics, (2) qualification and selection criteria, (3) development and training, (4) recruitment procedures and techniques, (5) recruitment AI, (6) manpower supply-demand issues, (7) organizational culture and challenges, and (8) future expectations for recruitment AI.

Sampling and Data Collection

The target group consisted of Human Resource Managers, Department Heads, General Managers, and other higher-level supervisors working in registered hotels in Udaipur, Rajasthan. In order to identify respondents with sufficient knowledge about manpower planning within their organizations, purposive sampling was applied. In all, 120 valid responses were obtained during the six weeks' field study conducted between October and November 2024 by combining hotel visits and online distribution.

This number of 120 is in line with other empirical research done in the field of hospitality management. The study undertaken by Kevin (2007), for instance, involved analysis of employment decisions within the hotel

industry from datasets of similar size, whereas Agarwal et al. (2013) performed their primary data collection from a sample set of similar size for the real-estate construction industry of India.

Table 1: Gender Distribution of Respondents (N = 120)

Gender	Frequency	Percentage (%)
Female	67	55.8
Male	53	44.2
Total	120	100.0

Note. Data collected via primary survey, Udaipur hotel sector, 2024-2025.

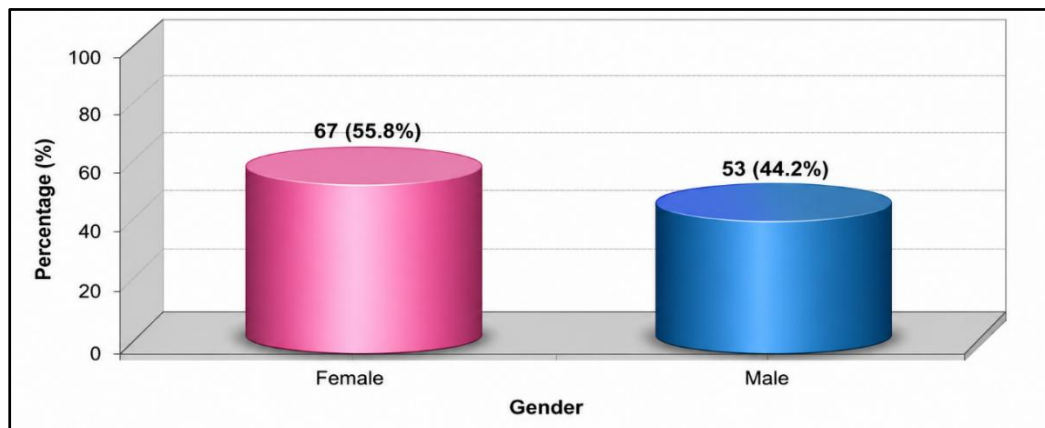


Figure 1: Gender-wise Distribution of Respondents (N = 120)

Table 2: Age Distribution of Respondents (N = 120)

Age Group	Frequency	Percentage (%)
Below 20	39	32.5
21–30 years	27	22.5
31–40 years	32	26.7
Above 40 years	22	18.3
Total	120	100.0

Note. A substantial proportion of respondents (32.5%) were below 20 years, reflecting the hotel industry's reliance on young entrant workers.

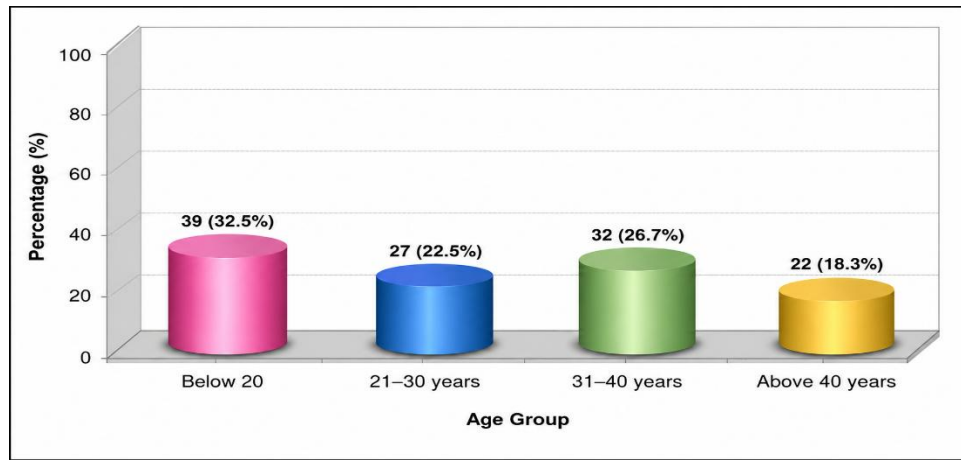


Figure 2: Age-wise Distribution of Respondents (N = 120)

Data Analysis

Data were coded and entered using Microsoft Excel software and analyzed using the approach of descriptive statistics which included frequency distribution and cross tabulations. It should be noted that all questions were of closed-ended type to ensure consistency and objectivity. The following hypotheses was tested during research: "The application of AI-based technologies will help in overcoming problems associated with demand-supply mismatch within the hospitality industry of Udaipur."

3. RESULTS AND DISCUSSION

The above-mentioned gap has been bridged by means of three major contributions of this research:

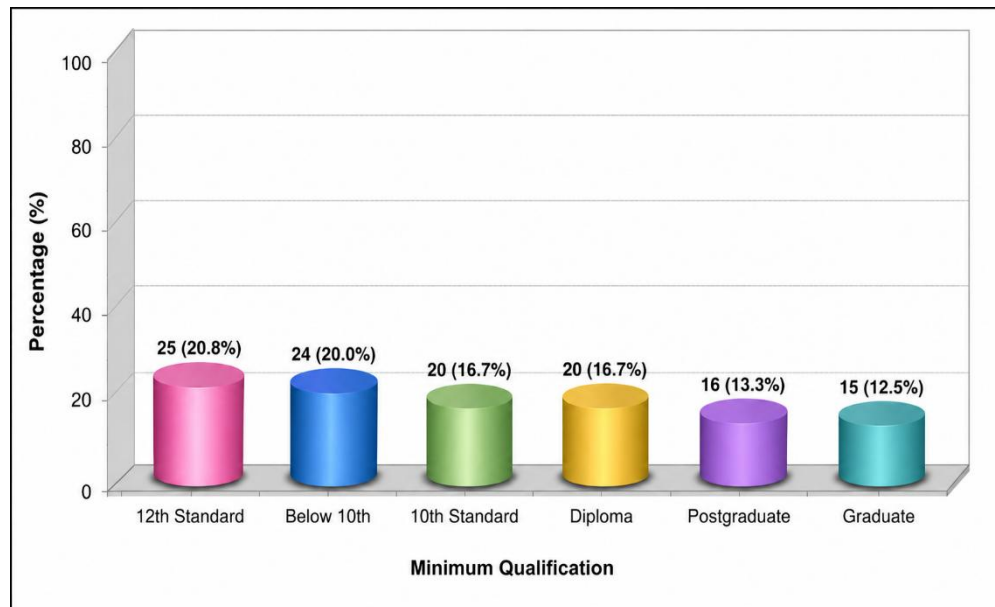
- (a) The analysis of demand and supply perceptions and HRM practices of hotel managers from Udaipur based on 120 responses;
- (b) The analysis of the existing position and the future potential of using AI for hospitality HRM;
- (c) The development of an AI-based manpower forecast model designed for Udaipur hotels.

Qualification and Hiring Standards

The minimum qualification criteria for employment in the hotel industry in Udaipur are remarkably diverse. As per Table 3, the top four minimum qualification requirements included 12th standard (20.8%), Below 10th (20.0%), 10th Standard (16.7%), and Diploma (16.7%). The postgraduate degree was found to be a minimum criterion only in 13.3% cases. This reflects that the hotels operate with a predominantly non-specialized labour force, similar to the observations made by Khare (2014).

Table 3: Minimum Qualification Requirements and Preferred Entry-Level Standards (N = 120)

Minimum Qualification	Frequency	Percentage (%)
12th Standard	25	20.8
Below 10 th	24	20.0
10th Standard	20	16.7
Diploma	20	16.7
Postgraduate	16	13.3
Graduate	15	12.5
Total	120	100.0

**Figure 3: Minimum Educational Qualification of Respondents (N = 120)**

As for special training arrangements, it can be stated that special training is offered to employees at 53.3% of hotel facilities, while at 46.7%, it is not; thus, almost half of the industry uses only pre-employment qualifications. Moreover, e-learning has been offered by 50.8% of facilities. Such statistics reveal a mixed situation regarding the training system used in the hotels, which is similar to the issues highlighted by Sereyvuth (2023).

Manpower Demand-Supply Perceptions

The main question pertains to how people perceive the balance between manpower supply and demand within the hotel industry in Udaipur. A conceptual distribution of responses is depicted. From the 120 individuals interviewed, 44 (36.7%) saw the balance as equal, with supply and demand at an equilibrium point, 40 (33.3%) saw the supply as greater than the demand, and 36 (30.0%) saw the demand as being greater than the supply. It is significant that no predominant answer existed towards either side of this balance, implying a highly fragmented

market according to types of properties, departments, and seasons. This is consistent with what Maier et al. (2015) noted about forecasting.

Table 4: Perceived Demand-Supply Balance and Shortage Frequency (N = 120)

Variable / Category	Frequency	Percentage (%)
<u>Demand-Supply Perception</u>		
Equal (balanced)	44	36.7
Supply higher than demand	40	33.3
Demand higher than supply	36	30.0

<u>Manpower Shortage Frequency</u>		
Monthly	32	26.7
Never	32	26.7
Occasionally	28	23.3
Weekly	28	23.3

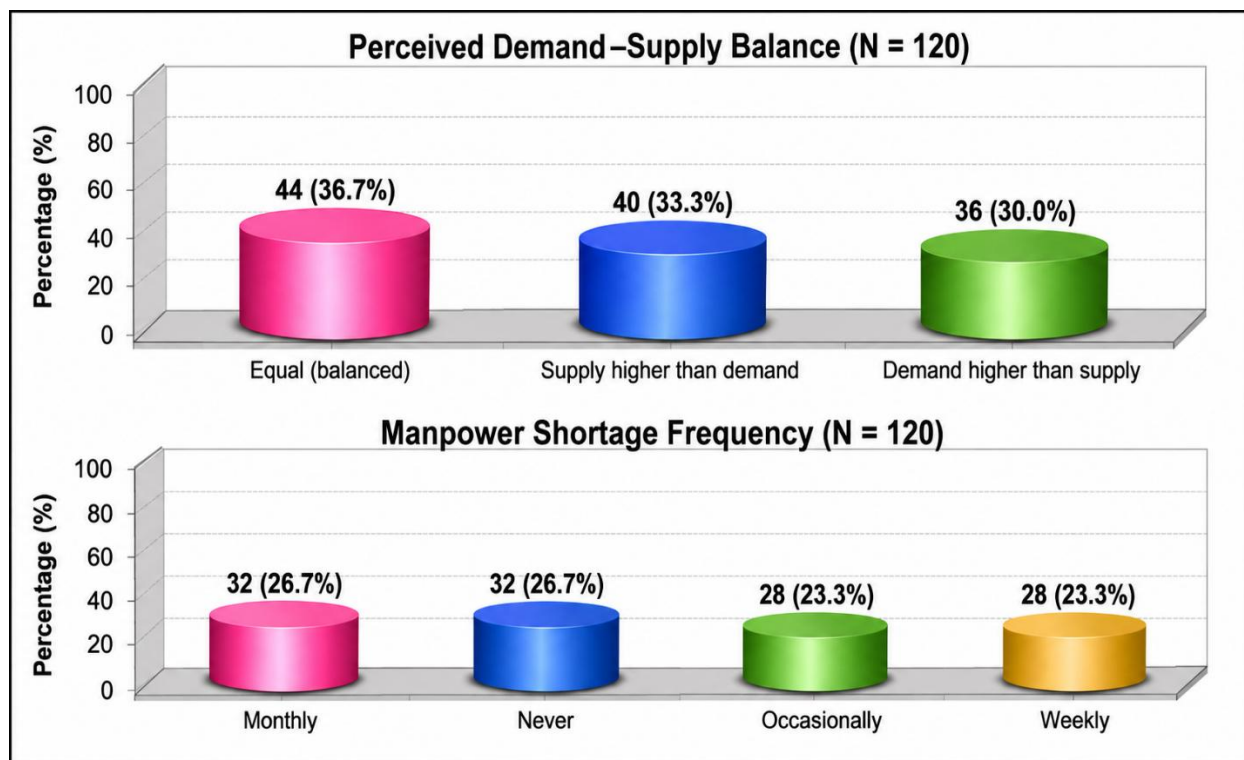


Figure 4: Perceived Demand-Supply Balance and Shortage Frequency (N = 120)

Data for manpower shortage frequency (Table 4) further emphasizes the difference in workforce experiences. Although 26.7% of hotels reported having never faced manpower shortages, another 26.7% of them have reported experiencing shortages on a monthly basis, while 23.3% have experienced shortages on a weekly basis, showing

considerable differences among various hotels. These observations are quite similar to the seasonality of tourism operations in Udaipur because of high tourist influx during the winter season (October-March) (UCCI, 2023).

Recruitment Practices and Challenges

The recruitment environment in the hotel industry in Udaipur reflects the use of conventional recruitment sources. As per the data in Table 5, referral was the most frequently used method of recruiting (30.0%), internal promotion being the next most popular at 29.2%, followed by campus recruiting at 22.5% and external recruiting at 18.3%. On asking about which recruitment source is “best,” more agreement with electronic recruiting emerged, with online portals being named by 34.2%, referral by 24.2%, and internal and campus promoting both at 20.8%.

Table 5: Recruitment Methods and Hiring Preferences (N = 120)

Category	Frequency	%	Best Method %
Referrals	36	30.0	24.2
Internal Promotion	35	29.2	20.8
Campus Recruitment	27	22.5	20.8
External Hiring	22	18.3	—
Online Job Portals	—	—	34.2

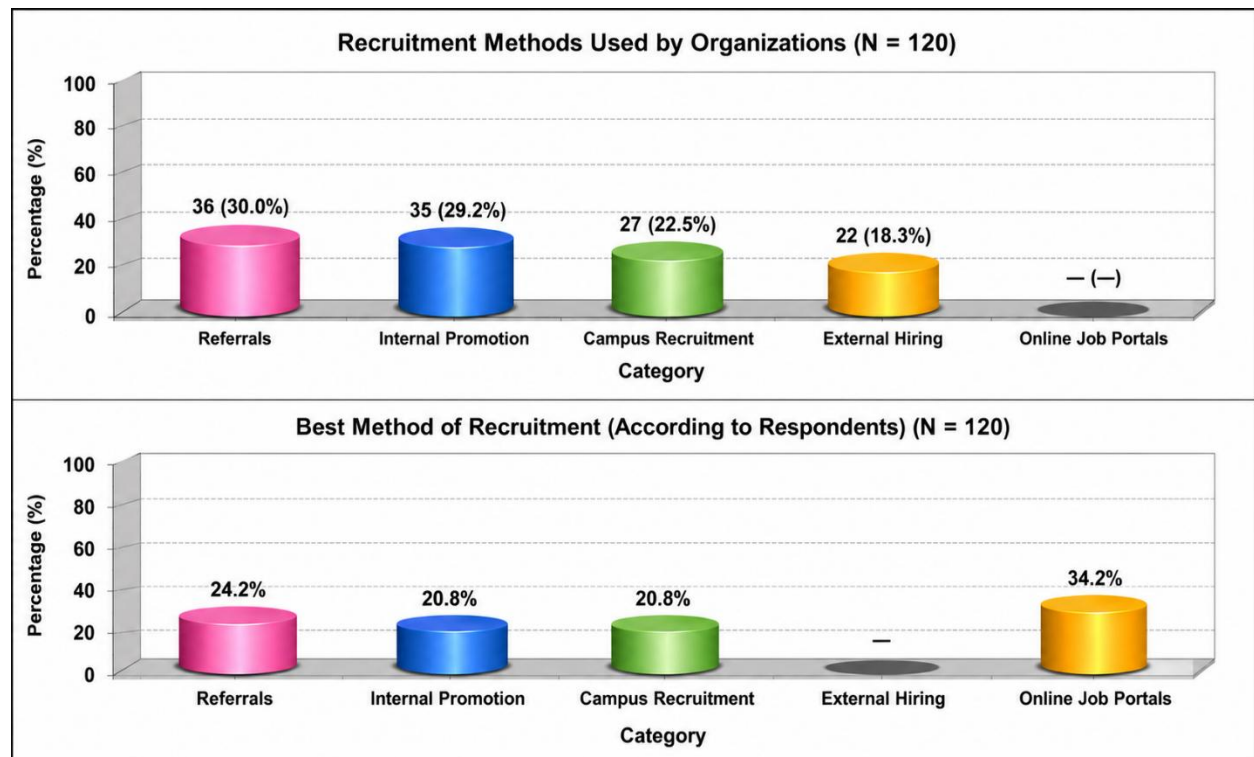


Figure 5: Recruitment Methods and Preferred Hiring Sources (N = 120)

Preferred mode of hiring is roughly evenly distributed among freshers (36.7%), experience (35.8%), and a combination of both (27.5%), showing a sector where there is no strong agreement regarding the recruitment

pipeline approach. This lack of clarity regarding the recruitment process philosophy aligns well with the nature of a “dual-channel” labour market, described by Gibson & Flaherty (2017), in which the properties make use of both new entrant and experience mobility pools simultaneously.

The most important difficulties encountered in manpower management include, first, high employee turnover (27.5%), secondly, high cost of recruitment (24.2%), thirdly, shortage of skilled labour (24.2%), and fourthly, demand variation (24.2%). As seen in the table, these difficulties are evenly distributed among four different categories of problems. That points to the existence of multiple crises at once instead of a single problem—an essential insight for designing an AI-based solution.

Table 6: Top Manpower Management and Operational Challenges (N = 120)

Challenge Category	Frequency	Percentage (%)
Primary Manpower Challenges		
High employee turnover	33	27.5
High recruitment cost	29	24.2
Shortage of skilled labour	29	24.2
Seasonal demand fluctuations	29	24.2

Current Operational Challenges		
Meeting guest expectations	26	21.7
Seasonal demand fluctuations	26	21.7
Shortage of skilled staff	25	20.8
High employee turnover	22	18.3
High recruitment cost	21	17.5

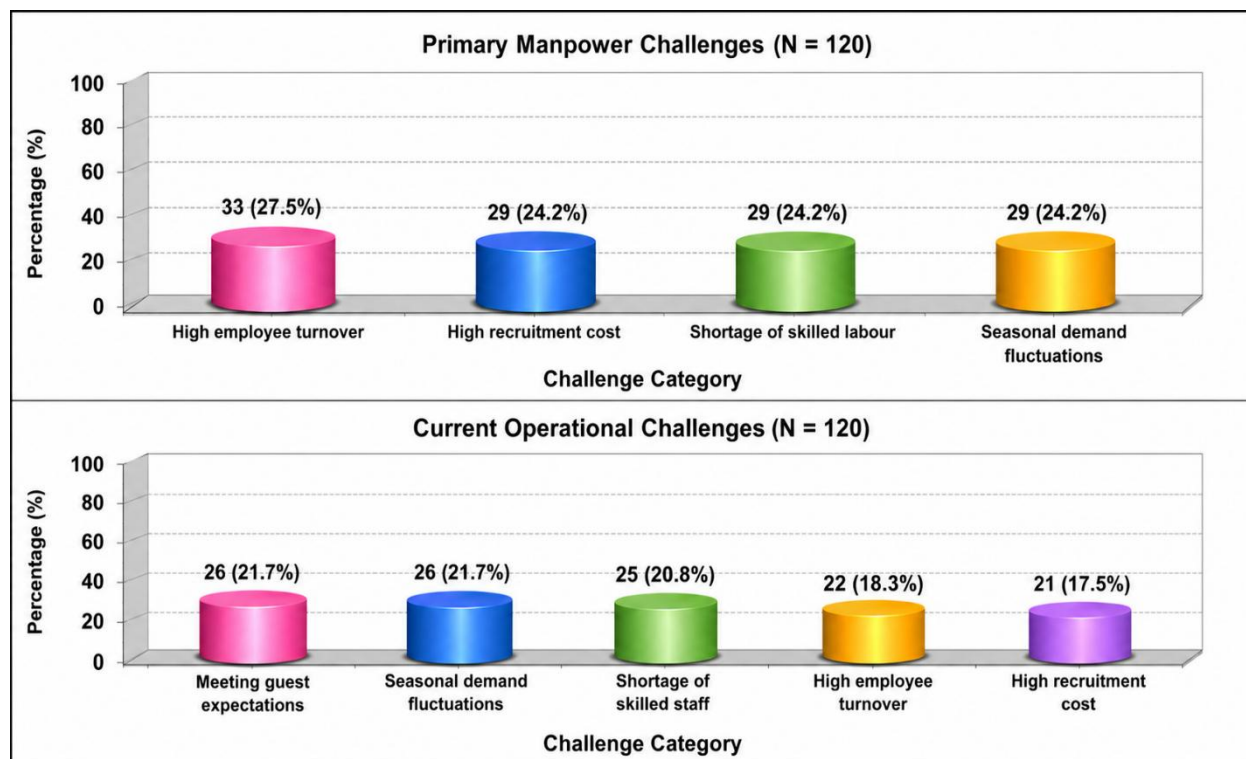


Figure 6: Manpower Management and Operational Challenges (N = 120)

Artificial Intelligence Adoption in Recruitment and Forecasting

Among the most interesting findings of this study relates to the present adoption of AI, as well as expected adoption within hotel HR processes. According to Table 7, 49.2% of the respondents utilize AI systems in candidate assessment, while the remaining 50.8% do not. It can be seen that the industry stands at a critical juncture when adoption of AI technology remains on a knife's edge.

Table 7: AI Adoption in Recruitment and HR Forecasting (N = 120)

AI-Related Variable	Yes / Value	Percentage (%)
Currently uses AI in recruitment	59 Yes	49.2
AI helps forecasting manpower	59 Yes	49.2
AI will replace manual HR processes	59 Yes	49.2
AI use will increase in 5 years	41 Yes	34.2
Unsure about AI growth in 5 years	41 Not sure	34.2
AI Job Match Rating — Mean	3.03 / 5	—

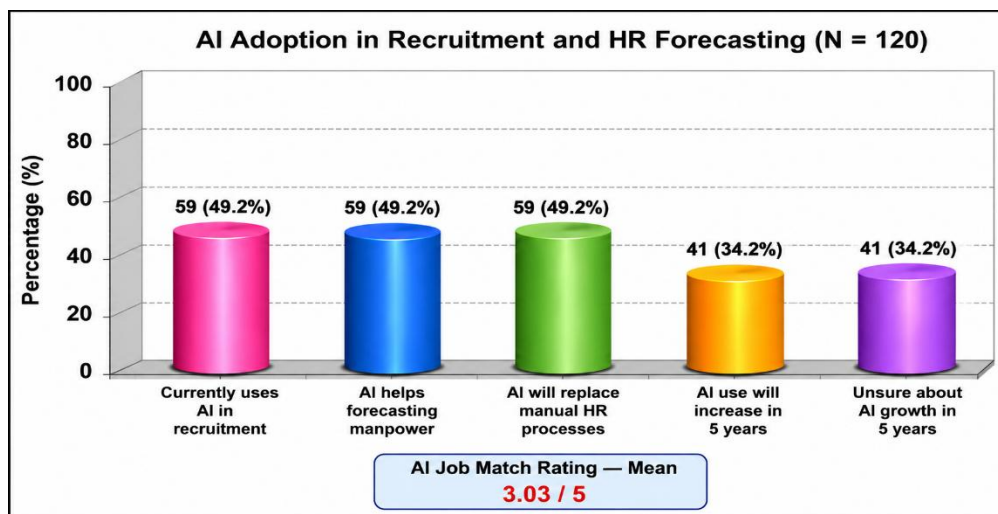


Figure 7: AI Adoption in Recruitment and HR Forecasting (N = 120)

The mean of 3.03 out of 5 on the AI Job Match Rating shows moderate satisfaction from the current AI matching systems. The neutral view regarding the implementation of AI suggests that AI may be at its early stages of maturity compared to dissatisfaction with the performance of AI because research shows that AI forecasting accuracy is greatly enhanced when complex data is used within long periods of time.

Perceptions of AI forecasting accuracy are provided in Table 8 below. It shows that only 22.5% viewed the forecasts as very accurate while 20.8% viewed them as very inaccurate.

Table 8: Perceived Accuracy of AI-Based Manpower Forecasting (N = 120)

Accuracy Level	Frequency	Percentage (%)
Highly accurate	27	22.5
Moderately accurate	38	31.7
Slightly accurate	30	25.0
Not accurate	25	20.8
Total	120	100.0

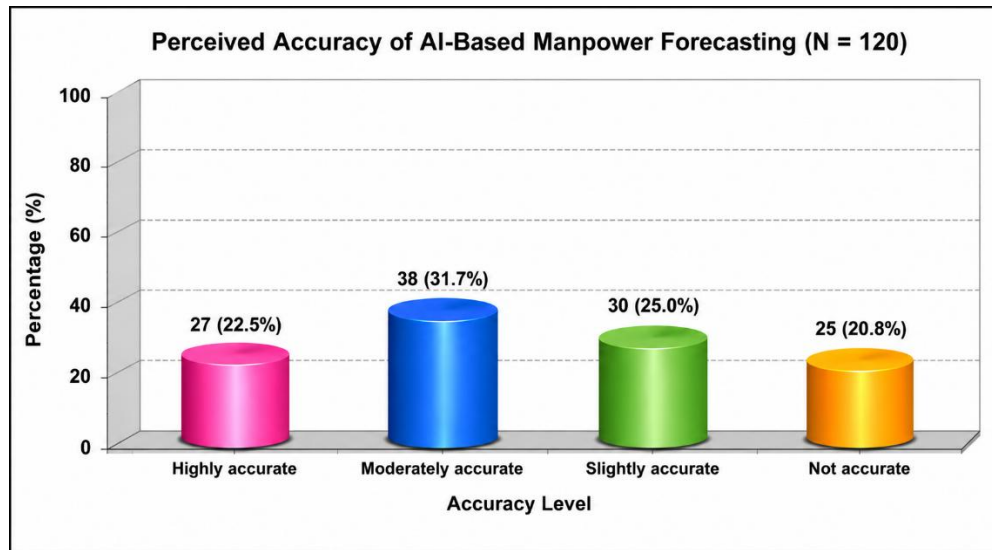


Figure 8: Perceived Accuracy of AI-Based Manpower Forecasting (N = 120)

Improving the Demand-Supply Balance: Respondent Perspectives

Participants were tasked with suggesting a single most effective solution to address the manpower supply-demand problem within the hospitality industry. Four responses stood out as being suggested with almost equal frequency (Table 9). The most popular among all solutions suggested was collaboration between academia and the industry (27.5%), followed by forecasting using artificial intelligence (AI) technologies (25.8%), offering better salaries to employees (25.0%) and flexible training programs (21.7%). These diverse methods of addressing an industry challenge correspond with Mamba and Asogwa's (2022) proposed policies for the African higher education sector and support Wong et al.'s (2012) finding that multiple solutions trump a singular approach.

Table 9: Recommended Strategies to Improve Manpower Demand-Supply Balance (N = 120)

Recommended Strategy	Frequency	Percentage (%)
Industry-academia collaboration	33	27.5
AI-driven forecasting systems	31	25.8
Better salary packages	30	25.0
Flexible training programmes	26	21.7
Total	120	100.0

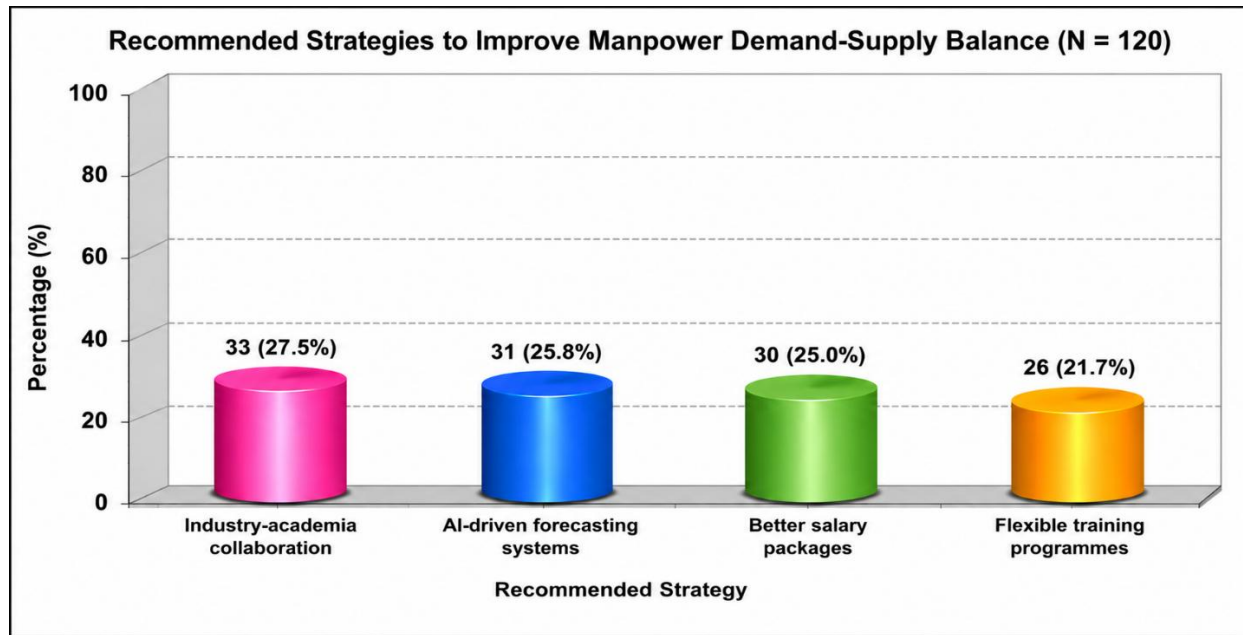


Figure 9: Recommended Strategies to Improve Demand–Supply Balance (N = 120)

4. PROPOSED AI-BASED MANPOWER FORECASTING FRAMEWORK

Based on the survey results and relevant literature review, this chapter suggests an AI-based manpower forecasting and optimisation model for Udaipur’s hospitality industry, comprising four layers. This proposed model is based on two key lessons derived from the previous sections which are: (a) the demand-supply gap problem has an inherent heterogeneity and needs a disaggregated analysis; and (b) the current use of AI technology is incomplete and inaccurate.

Layer 1: Data Ingeystion and Labour Market Information (LMI) Hub

The starting point for the framework is the creation of a centralized LMI hub combining information from various sources:

- (i) Employment rolls of hotels kept by the Rajasthan Labour Department;
- (ii) Vacancy and applicant information on jobs from job sites like Naukri, indeed, and Hospitality Jobs India.
- (iii) Tourist arrivals from the Rajasthan Tourism Department;
- (iv) Hotel revenue and occupancy information from UCCI and property management systems;
- (v) Institute-wise number of graduates from hospitality programs from educational institutions registered with the Board of Technical Education, Rajasthan. The multi-source approach followed by the framework is a direct response to the gap identified.

Layer 2: Predictive Demand Forecasting Module

In this level, LSTM-GRU hybrid models will be applied based on the proposition suggested by Yurtsever (2023) to predict demands for six to twelve months on department basis (FO, F&B, H/K, Maintenance, and Management). The application of LSTM neurons would enable capturing seasonality through long-term dependency, whereas GRU can effectively capture short-term volatility associated with events and festivals, as well as any other macro shocks. For predicting purposes, the inputs of the neural network model include historic data related to occupancy percentages, room rates, number of tourists, GDP growth, CPI, and events. It is important to highlight the fact that the empirical analysis done by Kevin (2007) indicated the significant role of the number of rooms, F&B sales, and production index.

Layer 3: Supply-Side Skill Gap and Pipeline Analysis

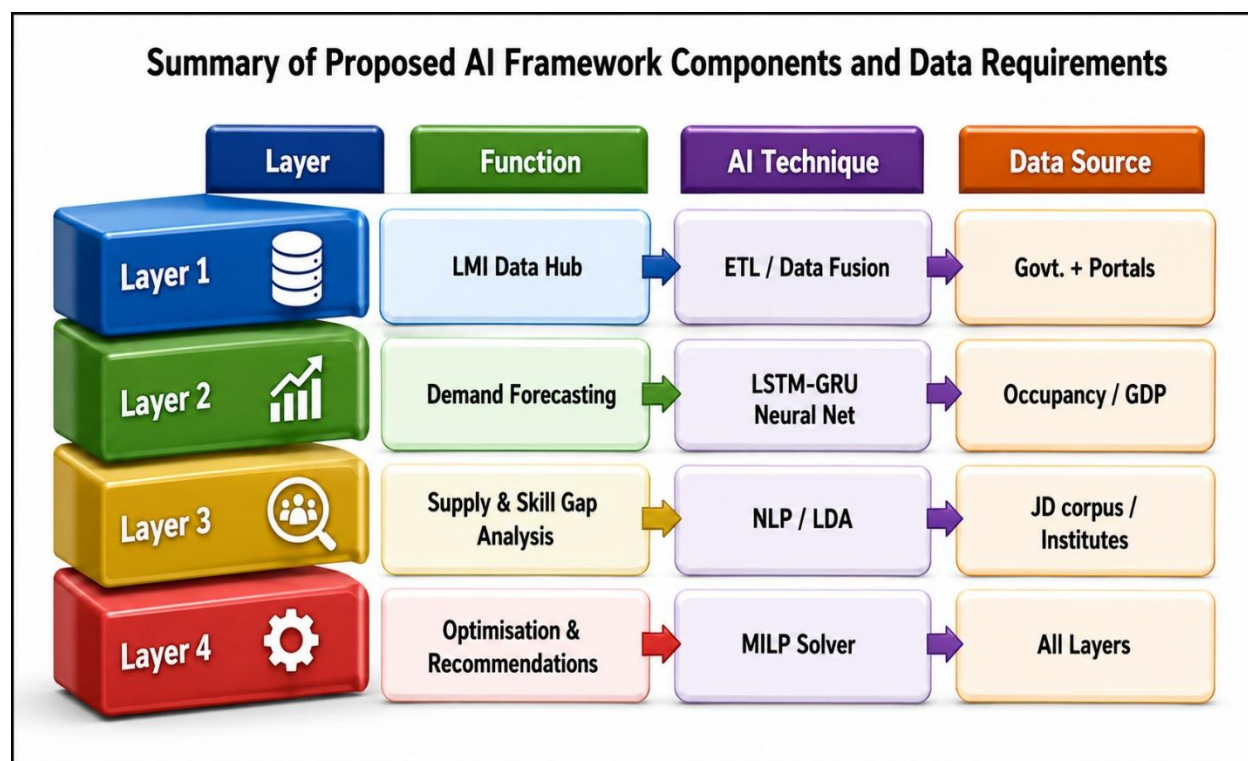
The Supply module utilises NLP to analyse the job descriptions (JDs) provided by hotel chains in relation to the fact that 51.7% of respondents indicated having established KPIs and a regular JD update cycle, as well as comparing them against the competence profiles for local hotel institutes' graduates. This is achieved through creating a skills taxonomy by utilising topic modelling techniques (Latent Dirichlet Allocation) on the JD database and comparing them against academic syllabuses and placement results. As a result, the supply module calculates a dynamic skill gap index by department and education level, providing direct feedback for the revision of curriculums at the respective hotel institutes, which are done in conjunction with the UCCI.

Layer 4: Optimisation and Recommendation Engine

The last stage is the use of constraint optimization (MILP) to generate staffing plans that match the predicted demand at minimum costs and adhere to labour laws (wage laws and hours of work), as well as satisfying quality standards. The software generates recommendations for three different time horizons: short-term (0-3 months; staffing planning and temp staffing), medium-term (3-12 months; recruiting on campus and trainings), and long-term (1-5 years; partnerships and wage comparisons). The proposed software will operate as a SaaS dashboard in cloud environment, addressing the problem raised by 24.2% of the participants that existing software is "not secure."

Table 10: Summary of Proposed AI Framework Components and Data Requirements

Layer	Function	AI Technique	Data Source
Layer 1	LMI Data Hub	ETL / Data Fusion	Govt. + Portals
Layer 2	Demand Forecasting	LSTM-GRU Neural Net	Occupancy / GDP
Layer 3	Supply & Skill Gap Analysis	NLP / LDA	JD corpus / Institutes
Layer 4	Optimisation & Recommendations	MILP Solver	All Layers

**Figure 10: Proposed AI-Based Manpower Forecasting Framework**

5.. CONCLUSIONS AND POLICY IMPLICATIONS

This study confirms that manpower demand exists in virtually every sector of the economy, and this pressure is especially pronounced in the hotel industry, where a fragmented perception of demand-supply balance (30.0% reporting demand higher than supply, 33.3% reporting supply higher than demand, and 36.7% reporting equilibrium) points to a persistent and unevenly distributed need for skilled labour across departments, seasons, and property types. The more pressing question, therefore, is not whether demand exists, but how a matching

supply of trained, job-ready manpower can be generated, tracked, and deployed in time - and this is precisely where artificial intelligence can make its greatest contribution.

Bridging this demand-supply gap requires a shift from reactive hiring to proactive, AI-enabled workforce planning. Three practical steps can help hotels build a resilient supply pipeline. First, hotel owners and HR managers should maintain structured job descriptions and KPIs (currently present in only 51.7% of hotels) as the data foundation for any AI-driven prediction, since forecast quality depends entirely on the quality of the data feeding it. Second, AI-based demand forecasting (LSTM-GRU) should be paired with an equally robust supply-side pipeline that tracks institute output, skill taxonomies, and placement data, so that recruitment and training can be planned months ahead of an anticipated shortfall rather than after it occurs. Third, an AI-powered LMI dashboard, continuously updated with vacancy, occupancy, and graduate-output data, can flag emerging demand-supply gaps early enough for hotels, training institutes, and government bodies to respond - using AI not merely to predict demand, but to actively help fulfil the supply of manpower needed to meet it.

From a policy standpoint, the study underscores the need for the Rajasthan Employment Department to institute standardised manpower reporting for registered hotels, comparable to the reporting systems developed by Venning (2003) for the UK engineering sector, and for the proposed LMI hub to be jointly operated by UCCI and the Rajasthan Labour Department so that supply-side data keeps pace with demand-side forecasts. As it stands, schemes such as MNREGA, with their rural focus, meet only about half of the hotel industry's labour demand, reinforcing the need for a dedicated hospitality workforce supply strategy.

Three directions are proposed for future research:

1. longitudinal studies tracking the same establishments over three to five years to observe how AI adoption affects manpower supply outcomes.
2. A pilot of the proposed framework across 20 to 30 Udaipur hotels in collaboration with UCCI.
3. Extension of the NLP-based skill-gap module to other vocational education programmes beyond hotel management in the region.

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