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Tourism Employment and Digital Transformation: ARIMA Forecast insights for India with Regional Focus on Himachal Pradesh

Gitika Nagrath[1], Surbhi Sood[2*]
DAV University, Jalandhar, India[1,2]
gitika.nagrath@yahoo.co.in[1], modisur10@gmail.com[2]
Corresponding Author: modisur10@gmail.com[*]

ABSTRACT
This study forecasts tourism employment trends in India at both national and regional levels while examining the role of automation in reshaping sectoral employment structures. Utilizing the Auto Regressive Integrated Moving Average (ARIMA) model, the research analyzes annual secondary employment data for India (2009–2023) and Himachal Pradesh (2014–2024). Model adequacy is confirmed through standard residual diagnostics and goodness-of-fit measures, supplemented by a qualitative analysis of how digitalization influences skill requirements.Findings indicate a steady upward trend in national tourism employment through 2030, suggesting sustained expansion despite pandemic-related disruptions. Conversely, Himachal Pradesh exhibits significant fluctuations driven by seasonality, climatic vulnerability, and informal labor dependence. The analysis further reveals that automation acts as a complementary force, transforming routine tasks and increasing demand for hybrid skills rather than reducing overall headcount. Originality lies in the dual-level forecasting approach combined with an automation-based workforce interpretation, extending research beyond traditional demand metrics. While the study is limited by the use of annual data and potential structural breaks from COVID-19, it offers critical implications for policymakers. The results highlight the need for region-specific workforce planning and strategic digital adoption to enhance resilience in vulnerable areas like hill states. Future research should consider machine learning models and granular datasets to better capture seasonal dynamics..

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1. Introduction

Tourism plays a critical role in India's economy as one of its most labour-intensive service sectors, generating employment across accommodation, transportation, food and beverage services, cultural activities, and travel facilitation (World Tourism Organization, 2022; World Travel & Tourism Council, 2023). In a developing economy such as India, tourism contributes substantially to economic growth, supports livelihood diversification, enhances women's workforce participation, and promotes regional development (Confederation of Indian Industry & Ernst & Young, 2024). Official estimates indicate that the tourism sector accounted for approximately 5.22% of India's GDP in 2023–24, reflecting strong post-pandemic recovery (Press Information Bureau, Government of India, 2025;

Ministry of Tourism, Government of India, 2025). In employment terms, the sector supported nearly 46.5 million jobs in 2024, representing around 9.1% of total national employment, underscoring tourism's importance as a major absorber of India's working-age population (IBEF, 2024; WTTC, 2024). Tourism activity has also driven record expenditure levels, with domestic visitor spending exceeding ₹15 trillion and international visitor spending surpassing ₹3.1 trillion in 2024, highlighting the sector's expanding footprint in India's growing service economy (WTTC, 2025). Given these contributions, understanding and forecasting tourism employment trends is essential for effective workforce planning and evidence-based policy formulation in India.

Despite its employment-generating potential, the nature of tourism employment is undergoing rapid transformation due to increasing automation and digitalization. Globally, tourism enterprises are adopting AI-enabled chat-bots, automated check-in systems, robotic housekeeping solutions, biometric verification, digital concierge services, and contactless ticketing to improve operational efficiency and service delivery (Ivanov & Webster, 2019). The COVID-19 pandemic further accelerated this transition, as touchless and technology-supported operations became crucial for health security and business continuity. Scholars argue that automation represents not merely a technological upgrade but a broader socio-economic transformation that restructures job roles, alters skill requirements, and shifts workforce composition (Huang & Rust, 2018).

India presents a distinctive context for examining the interaction between tourism employment and automation. At the national level, tourism continues to expand due to rising disposable incomes, growing domestic travel demand, improved digital connectivity, and policy initiatives such as *Dekho Apna Desh* (Ministry of Tourism, 2023). Simultaneously, digital adoption across hotels, airports, transport services, and travel intermediaries has increased, with online booking platforms, automated kiosks, and AI-supported customer service becoming mainstream (WTTC, 2023; CII & EY, 2024). While these advancements enhance efficiency and competitiveness, they also raise concerns regarding labour displacement, skill mismatches, and changing employment structures within tourism (CII & EY, 2024). Against this backdrop, the present study is guided by two specific objectives:

1. To forecast tourism employment trends at the national level (India) and the regional level (Himachal Pradesh) using ARIMA models, and
2. To examine the role of automation and digitalisation in transforming skill requirements within the framework of predicted tourism employment.

The incorporation of automation adds a strategic dimension to employment forecasting. While automation may reduce demand for routine and repetitive tasks, it simultaneously creates new employment opportunities in digital operations, revenue analytics, technology maintenance, and customer experience design. Empirical and theoretical studies suggest that automation does not uniformly reduce employment but instead shifts labour toward higher-order tasks involving creativity, emotional intelligence, and problem-solving, competencies that remain central to tourism services (OECD, 2020; Huang & Rust, 2018). Understanding this transformation is essential for interpreting future employment trajectories beyond mere job counts.

Regional disparities further justify the need for a dual-level analysis. Himachal Pradesh, one of India's leading mountain tourism states, exhibits labour dynamics that differ markedly from national trends. Tourism employment in the state is characterised by strong seasonality, climatic vulnerability, limited regional connectivity, and a heavy dependence on informal and temporary labour arrangements, resulting in fluctuating employment patterns over time (Thakur, 2023; Gupta, Kumar & Pathania, 2025). These structural characteristics make tourism employment in hill states particularly sensitive to technological change, reinforcing the need for region-specific workforce analysis.

India's demographic profile intensifies the importance of accurate employment forecasting. As one of the world's youngest nations, India must continuously generate large volumes of employment to absorb its expanding labour force (Shriwas, Shirbad & Khamborkar, 2019). Tourism possesses significant potential to meet this demand if supported through targeted skill development and digital readiness initiatives (Thakur, 2023; Raj, Sharma, Kaushal & Choudhary, 2023). However, without forward-looking employment forecasts, the risk of skill mismatches and structural unemployment may increase, particularly as automation becomes more deeply embedded in tourism value chains (OECD, 2020). Aligning national skill development programmes such as the *Pradhan Mantri Kaushal Vikas Yojana* (PMKVY) with data-driven labour projections is therefore critical (Raj et al., 2023).

A review of existing literature reveals three key gaps. First, although tourism demand forecasting is well established, tourism employment forecasting in the Indian context remains limited. Second, research on automation in Indian tourism is largely descriptive and insufficiently integrated with empirical employment projections. Third, studies linking national and state-level tourism employment forecasting with automation-driven workforce transformation are virtually absent. Addressing these gaps is particularly important for understanding how employment growth and technological change interact across diverse tourism economies.

Time-series forecasting using the Autoregressive Integrated Moving Average (ARIMA) model provides a robust framework for analysing long-term employment trends. Grounded in the Box and Jenkins (1970) methodology, ARIMA models are widely applied in economic forecasting due to their ability to capture trends, fluctuations, and temporary shocks. Prior studies demonstrate the usefulness of ARIMA-based forecasts for labour planning and identifying structural shifts in employment patterns (Petrevska, 2017). Given disruptions arising from demonetisation (2016), GST implementation (2017), economic slowdown (2019), and the COVID-19 pandemic (2020–2021), ARIMA modelling is particularly suited to analysing India's tourism labour market.

The novelty of this study lies in its integrated national–regional employment forecasting framework combined with an automation-informed interpretation of workforce transformation. By simultaneously forecasting tourism employment for India and Himachal Pradesh and examining how automation reshapes skill demand, the study advances tourism employment research beyond conventional demand-focused analyses.

Overall, the study offers important contributions to policy formulation, workforce planning, and academic research. The findings provide evidence-based insights for designing targeted skill development initiatives, promoting strategic digital adoption, and stabilising employment in regionally sensitive destinations. The study bridges tourism employment forecasting with automation theory, offering a framework for future research on technology-driven labour transformation in tourism.

2. Literature Reviews

Understanding employment behaviour within the tourism sector has gained significant momentum in recent research due to the industry's rising economic contribution and job-creating potential. Tourism is widely recognized as a labour-intensive service sector that generates employment across transport, accommodation, hospitality, adventure tourism, and cultural services. According to Cooper (2021), tourism employment operates within a broader ecosystem of economic interactions, making it highly sensitive to policy shifts, market conditions, and demand cycles. In India, the tourism sector has shown a long-term upward movement driven by economic growth, increasing domestic travel, and government initiatives; however, employment patterns have not always followed a smooth trajectory (WTTC, 2023). In contrast, Himachal Pradesh though highly tourism-dependent, exhibits fluctuating employment trends influenced by seasonality, regional connectivity, and periodic shocks. This divergence between India's upward-moving employment trend and the state's fluctuating pattern highlights the need for comparative empirical analysis.

Tourism employment is inherently fragmented and subject to volatility. Baum and Hai (2020) describe the tourism labour market as highly exposed to seasonality, crisis-driven disruptions, and technological transitions, conditions that make employment forecasting complex yet essential. For India, Mishra (2021) & Modi (2024) emphasize that tourism acts as both an employment opportunity and vulnerability, especially for women, youth, and rural workers. The global tourism collapse during COVID-19 further magnified the fragility of tourism jobs, causing disproportionate employment contractions (UNWTO, 2021). Himachal Pradesh, being a hill destination dependent heavily on seasonal inflow, experienced sharper fluctuations compared to nationwide trends. These studies collectively highlight that both stable and unstable labour markets require differentiated analytical approaches, strengthening the justification for a dual-level India–Himachal employment analysis.

A growing body of literature has examined how automation, robotics, and AI-based systems reshape tourism labour markets. Berezina, Ciftci & Lopez (2024) argue that automation will reduce repetitive, low-skill roles while creating demand for technologically skilled workers. Examples include automated check-in systems, robot-assisted concierge services, biometric verification at airports, and AI-driven customer support. However, scholars also emphasize that automation does not entirely replace human labour. Brynjolfsson and McAfee (2017) highlight that technology complements human qualities such as empathy, creativity, and emotional engagement, skills central to tourism experiences. Likewise, Huang and Rust (2018) observe that service automation generates new job categories related to experience design, digital operations, and data analytics.

In India, technological adoption in tourism is advancing unevenly. Larger enterprises adopt automation faster, while small-scale operators remain labour-intensive (Anuj, Upadhyay, Kargeti & Sharma 2023). Arora et al. (2025) note that Indian hospitality firms increasingly value hybrid skills that combine customer interaction with technological proficiency. For Himachal Pradesh, digital integration is still emerging, resulting in slower structural labour transitions compared to national trends. This contrast reinforces the importance of interpreting employment forecasts through the lens of differential automation readiness.

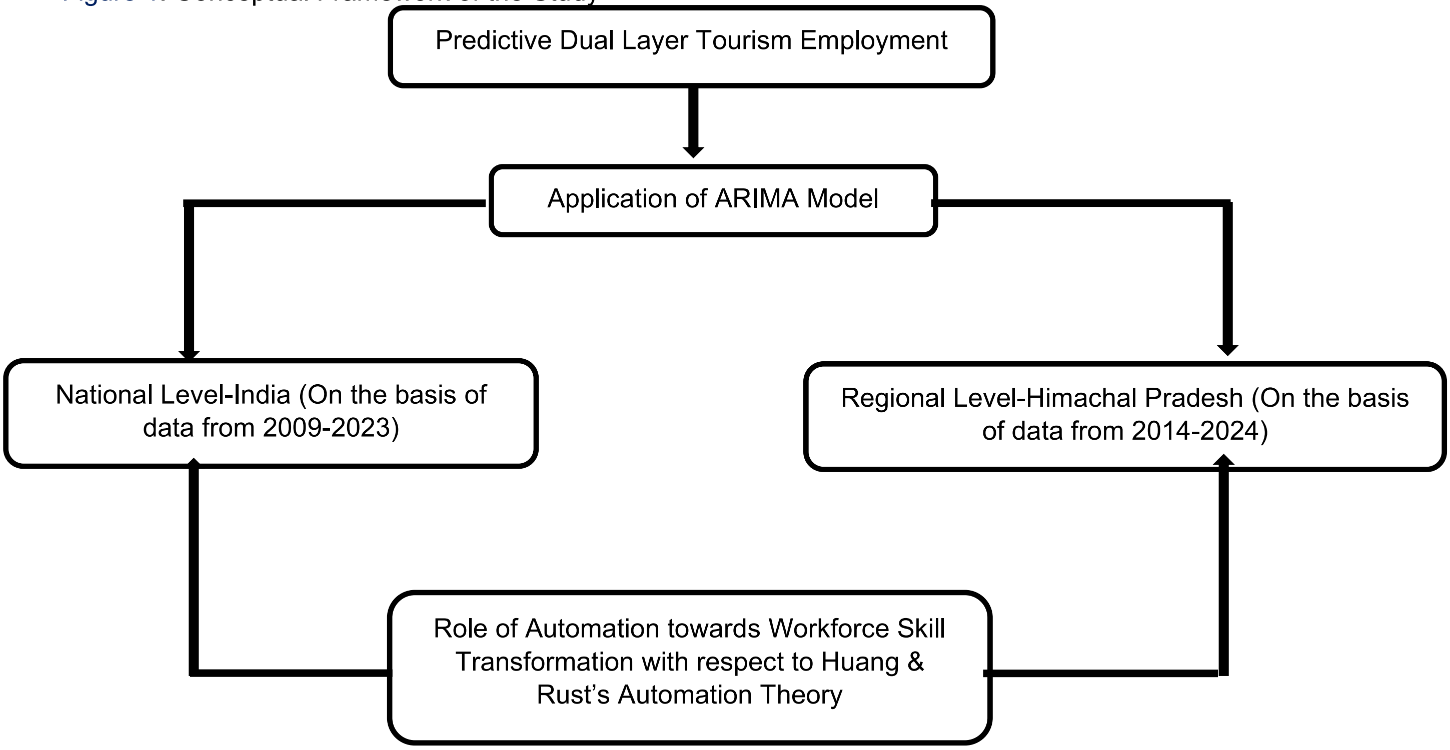
Forecasting is extensively used in tourism research to predict demand, arrivals, and revenue; yet employment forecasting remains limited, especially in the Indian context. Time-series models, particularly ARIMA, have been dominant because tourism data generally show trends, seasonality, and structural shocks. The foundational work of Box and Jenkins (1970) underscores ARIMA's suitability for modeling non-stationary economic data. Empirical studies show its consistent performance: Putri et al. (2024) used ARIMA for hotel occupancy prediction, and Gülay (2024) demonstrated its accuracy in modelling tourism revenue under irregular fluctuations. Employment-specific applications have also yielded promising results. Tovmasyan (2021) confirmed that tourism labour demand often follows identifiable patterns that ARIMA can effectively forecast even during periods of volatility.

2.1. Theoretical Framework

Indian literature remains skewed toward tourist arrivals forecasting, with minimal emphasis on employment prediction and almost no comparative forecasting between national and state-level labour trends. This gap strengthens the rationale for modeling tourism employment in India and Himachal Pradesh simultaneously, particularly because India shows long-term growth while Himachal experiences irregular oscillations that require separate modelling parameters.

Although forecasting and automation are widely researched individually, few studies integrate the two, especially within India's tourism economy. Borup and Schütte (2022) stress that linking employment forecasts with automation trends enables policymakers to anticipate not only future workforce levels but also evolving skill requirements. In this context, Huang and Rust's (2018) automation theory provides a useful conceptual lens for interpreting how technological change affects employment in service industries such as tourism. The theory conceptualises automation as progressing across four levels of intelligence, mechanical, analytical, intuitive, and empathetic, where routine and rule-based tasks are most susceptible to automation, while tasks requiring judgement, creativity, emotional intelligence, and interpersonal interaction remain predominantly human-driven. Unlike manufacturing contexts where automation often substitutes labour, service industries are characterised by high levels of human interaction, making full labour replacement unlikely. Instead, Huang and Rust (2018) argue that technology and human labour coexist in services, with automation complementing the workforce by enhancing efficiency, supporting decision-making, and enabling service personalisation rather than eliminating employment. For tourism, this implies that while technology may automate operational functions such as ticketing, check-in, and information processing, human labour continues to play a central role in experience creation, relationship management, and service recovery, reinforcing the importance of analysing employment forecasts alongside automation-driven workforce transformation.

Figure 1. Conceptual Framework of the Study



India's long-term upward trend in tourism employment suggests potential expansion, whereas Himachal Pradesh's fluctuating pattern reflects regional labour vulnerabilities. Analysing these patterns together helps uncover structural differences between a large national economy and a regionally specialized tourism state. Connecting these forecasts with automation literature allows for richer strategic interpretation, highlighting whether employment growth will be labour-led, technology-driven, or hybrid.

3. Research Methods

This study employs a quantitative, time-series–based forecasting approach to examine employment trends in India's tourism sector and the tourism workforce of Himachal Pradesh, while also assessing how the projected employment patterns relate to the growing integration of automation technologies. The methodological framework combines empirical ARIMA-based forecasting with qualitative interpretation, thereby enabling both a numerical assessment of future employment trajectories and a conceptual understanding of workforce transformation within the tourism sector. Himachal Pradesh was selected as the regional case study owing to its strategic importance as one of India's leading mountain tourism destinations and its distinct labour-market characteristics. Tourism employment in the state is highly seasonal, climate-sensitive, and strongly reliant on informal and temporary labour arrangements, resulting in pronounced fluctuations in employment levels over time (Thakur, 2023; Gupta, Kumar & Pathania, 2025). Compared with diversified national tourism markets, hill-state tourism economies are more vulnerable to climatic shocks, infrastructure constraints, and seasonal demand variations, making Himachal Pradesh a relevant and policy-significant case for analysing tourism employment behaviour under conditions of structural volatility and for assessing how such patterns may respond differently to automation than national-level trends.

The study is based on a secondary data based on annual tourism employment figures. As the analysis relies on aggregate national- and state-level employment data, traditional sampling procedures are not applicable. Instead, purposively selected secondary datasets were used, drawn from institutional sources commonly employed in tourism and labour research. Tourism employment data for India covering the period 2009–2023 were collected exclusively from the official public-domain resources of the Ministry of Tourism, Government of India, accessed through its official website and published India Tourism Statistics, 2023 reports. Employment data for Himachal Pradesh spanning 2014–2024 were collected through personal visits to the Himachal Pradesh Tourism Development Corporation (HPTDC) Tourism Office, Shimla. All data were used strictly for academic and non-commercial research purposes, and no modification of the original figures was undertaken. The primary variable analysed is total tourism employment, encompassing both direct and indirect employment in order to capture the overall labour engagement generated by tourism activities. For Himachal Pradesh, particular attention was paid to employment volatility arising from seasonal tourism cycles and climatic sensitivity characteristic of hill destinations.

Several data-preparation procedures were undertaken to ensure the suitability of the datasets for time-series modelling. The series were first examined for missing observations, and interpolation techniques were applied where necessary to maintain continuity. Extreme deviations observed during the COVID-19 period were treated separately, and dummy variables were considered to account for pandemic-related structural shocks. Stationarity was assessed using the Augmented Dickey–Fuller (ADF) test in conjunction with visual trend analysis to determine the appropriate level of differencing. Variance-stabilising transformations, including logarithmic adjustments, were evaluated and applied only when essential to improve model performance. In addition, the Himachal Pradesh employment series was normalised to address the pronounced seasonal and climatic variability inherent in hill-tourism regions.

The principal analytical technique employed is the Autoregressive Integrated Moving Average (ARIMA) model, selected for its robustness in modelling non-stationary economic time-series data (Box & Jenkins, 1970). ARIMA modelling was conducted separately for India and Himachal Pradesh following the Box–Jenkins methodology. Model identification involved examination of autocorrelation (ACF) and partial autocorrelation (PACF) plots to determine appropriate autoregressive (p), differencing (d), and moving average (q) parameters, while candidate models were shortlisted using information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Model estimation was carried out using SPSS, and only parameters that were statistically significant at the 5% level were retained. Final model selection was based on overall goodness-of-fit, parameter stability, and diagnostic performance. Diagnostic checks included the Ljung–Box Q test to verify residual independence, stationary R-squared values to assess explanatory adequacy, residual ACF and PACF plots to detect any remaining autocorrelation, and normality tests of residuals. Only models exhibiting white-noise residuals and non-significant Ljung–Box statistics were accepted as valid for forecasting.

The validated ARIMA models were subsequently used to generate tourism employment forecasts for the period 2025–2030, producing point forecasts, 95% confidence intervals, and comparative trend analysis between national- and state-level employment trajectories. While the forecasts for India indicate long-term structural growth in tourism employment, projections for Himachal Pradesh reveal more complex patterns shaped by seasonality, climate sensitivity, policy-driven variations, and reliance on informal labour structures typical of hill tourism economies. To enhance interpretative depth, a qualitative analytical layer was incorporated to contextualise the forecasted employment trends within emerging automation dynamics. This involved a structured review of global and Indian literature on tourism automation, identification of tourism roles with high, moderate, and low automation susceptibility, and interpretation of the quantitative forecast results in relation to anticipated levels of digital adoption across accommodation, transport services, travel intermediaries, and destination management. This integrated approach facilitates an assessment of whether projected employment growth can coexist with technological substitution and highlights the growing importance of digital and hybrid skills in shaping future workforce readiness at both national and regional levels.

The study relies exclusively on publicly available secondary data obtained from official government and institutional sources, including the Ministry of Tourism (Government of India), the Himachal Pradesh Tourism Development Corporation (HPTDC), and the World Travel & Tourism Council (WTTC). No primary data were collected, no human participants were involved, and no sensitive or confidential information was used. Consequently, formal ethical clearance was not required. All data sources are appropriately acknowledged, and the study adheres to accepted academic and ethical research practices.

4. Result

This section presents the results derived from the ARIMA forecasting model applied to annual tourism employment data for India (2009–2023) and Himachal Pradesh (2014-2024). The primary objective was to estimate future employment levels in the tourism sector up to 2030 and interpret these trends within the broader context of technological advancement and automation.

Table 1. Employment Trends in Tourism Industry of India (2009-2023)

Year	Employment (million)
2009	54.47
2010	57.44
2011	60.40
2012	63.37
2013	66.33
2014	69.30
2015	72.26
2016	73.46
2017	74.65
2018	75.85
2019	79.86
2020	68.07
2021	70.04
2022	76.17
2023	84.63

Table 2. Model FIT: Employment Trends in Tourism Industry of India

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.155	.	.155	.155	.155	.155	.155	.155	.155	.155	.155
R-squared	.696	.	.696	.696	.696	.696	.696	.696	.696	.696	.696
RMSE	4.471	.	4.471	4.471	4.471	4.471	4.471	4.471	4.471	4.471	4.471
MAPE	3.571	.	3.571	3.571	3.571	3.571	3.571	3.571	3.571	3.571	3.571
MaxAPE	18.499	.	18.499	18.499	18.499	18.499	18.499	18.499	18.499	18.499	18.499
MAE	2.523	.	2.523	2.523	2.523	2.523	2.523	2.523	2.523	2.523	2.523
MaxAE	12.592	.	12.592	12.592	12.592	12.592	12.592	12.592	12.592	12.592	12.592
Normalized BIC	3.561	.	3.561	3.561	3.561	3.561	3.561	3.561	3.561	3.561	3.561

Table 3. Model FIT: Employment Trends in Tourism Industry of India

Model		2024	2025	2026	2027	2028	2029	2030
Employment Trends in Tourism Industry of India	Forecast (in million)	85.77	87.19	88.77	90.46	92.21	94.01	95.83

Figure 2. Forecast of Employment Trends in Tourism Industry of India (2025-2030)

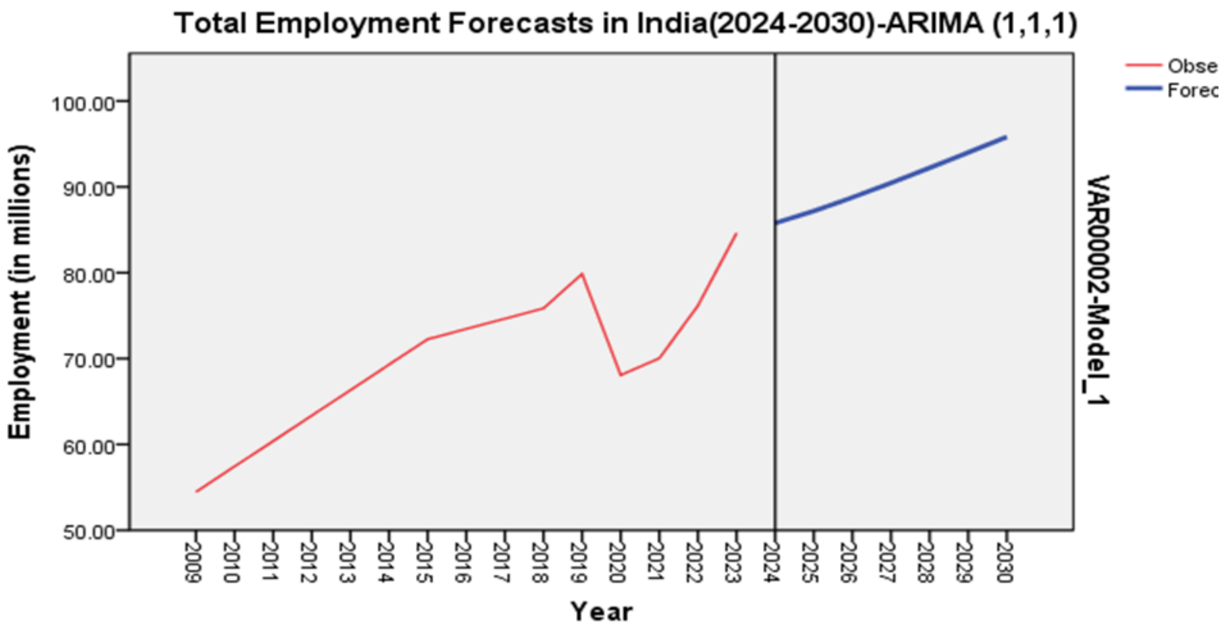


Table 4. Employment Trends in Tourism Industry of Himachal Pradesh (2014-2024)

Years	Employment
2014	21896
2015	22417
2016	22879
2017	23329
2018	23935
2019	24677
2020	25101
2021	15719
2022	17786
2023	21696
2024	25123

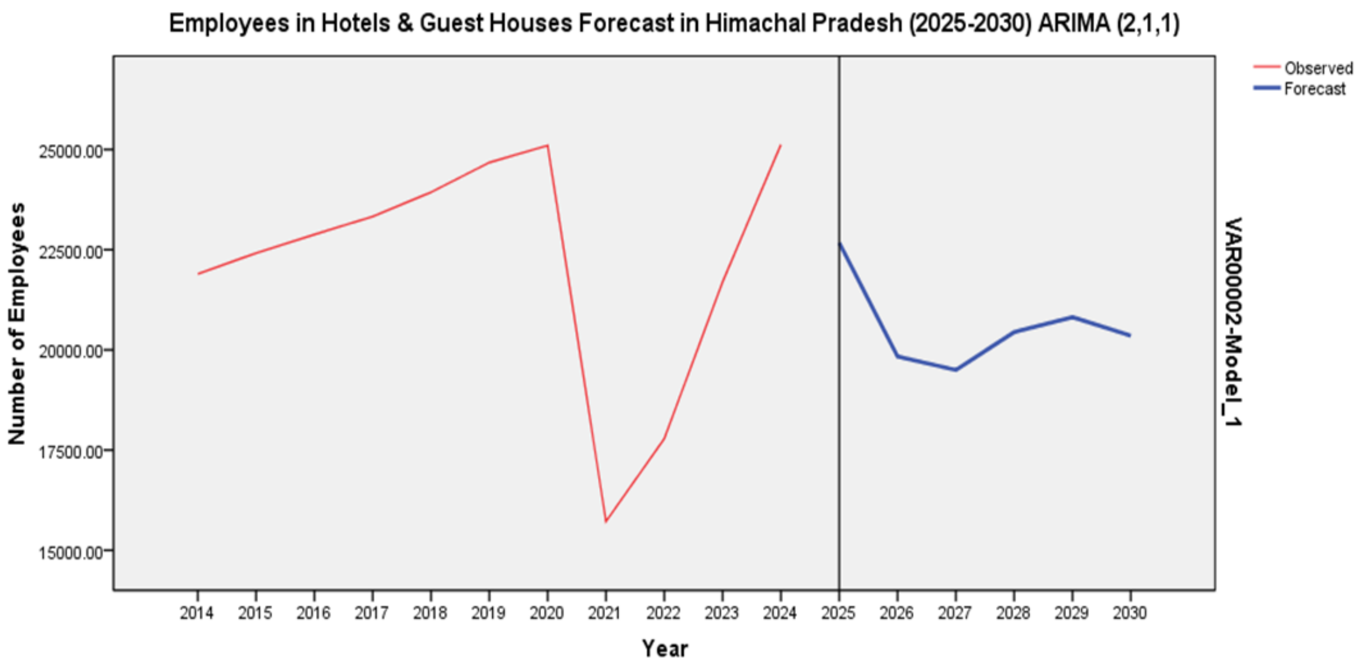
Table 5. Model fit- Employment Trends in Tourism Industry of Himachal Pradesh

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.411	.	.411	.411	.411	.411	.411	.411	.411	.411	.411
R-squared	.211	.	.211	.211	.211	.211	.211	.211	.211	.211	.211
RMSE	3432.502	.	3432.502	3432.502	3432.502	3432.502	3432.502	3432.502	3432.502	3432.502	3432.502
MAPE	9.415	.	9.415	9.415	9.415	9.415	9.415	9.415	9.415	9.415	9.415
MaxAPE	45.822	.	45.822	45.822	45.822	45.822	45.822	45.822	45.822	45.822	45.822
MAE	1871.283	.	1871.283	1871.283	1871.283	1871.283	1871.283	1871.283	1871.283	1871.283	1871.283
MaxAE	7202.753	.	7202.753	7202.753	7202.753	7202.753	7202.753	7202.753	7202.753	7202.753	7202.753
Normalized BIC	17.203	.	17.203	17.203	17.203	17.203	17.203	17.203	17.203	17.203	17.203

Table 6. Forecast of Employment Trends in Tourism Industry of Himachal Pradesh (2025-2030)

Year		2025	2026	2027	2028	2029	2030
Employment Trends in Tourism Industry of Himachal Pradesh	Forecast	22672.00	19834.17	19499.12	20444.63	20817.00	20353.98

Figure 3. Forecast of Employment Trends in Tourism Industry of Himachal Pradesh (2025-2030)



4.1. Model Summary and Diagnostic Assessment

The ARIMA models selected for both India (ARIMA 1,1,1) and Himachal Pradesh (ARIMA 2,1,1) were identified as the most suitable based on a series of diagnostic tests. For the Indian model, the Stationary R-squared value of 0.155 suggests that approximately 15.5% of the variance in the differenced series is explained by the model. Although this value appears modest, it is acceptable within the context of socio-economic and tourism employment forecasting, where structural breaks such as the Covid-19 pandemic significantly interrupt historical patterns. Similarly, the Himachal Pradesh model demonstrated appropriate fit despite the relatively short time-series (2014–2024), which naturally restricts explanatory power. In both cases, the Ljung–Box Q(18) statistic was non-significant, confirming that residuals behaved like white noise and exhibited no autocorrelation. The absence of outliers in the residual structure further validated the internal stability of the models. Altogether, the diagnostics indicate that the ARIMA specifications for both national and state-level data are statistically sound and capable of producing reliable employment projections for the 2025–2030 period.

4.2. Employment Forecasts for 2025-2030

The tourism employment forecasts demonstrate two distinct patterns across national and state-level labour markets, characterised by a stable and gradually rising trajectory at the national level and a fluctuating, non-linear pattern for Himachal Pradesh. India's ARIMA (1,1,1) projections depict a clear upward trend, with tourism employment increasing from 85.77 million in 2024 to 95.83 million by 2030, indicating sustained recovery and long-term sectoral expansion. This slow but steady growth reflects a sector that has successfully recovered from pandemic-related disruptions and is benefiting from expanding tourism infrastructure, government branding campaigns, and the growing integration of digital tourism initiatives across the country (CII & EY, 2024; WTTC, 2023). The relatively narrow confidence intervals associated with the national forecasts indicate high predictability, suggesting that India's tourism labour market is stabilising and transitioning into a phase of structural resilience.

In contrast, the ARIMA (2,1,1) model estimated for Himachal Pradesh reveals an irregular employment trajectory. The forecasts project tourism employment at 22,672 workers in 2025, followed by a decline to 19,499 workers in 2027, and subsequently a mild recovery and stabilisation around 20,353 workers by 2030. These fluctuations reflect the state's strong dependence on seasonal tourism demand, environmental vulnerabilities, and the sensitivity of small-scale tourism enterprises to changes in visitor inflows and climatic conditions (Thakur, 2023; Gupta, Kumar & Pathania, 2025). Unlike the national trend, Himachal Pradesh does not display consistent upward growth, highlighting a structural divergence in employment behaviour between India's diversified tourism economy and a high-altitude, destination-specific tourism region characterised by seasonal and ecological constraints.

4.3. Interpretation of Trends in the Context of Automation

Interpreting the employment forecasts alongside the rising integration of automation technologies in tourism indicates that technology is transforming workforce structures without displacing employment (Huang & Rust, 2018; OECD, 2020). At the national level, the continued upward employment trajectory suggests that automation is operating primarily as a complement to labour rather than a substitute. Technologies such as AI-enabled chatbots, facial-recognition check-ins, robotic concierges, and self-service kiosks typically reduce repetitive administrative and operational tasks while simultaneously generating demand for new skill sets related to digital supervision, system monitoring, customer experience analytics, and AI-supported service personalisation (Ivanov & Webster, 2019; Huang & Rust, 2018).

In the case of Himachal Pradesh, despite fluctuating employment levels, the integration of automation is also expected to reshape tourism work, although at a slower pace due to smaller enterprise sizes, limited digital infrastructure, and a stronger reliance on personalised service delivery (Thakur, 2023). Importantly, neither the national nor the state-level forecasts indicate a decline in employment attributable to automation through 2030.

Instead, the projections align with global evidence suggesting that service-intensive sectors such as hospitality and tourism rely heavily on human capabilities, including emotional intelligence, interpersonal communication, cultural sensitivity, and situational problem-solving, which remain difficult to automate (Brynjolfsson & McAfee, 2017; Baum & Hai, 2020). Thus, both national and state-level employment projections point toward technological transformation rather than labour displacement, reinforcing the coexistence of human labour and technology in tourism service delivery.

4.4. Sectoral Implications

The integrated analysis carries several important implications for tourism workforce development and policy formulation at both national and regional levels. First, automation is reshaping job roles across India and Himachal Pradesh, underscoring the need for continuous upskilling and reskilling of the tourism workforce (OECD, 2020). Tourism workers must increasingly combine traditional hospitality competencies with skills related to digital systems, customer-data handling, technology-enabled service delivery, and human–machine coordination (CII & EY, 2024). Second, although employment is projected to remain stable at the national level and moderately volatile at the state level, the nature of tourism work is evolving rather than declining. Job roles are gradually shifting toward digital service management, technology-enabled guest relations, and multi-skilled operational profiles that integrate human interaction with digital support systems (WTTC, 2023).

Third, India must adopt policy frameworks that actively support digital transformation within the tourism sector, particularly among micro, small, and medium enterprises (MSMEs), which form the backbone of tourism employment across the country (CII & EY, 2024). Skill development aligned with automation, public–private training partnerships, and technology-readiness programmes are essential to strengthen workforce resilience and future employability (OECD, 2020). Lastly, while the upward national employment trend and post-pandemic stabilisation highlight the sector's resilience, the fluctuating projections for Himachal Pradesh serve as a warning that climate-sensitive destinations require tailored strategies. These include year-round tourism planning, diversification of tourism products, digital marketing expansion, and climate adaptation initiatives to stabilise employment and reduce vulnerability to seasonal and environmental shocks (Thakur, 2023; Gupta et al., 2025).

4.5. Discussion

This study examined tourism employment trends at both the national level (India) and the state level (Himachal Pradesh) using ARIMA-based time-series forecasting and interpreted these projections within the broader context of increasing automation in the tourism and hospitality sector. The dual-level analysis provides a holistic understanding of how employment is evolving across different scales of the tourism economy and highlights contrasting trajectories between national-level stability and state-level fluctuations (Petrevska, 2017).

The combined results indicate a moderately rising employment trend for India and a more unstable, cyclical pattern for Himachal Pradesh, offering a nuanced understanding of tourism labour dynamics in the context of technological acceleration. At the national level, the positive employment trajectory through 2030 suggests that automation is not reducing labour demand but is instead restructuring job profiles toward hybrid human–technology roles (Huang & Rust, 2018). Human labour remains central to delivering hospitality services, reinforcing the argument that automation enhances service efficiency rather than replacing workforce capacity (Ivanov & Webster, 2019). In Himachal Pradesh, although employment does not follow the national upward pattern, the sector shows potential for stabilisation if supported by strategic interventions in digital infrastructure, all-weather tourism development, and workforce technological training (Thakur, 2023).

The ARIMA model developed for India demonstrated robust statistical adequacy, supported by clean residual diagnostics such as non-significant Ljung–Box Q statistics and acceptable goodness-of-fit indicators, reinforcing the reliability of the national employment forecasts (Box & Jenkins, 1970; Petrevska, 2017). In contrast, the Himachal Pradesh model revealed a more irregular employment pattern, with projected dips in specific years such as 2026 and 2027 before recovering again. This volatility indicates that Himachal Pradesh's tourism labour market is more sensitive to seasonal variations, local economic conditions, infrastructural constraints, and periodic demand shocks compared to the national trend (Gupta et al., 2025).

A central finding of the study is that automation, while increasingly visible across both national and state tourism ecosystems, does not pose a significant threat to employment levels. Nationally, the steady rise in employment despite technological integration confirms that automation functions as a complementary mechanism, reducing operational inefficiencies while creating new roles in digital service management, system supervision, AI-interface handling, and technology-supported guest experience enhancement (Huang & Rust, 2018; OECD, 2020). In Himachal Pradesh, where tourism is driven by personalised service, local hospitality culture, and nature-based offerings, technology adoption remains supportive rather than substitutive. The labour-intensive nature of hill tourism, characterised by guest assistance, guided activities, homestay operations, and high-touch hospitality, continues to rely strongly on human labour even as digital tools are gradually incorporated into booking, communication, and property management systems (Baum & Hai, 2020).

Overall, the findings underscore that the future of tourism employment in both India and Himachal Pradesh is defined not by job displacement but by job transformation. While national employment is projected to grow steadily and state-level employment remains fluctuating yet broadly positive, skill requirements within the sector are evolving rapidly. Hybrid roles that merge hospitality expertise with digital proficiency are becoming increasingly necessary (CII & EY, 2024). These insights point to the need for targeted policy and institutional interventions. At the national level, tourism education and vocational training must integrate digital literacy, automation management, and hospitality technology modules (OECD, 2020). At the state level, Himachal Pradesh should focus on capacity building for small and medium tourism enterprises, technology adoption in homestays and eco-tourism units, and workforce development aligned with its unique seasonal and geographical tourism context (Thakur, 2023). Strengthening collaboration among government agencies, tourism boards, and hospitality institutions will be essential to ensure workforce readiness and long-term sustainability across both national and regional tourism economies.

5. Conclusion

This study highlights the contrasting yet complementary significance of analysing tourism employment at both the national and state levels. India represents a large, diversified tourism economy with expanding infrastructure, policy support, and increasing digital integration, while Himachal Pradesh exemplifies a regionally specialised, climate-sensitive, and seasonally driven tourism destination. Examining these two contexts together provides a nuanced understanding of how tourism employment evolves across different spatial scales and structural conditions. The national–state comparison demonstrates that while aggregate employment growth may appear stable at the macro level, regional labour markets can exhibit volatility that requires targeted and context-specific policy responses.

In relation to the first objective, which sought to forecast tourism employment trends in India and Himachal Pradesh using ARIMA models, the findings indicate that tourism employment in India is on a stable and gradually rising trajectory through 2030. This reflects post-pandemic recovery, sectoral resilience, and sustained demand for tourism services. In contrast, Himachal Pradesh exhibits a fluctuating but broadly resilient employment pattern, shaped by seasonality, climatic sensitivity, and dependence on informal and temporary labour. These results confirm the usefulness of ARIMA modelling in capturing both long-term growth trends and region-specific employment volatility.

Addressing the second objective, which examined the role of automation and digitalisation in transforming tourism employment, the study finds that automation is not reducing overall employment levels in either context. Instead, automation is reshaping job roles and skill requirements by reducing routine tasks and increasing demand for hybrid roles that combine hospitality expertise with digital competencies. The findings reinforce the view that in service-intensive sectors such as tourism, technology complements rather than replaces human labour, with emotional intelligence, interpersonal interaction, and experiential service delivery remaining central to tourism work.

The findings offer several practical implications for policymakers, industry stakeholders, and training institutions. Strengthening digital skill development is essential, as tourism organisations and training centres must equip workers with competencies in AI-enabled service tools, customer analytics, robotics-assisted operations, and technology troubleshooting to meet emerging hybrid job demands. Policy support is particularly important for micro, small, and medium enterprises (MSMEs) and homestay operators, who form the backbone of tourism employment and require incentives, structured training, and technical assistance to adopt automation tools without undermining job opportunities.

At the regional level, destinations such as Himachal Pradesh require tailored workforce strategies, including year-round tourism planning, diversification of tourism products, and climate-adaptive employment planning to reduce seasonal volatility. Tourism enterprises should also redesign job roles to emphasise human–technology collaboration, ensuring that efficiency gains from automation are balanced with the preservation of personalised service experiences.

From an academic perspective, this study contributes to tourism employment literature by extending the application of time-series forecasting beyond tourist arrivals to employment dynamics, particularly within a developing economy context. By integrating ARIMA-based employment forecasts with automation theory, the study bridges two strands of literature that are often examined independently. The dual-level national–state approach further advances understanding of spatial heterogeneity in tourism labour markets and provides a framework for future comparative studies linking employment forecasting with technological transformation.

Despite its contributions, the study has certain limitations. First, the analysis relies on annual secondary employment data, which restricts the ability to capture short-term seasonal fluctuations and intra-year employment adjustments, particularly relevant for hill destinations such as Himachal Pradesh. Second, the forecasting models do not incorporate exogenous variables such as tourist arrivals, investment flows, climatic indicators, or policy shocks, which may influence employment dynamics. These limitations suggest that the forecasts should be interpreted as indicative long-term trends rather than precise short-term predictions.

Future research can build on this study in several ways. Methodologically, advanced forecasting techniques such as ARIMAX or SARIMA models could be employed to incorporate seasonality and exogenous variables, thereby improving predictive accuracy. The use of higher-frequency data, such as monthly or quarterly employment figures, would allow for more sensitive modelling of seasonal labour dynamics. Additionally, primary surveys and firm-level studies on automation adoption could generate empirical evidence on how technology is being implemented across different tourism segments and how it affects job roles, skills, and employment stability. Comparative studies across multiple hill states or tourism regions would further enhance understanding of region-specific workforce challenges and resilience strategies.

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