IJCESA
International Journal of Community Empowerment & Society Administration
ISSN: 3139-597X / Volume 3 Issue 3 July-September 2026
Paper Id: IJCESA-V3I3P102/ Page No: 07-16

Original Article

The Impact of Artificial Intelligence on Employment Structure in South Asian Economies: A Theory-Driven Review and Secondary Evidence

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Received Date: 15 July 2026 Revised Date: 25 June 2026 Accepted Date: 30 July 2026

Abstract: *Artificial intelligence is increasingly changing the way work is done, including organization, allocation, and the importance of skills. However, while there is substantial research on the effects of AI on work in developed economies, the same is not true for South Asian countries, where there is a lack of theory and research. This paper attempts to bridge this gap through a theory-informed analysis of the effects of AI on employment structures in South Asian economies, supported through a systematic review of secondary literature. Through task-based theories, skill-based biased technological change, and various socio-institutional perspectives, this paper views AI as a structural driver of employment change, where AI influences employment structures through task re-allocation, skill change, and institutional mediation. Based on the review of secondary literature, the findings suggest that AI adoption in South Asian economies leads to reduced employment prospects in routine, clerical, and similar types of work, while at the same time creating new prospects in digital and service-based occupations. However, these processes are moderated through high rates of labor informality, limited education capacity, and institutional readiness. The research suggests an integrated approach for how AI affects job structures in order to capture these nuances. It offers a comprehensive paradigm for how AI affects job hierarchies. Based on theory and South Asian realities, it provides an insight of how AI affects job structures. It adds to the general discussion about job arrangements in developing nations.*

Keywords: *South Asian Economies, Artificial Intelligence, Job Structure, Work Reallocation, Skill-Biased Technology Change, Institutional Capability*

I. INTRODUCTION

Artificial intelligence (AI) is one of the most important general-purpose technologies affecting contemporary labor markets. In contrast to earlier waves of mechanization and automation that mostly affected regular manual tasks, recent advances in AI increasingly target cognitive, analytical, and decision-making positions that were previously assumed to be resistant to technology substitution (Acemoglu & Autor, 2011). The impact of artificial intelligence (AI) on employment relationships, the distribution of work between people and machines, and skill formation processes is driving change in labor markets, with consequences for the organization of work across economic sectors. This process has raised questions about the potential of AI to transform profoundly patterns of human activity, and about the ways in which such changes might affect employment, skills and working life more generally.

An increasing amount of empirical research from developed nations shows that not all jobs are equally affected by the use of AI. AI tends to increase the need for high-skill occupations while decreasing the demand for ordinary and semi-routine jobs, according to certain empirical research based on skill-biased technological change and task approaches. AI can also eliminate some professions while creating new ones related to data analysis, algorithm monitoring, and digital services, according to current simulation and business-level research. Overall, these research point to a shift in labor markets and suggest that the story of catastrophic technological unemployment may be overstated. (Frey et al., 2017). According to Tabash et al. (2025), "such structural factors are influencing the pace at which the technology diffuses and its labor implications, which can, in turn, yield a different story than what is being observed in North America and European countries." The WB's study based on data up to 2025 indicates that employment in South Asia is associated with lower demand for certain entry-level and clerical occupations, whereas demand for digital labor service jobs is still growing. However, the transferability of such patterns to developing nations is not immediately apparent.

The phenomena is explained by a number of ideas, including conventional compensation theories on technological advancement, which contend that the overall creation of new jobs due to productivity gains and the emergence of new industries eventually outweighs the losses (Acemoglu & Autor, 2011). On the other hand, theories of skill-biased technological transformation contend that AI would worsen the income and employment disparity while benefiting those with higher levels of education. According to the task approach, which considers the different kinds of work that fall under a given occupational category, AI will not completely eliminate jobs; rather, it will induce a partial displacement due to task reallocation across industries (Lane et al., 2023).

There is conflicting empirical evidence to support these views in recent South Asian studies. In addition to pointing out new prospects in AI-enabled services, Batool et al. (2025) present evidence of employment displacement in routine-intensive occupations in Pakistan. Low-skilled workers are more vulnerable to the effects of automation, according to a comparative study by Ganuthula and Balaraman (2025), which found that labor market polarization is more prominent in India than in the US. However, regional assessments indicate that institutional constraints and inadequate skill absorption capacity may impede the revolutionary impact of AI, resulting in the cohabitation of new digital forms of labor with current job structures (Tabash et al., 2025).

From the standpoint of traditionalists, Zaheer et al. (2025a) argue that socio-institutional and cultural factors should be considered when determining the impact of artificial intelligence (AI) on the labor market. Their study revealed that AI integration might improve current trends in employment rather than create a significant number of new jobs in the absence of appropriate training and regulatory frameworks. Such a view, which is particularly relevant to the South Asian region, where employment is largely dictated by socio-cultural norms, enriches the overall understanding of how technology disrupts labor markets by incorporating additional variables beyond automation and economic performance.

While the topic of AI-driven labor market changes has been gaining traction among science and public media, there is a limited number of conceptual pieces discussing how AI technologies might affect employment trends in South Asia. At the same time, research findings and reports often concentrate on either a particular issue or a single country, while neglecting the importance of context-specific nuances. As a result, there is currently no comprehensive framework outlining potential relationships between the labor market and AI technologies. Addressing this gap is crucial for advancing further research and informing policymakers, as it allows for generating informed recommendations for both researchers and decision-makers. This paper, therefore, explores how AI impacts the employment structure of South Asia through a theory-driven analysis that utilizes secondary data. Specifically, the study aims to respond to three questions: (1) How do major labor economics theories conceptualize the relationship between AI-driven disruption and employment structure? (2) What do the findings of the selected pieces of research and secondary data say about the connection between AI advances and labor market trends in South Asia? and (3) How can institutional and skill-related factors attenuate the influence of AI on the labor market? By combining theoretical foundations with regional realities, the current analysis seeks to contribute to a growing body of research on AI's impact on job markets and support policy development on the national level.

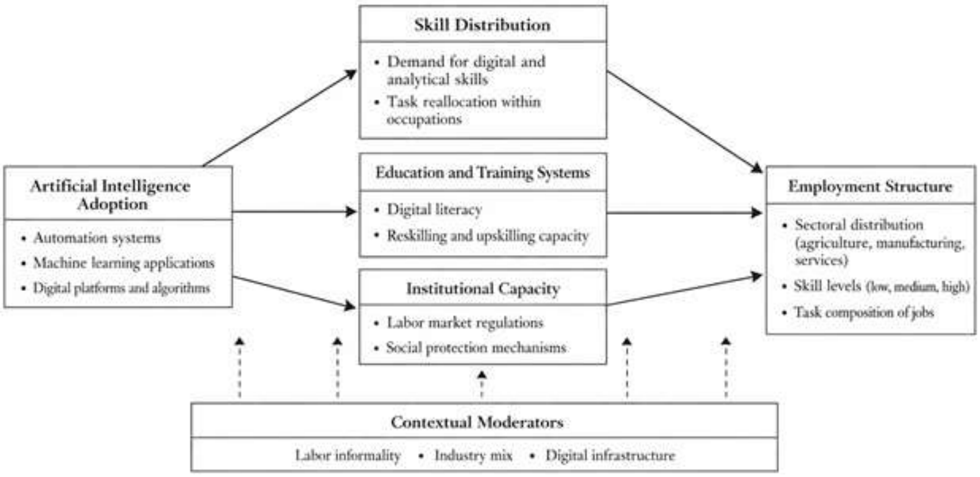

Figure 1: Conceptual Pathways Linking Artificial Intelligence Adoption and Employment Structure in South Asia

Figure 1 represents the conceptual pathway through which AI affects labor arrangements in South Asian countries. In general, labor markets in South Asian countries experience AI either directly or indirectly. It is evident from the diagram that AI affects employment indirectly through the distribution of skills, responsiveness of education/training systems, and institutional capacities, and this determines employee adaptation to AI-driven tasks rather than displacing people immediately. Institutional and technical factors are critical considerations in the model as it demonstrates the role of these variables in employment transformations and interactions in a given context or country. It is essential to consider the contexts influencing labor informality, sectoral composition, and digital technology as they influence the overall relationship between AI and employment arrangements.

A. Research Questions

The following research questions have been formulated based on the provided theoretical background on artificial intelligence, employment and the specifics of the South Asian labor market:

Research questions:

- Q1: What are the ways in which artificial intelligence is likely to redefine the nature of employment as suggested by the classical labor economics theories?
- Q2: What patterns and trends of employment restructuring related to the emergence of artificial intelligence technologies can be observed in South Asian countries?
- Q3: How do differences and similarities in institutional capabilities, education and training opportunities, and skill sets influence the patterns and trends of employment restructuring in South Asia?

B. Research Gap and Contribution of the Study

Research on the nexus between artificial intelligence (AI) and employment is currently gaining momentum. However, the literature is overwhelmingly concentrated on developed economies, neglecting the regional particularities of South Asia. Second, there is a need for a theoretical synthesis of the evidence generated in developing economies concerning the impact of AI on jobs. Most of the existing literature is fragmented and limited in its conceptualization of the mechanisms through which AI affects employment prospects. For instance, studies by Acemoglu & Autor (2011) and Lane, et al. (2023) overlook the mediating role of institutions, skill premiums, and reallocation of tasks in understanding the link between automation technologies and jobs. Recently, emerging empirical evidence suggests that labor informality, industrial structure, and skill endowments interact with varying intensities to determine the nature of employment outcomes in South Asia (Tabash et al., 2025; World Bank, 2025). This study aims to contribute to addressing the aforementioned research gaps by offering a context-specific theoretical framework within which AI-related occupational changes can be examined. By relying on regional employment theories and emphasizing the mediating role of skills, education systems, and institutional infrastructure, this study bridges the extant literature on AI and jobs, particularly in South Asia. The analysis by Zaheer, Sadiq, and Safi (2025a) offers a much-needed theoretical underpinning for subsequent empirical and policy-oriented studies concerned with the indirect impact of AI on labor markets.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

A. Artificial Intelligence and Employment: Global Perspectives

The relationship between advances in technology and employment has long been of interest to labor economists, but the rise of artificial intelligence (AI) has breathed new life into the discussion. Unlike previous innovations that were typically focused on mechanization, modern developments in AI have the potential to disrupt intellectual work, broadening the range of occupations that may be displaced (Brynjolfsson & McAfee, 2014). Recent studies suggest that adoption of AI has negative and positive effects on the labor market by changing the number and type of available jobs, their content, and compensation levels (Autor, Levy, & Murnane, 2003). The impact of AI on employment may differ across occupations, as found in a study conducted among developed countries. For instance, at the firm level, adoption of AI was associated with reduced need for lower-skilled administrative and clerical workers, while production was facilitated (Aghion, Jones, & Jones, 2019). The effect of automation on employment has been found to be non-trivial, as automation tends to affect tasks, not jobs, resulting in transformation and partial substitution within occupations (Choi et al., 2024). Such evidence highlights the importance of considering variation in tasks when forecasting the effects of technology on employment.

B. Skill-Biased Technological Change and Labor Market Polarization

One of the theories that explain the impact of AI on employment is the skill-biased technological change (SBTC). The SBTC posits that technological changes favor high-educated workers over the low-educated ones and worsen inequality at the level of employment and wages (Katz & Murphy, 1992). From the more recent application of the theory to AI, the algorithms tend to raise abstract reasoning abilities and replace humans with lower cognitive capabilities (Autor, 2015). These hypotheses have found empirical evidence in several studies. In the current situation, the middle-skill jobs have stagnated while high-skill professional occupations and low-skill service occupations have experienced job growth (Goos, Manning, & Salomons, 2014). However, the experience of the developing countries suggests that the patterns of SBTC are not necessarily the same due to differences in the education systems and structures of their economies. In particular, Ganuthula and Balaraman (2025) report that India has more polarized labor markets than the US, meaning that low-skill workers there may be more affected by the adoption of AI technologies and further widen the gap between the low-skilled and high-skilled workers.

C. Task-Based Models and Employment Restructuring

By concentrating on the particular tasks carried out inside professions rather than the occupational categories themselves, task-based models expand upon SBTC. Instead of completely eliminating jobs, Autor and Handel (2013) contend that technological innovation reallocates employment between humans and robots depending on comparative advantage. This strategy is especially pertinent to artificial intelligence (AI), which struggles with social interaction and contextual judgment but excels in data processing, pattern recognition, and forecasting. Task-based frameworks are applied to AI exposure in recent empirical investigations. According to Marguerit (2025), the tendency shows that AI development will create new jobs related to maintaining, managing, developing, and supporting AI systems, thus substituting humans in the specific tasks. According to Lane et al. (2023), in turn, it can be stated that the jobs involving the use of social interactions and non-routine cognitive tasks will be less susceptible to automation than those including the heavy use of routine cognitive tasks. Therefore, based on the findings of the research, it can be concluded that AI will create new jobs while substituting humans in the certain functions.

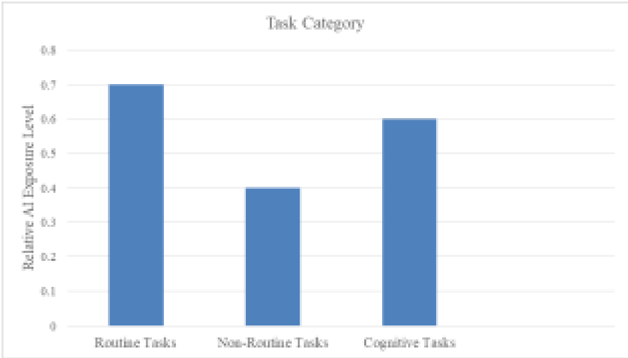

Figure 2: Task Exposure to Artificial Intelligence in Different Occupation Categories

The level of exposure of different categories of activities to artificial intelligence technologies is demonstrated in Figure 2. First of all, it should be noted that routine tasks have the highest exposure to AI since they can be easily substituted by automatized procedures. At the same time, the figure shows that cognitive tasks are exposed to artificial intelligence technologies at a relatively low level. It means that AI systems are applied in the spheres of cognition and decision-making to assist human workers rather than replacing them. In turn, non-routine activities have the lowest level of exposure to AI. Considering the complexity of interactions with the environment, they require human involvement in processes that is hardly substituted by machines. In this manner, the figure above illustrates task-based theories of employment and the impact of AI on the distribution of tasks in the economy.

D. AI and Employment in Developing and South Asian Economies

Worldwide, there is a growing body of research on the impact of artificial intelligence on employment, but there is a lack of South Asian data, which is both limited and contradictory. The current state of knowledge indicates that structural factors such as informality, overstaffing, and the level of internet development mediate the relationship between AI and employment. The use of artificial intelligence in South Asia reduces the demand for unskilled clerical workers but increases the need for digital service employees, as found by Tabash et al. (2025). At the same time, according to Batool et al. (2025), in Pakistan, there is a decrease in the number of jobs requiring routine cognitive work, combined with a need for upskilling those who remain employed. As the World Bank labor market report for South Asia 2025 notes, the adoption of AI is uneven across sectors, with services being more affected than industry and agriculture. Moreover, high levels of informality reduce the ability of workers to acquire the necessary skills through formal channels and social security, lowering their adaptability. Thus, the current trends suggest that, rather than a straightforward process, the disruption of the labor market by AI occurs in South Asia through mediation by institutional and educational factors.

E. Socio-Institutional and Traditionalist Perspectives

Besides economic forces, some literature has demonstrated the role of socio-institutional factors in technological-employment relationships. Authors emphasize that governance, factors affecting labor, social relations, and technology itself are critical resources shaping the connection between artificial intelligence (AI) and employment. Similar findings are revealed in the study of non-governmental organizations in Afghanistan, which show that technology application in human resource management and organizational processes significantly improves employee performance and adaptability if digital competence and institutional capacity are present (Zaheer & Sadiq, 2024). Technological changes in enterprises, professional activities transformation, and employees' adaptation to new conditions depend on institutional capacity (Rodrik, 2018). The study also found that apart from technological competence, governance, labor laws, and societal norms affect employment changes induced by AI technologies. Zaheer, Sadiq, and Safi (2025a) provide a conventional view on the impact of AI on employment in developing countries. The authors state that institutional capacity and competency development contribute to moderate disruption of employment arrangements caused by robotization and automatization of processes. Underdeveloped institutional infrastructure and poor competencies prevent radical changes, allowing traditional modes of employment to co-exist with new forms and only partially transforming some areas.

III. THEORETICAL FRAMEWORK DEVELOPMENT

Based on the reviewed literature, the current study uses an integrated theoretical framework that combines the theories of skill-biased technology development, task-based models, and socio-institutional theory. The theory highlights mechanisms such as institutional moderation, skill composition, and education and training systems, under which the adoption of artificial intelligence may affect employment processes. In this perspective, employment structure refers to the distribution of occupations across different economic sectors, levels of skill intensity, and categories of tasks performed. The theory also introduces several contextual moderators, including labor informality, industrialization level, and digitalization level, which are deemed relevant to employment outcomes in South Asian countries. Overall, the current study seeks to operationalize an empirical model that would capture the process of change in employment in a gradual, institutional, and moderated manner rather than an oversimplified binary view of jobs destruction versus creation.

A. Conceptual Framework

This study aims to develop an integrated conceptual framework that explains how the integration of artificial intelligence (AI) affects jobs in South Asian countries through indirect mechanisms. Unlike previous studies, which postulate a direct and deterministic link between AI and its impact on employment, this study views technology as a structural factor, which triggers indirect processes, leading to labor adjustments. In other words, this article focuses on endogenous mechanisms, which are common in the modern labor market theory (Autor, 2015; Frey et al., 2017).

As seen in figure 3 below, the main independent variable that requires further investigation is "Adoption of artificial intelligence." "Adoption of artificial intelligence" implies the implementation of AI-driven technologies in businesses. Task-based models of technological change state that these technologies alter the relative productivity of activities by shifting regular and predictable work to machines while increasing the role of human labor in non-routine and judgment-intensive jobs (Autor & Handel, 2013). Furthermore, firm-level data indicates that rather than entirely eliminating jobs, the adoption of AI typically restructures work content and service procedures, particularly in service-oriented industries (Aghion et al., 2019).

The first mediating channel in the system is task reallocation and skill structure. Adoption of AI changes labor demand by decreasing reliance on repetitive cognitive and administrative duties and elevating the significance of digital literacy, analytical reasoning, and adaptable problem-solving abilities. The skill-biased technological transition theory, which forecasts growing employment polarization and a need for higher-order skills, is in line with this trend (Katz & Murphy, 1992; Goos et al., 2014). The task-level character of employment transformation is supported by evidence from AI-intensive service industries that shows how technology adoption changes job roles by refocusing attention on quality-sensitive and interaction-oriented tasks (Zaheer, Sadiq, & Safi, 2025b).

Institutional capacity and educational systems, which affect how successfully labor markets absorb AI-induced change, constitute the second mediating factor. Education and training systems determine the ability of workers to acquire AI-complementary skills, whereas labor market institutions shape employment mobility, adjustment costs, and wage security. As Rodrik (2018) notes, institutional quality is pivotal in alleviating negative social outcomes of technological progress, which is particularly relevant for developing countries. Due to the observed challenges in education and institutional capacity, the adoption of AI in South Asia is likely to produce differential impacts, affecting structural employment in an uneven manner (Tabash et al., 2025).

Employment structure, one of the primary outcome variables, therefore, encompasses shifts in sectoral composition, changes in the distribution of tasks, and alterations in skill sets demanded by employers. This definition reflects emerging research on the impact of AI on labor, which increasingly recognizes its role in mediating processes associated with worker performance, such as quality image, trust, and human-agent relations, not only automating tasks (Zaheer, Sadiq, & Safi, 2025b; Brynjolfsson & McAfee, 2014). In this respect, there is a growing body of evidence that AI affects employment by intervening in indirect ways, transforming job roles instead of eliminating them. By contrast, Zaheer, Sadiq, and Safi (2025a) demonstrate, from a socio-institutional and traditionalist perspective, that institutional readiness determines the extent and rate at which AI will be adopted, with implications for its employment impact. Specifically, researchers observe that in regions with weak institutional frameworks, AI technologies are likely to complement existing informal arrangements rather than replace them, resulting in hybrid labor systems. This consideration is particularly pertinent to South Asia, where institutional conservatism is still a significant factor influencing technological adoption.

Finally, the paradigm accounts for geographical and infrastructural determinants shaping the extent to which AI will intervene in labor processes and affect employment outcomes. Notably, the presence of a large informal labor force in South Asian developing countries has the potential to moderate the disruptive impact of technology on employment, as postulated by the World Bank (2025). The prevalence of informal employment decreases workers' access to formal education and social security benefits while presenting short-term relief against displacement. Consequently, it is predicted that South Asia will experience AI-driven changes in employment at a slow and uneven pace.

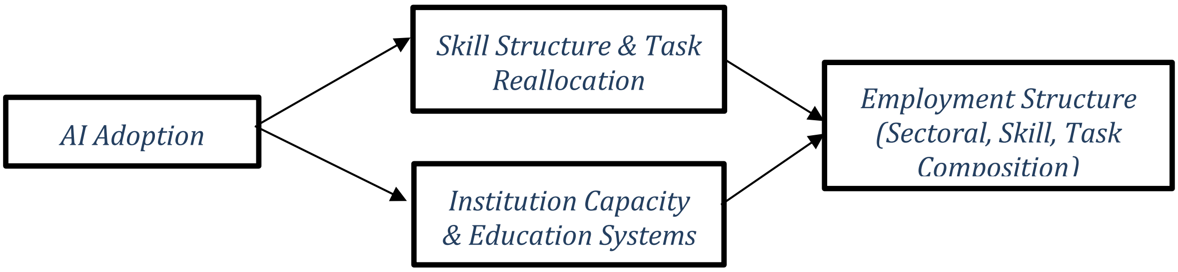

Figure 3: Integrated Theoretical Framework of AI, Skills, Institutions, and Employment Structure

The conceptual framework in Figure 3 builds upon the theories of task-based creation of jobs, skill-biased technological progress, and socio-institutional factors to understand how artificial intelligence (AI) will affect labor markets in South Asia. It goes beyond simply automation by providing an evidence-based foundation for analyzing the subsequent secondary data while also guiding further research. The framework is predicated on mediated, context-specific relationships that are also supported by the findings in the labor market and the AI service sector. For simplicity, the framework is constructed in three stages. It is merged into a comprehensive conceptual model in Figure 3, which tries to capture the essential institutional and technological mediating mechanisms. The methods in which AI affects jobs are categorized according to their task-exposure content in Figure 2. While Figure 1 captures the general mechanisms through which adopting AI will affect jobs, the arrows depict the theoretical relationships.

IV. METHODOLOGY AND SECONDARY EVIDENCE STRATEGY

This study involves the application of the theory-based qualitative study design, which utilizes a comprehensive set of secondary sources of information. In particular, approximately 80-100 scholarly and professional articles and reports, including peer-reviewed journals, books, and working papers, published in 2010 – 2025, will be analyzed using the strategy employed. The articles will be identified using keywords automation, artificial intelligence, employment dynamics, task-baed approach, and labor market polarization with the help of such databases as Scopus, Web of Science, and Google Scholar. Only articles that address specific issues of employment-related trends caused by automation and have a solid theoretical foundation or emprirical data related to the impact of automation on employment in the context of emerging and developing countries can be included. It is noteworthy that articles that only provide statistical data and are devoid of any significant theoretical or conceptual underpinning will be excluded from consideration.This approach will be more efficient and effective in the current situation since it will allow addressing the issue of the impact of automation on employment in the Global South, which does not have sufficient primary data. Theory-driven reviews are widely recognized as an effective method for enhancing conceptual clarity and integrating divergent empirical findings, especially in emerging research domains (Webster & Watson, 2002). By basing the analysis on well-established labor market theories, this study goes beyond descriptive reporting to provide an explanatory account of AI-induced employment shift.

A. Data Sources and Selection Criteria

Several peer-reviewed journals indexed by Scopus and Web of Science, international organization policy reports from the World Bank and International Labour Organization, and national labor market statistics for South Asia were among the reliable sources used to create secondary data for analysis and verification. It is possible to more accurately reflect emerging trends in AI use and labor force transitions by giving priority to papers produced between 2015 and 2025.

AI, automation, and/or advanced digital technologies and employment outcomes, task composition, skills, or labor market institutions were the only topics covered by the inclusion criteria. Research carried out in poor and growing economies, especially in South Asian countries, was given priority. This research did not include any literature that focused only on the technical performance of AI and had no bearing on labor force challenges. This selection process fits recommended practice in the field for thematic and theory-driven synthesis of management and economics studies (Tranfield et al., 2003).

B. Analytical Approach

The selected evidence was analyzed using thematic and theory-guided synthesis. First, based on the conceptual structure presented in Figure 3, I projected the findings onto the proposed conceptual framework to identify common themes and patterns in responses to AI-related disruptions, including changes in task allocation, acquisition of new competencies, and mediating factors. Second, I grouped similar patterns observed across countries and fields of application to explore differences related to informality and divergent institutional outlooks. This approach aligns with the integrative review method since theory construction and synthesis are prioritized over collecting descriptive findings, and evidence is organized by conceptual constructs rather than individual variables and relationships (Torraco, 2005).

C. Operationalization of Key Constructs

Artificial intelligence adoption was operationalized broadly and included the implementation of automated technologies and artificial intelligence software in production and service delivery in accordance with the findings of prior labor market studies (Autor, 2015; Rodrik, 2018). The restructuring of employment structures was operationalized via changes in the distribution of employment, skills, and tasks within occupations. In accordance with prior research, which identified the mediating role of perceived quality and human-AI interactions, the utilization of evidence from service industries was included to identify mechanisms (Zaheer, Sadiq, & Safi, 2025b).

D. Validity and Rigor

In accordance with the research design, which relied on academic, institutional, and policy reports, triangulation was implemented at the source level to improve validity. Additionally, to embrace theoretical triangulation, alternative approaches, such as task-based analysis, skill-biased technological change, and socio-institutional ones, were incorporated. At the analytical level, transparency was maintained and potential biases minimized by explicitly establishing the connections between the data and the theoretical constructs of the study. Although the allocation of secondary data compromises the causal inferences made in the paper, the research objective, which entailed theoretical development and contextualization, necessitated the reliance on this method. As such, the limitations of the study are justified by its contribution to theoretical advancement and regional analysis (Choi et al., 2024).

E. Ethical Considerations

No human subjects were used for this study as all information used was publically available. As such there is no need for ethical approval, and no secondary sources needed citation.

F. Methodological Contribution

By carefully integrating secondary data within a theory-driven framework, this study contributes methodologically by demonstrating how AI–employment connections can be investigated in developing nations with little data. The methodology offers a repeatable model for future research that aims to reconcile theory and data in emerging economies.

G. Analytical Propositions

Building on the conceptual framework shown in Figure 3, this study offers a number of analytical hypotheses that explain the expected relationships between the adoption of AI and job structure in South Asian economies. These assertions are not intended to be statistically tested in the current study, but rather to codify the framework and lead future empirical research.

H. Proposition 1: AI Adoption and Task Reallocation

Adoption of artificial intelligence is anticipated to change employment mostly through work reallocation as opposed to direct job displacement. Human labor is shifting toward non-routine, judgment-intensive, and interaction-based tasks while AI systems increasingly handle routine and predictable tasks. The comparative advantages of computers in structured environments and humans in situations demanding social intelligence and adaptability are reflected in this task-level shift (Autor & Handel, 2013). P1: Instead of widespread occupational elimination, the adoption of AI is positively correlated with task reallocation within occupations, resulting in qualitative changes in job content.

I. Proposition 2: Skill Structure as a Mediating Mechanism

Changes in skill requirements operate as a mediator between AI and employment structure. Adoption of AI decreases reliance on routine cognitive competencies while increasing demand for digital, analytical, and adaptive skills. These changes lead to employment polarization in line with skill-biased technological change theory, especially in labor markets where reskilling chances are scarce (Katz & Murphy, 1992; Goos et al., 2014). P2: Changes in skill demand mediate the relationship between AI adoption and employment structure, with increased exposure to AI raising the relative relevance of advanced and adaptive skills.

J. Proposition 3: Institutional Capacity as a Moderating Factor

Institutional competence is a critical moderating factor in determining the impact of technology on the employment structure. Training facilities, labor laws, and education systems are all vital in enabling the workforce to respond to the challenges of technological progress. Additionally, they determine whether the adoption of innovative technologies will lead to inclusive restructuring of labor markets or aggravate existing inequalities. Institutional mechanisms, when weak, may reduce the ability to adapt to new systems and hinder the diffusion of new technology in emerging economies (Rodrik, 2018). P3: The influence of adopting AI on the employment structure is conditional upon institutional infrastructure, signifying that advanced labor market and education systems will facilitate adaptive employment transformation.

K. Proposition 4: Contextual Constraints in South Asian Labor Markets

The extent and direction of AI's employment implications in South Asian countries are influenced by high levels of labor informality, uneven industry development, and inadequate digital infrastructure. Adoption of AI may coexist with conventional labor arrangements rather than quickly replace them, creating hybrid job systems. Further evidence from AI-enabled service sectors indicates that human-AI interaction and quality perception are mediated processes that influence labor results in addition to technological capabilities (Zaheer, Sadiq, & Safi, 2025b). *P4: Rather than uniform displacement effects, the deployment of AI in South Asian contexts results in a slow and uneven restructuring of employment, driven by sectoral features and informality.*

L. Positioning of the Propositions

By tying the adoption of AI to the work structure via context-sensitive and mediated mechanisms, these arguments jointly constitute the study's theoretical contribution. In line with the theory-building and secondary-evidence focus of this study, they serve as springboards for subsequent empirical investigations.

V. DISCUSSION AND POLICY IMPLICATIONS

Developing a theory-based perspective on how AI affects labour markets in South Asian economies while taking into account task-based theories, skill biased change patterns, and socio-institutional outlooks was the intent of this study. The obtained results demonstrate, based on the considered secondary sources, that in South Asia, employment trends are primarily driven by indirect and mediated effects related to job redistribution, skills transformation processes, and institutional capacities rather than direct transitions between unemployed and employed states.

The task-based content analysis conducted above allows for concluding that AI adoption primarily impacts occupations by transforming their content in favour of non-routine and relational tasks while displacing routine production and transactional elements to robots. As demonstrated by Autor and Handel (2013), this tendency to reshape occupations emerges within both manufacturing and service sectors, thus resulting in task-level change. Such change patterns are related to an increase in complexity and interactions within jobs, which can be projected as gradual disruptions to employment in South Asia, where manufacturing remains a considerable part of economic activity.

While the exercise contributes to understanding skill-based patterns of technological progress, it also serves to highlight key endogenous strengths that determine how quickly South Asia will witness disruptions to employment. Specifically, with higher levels of education, digital literacy, and technical expertise, societies can adopt AI faster and benefit from its capabilities to transform occupations. However, the capacity to actualize these opportunities is primarily determined by the availability of related skills and competences, with limited access to education being a possibility in South Asia that would slow down the rate of change.While in advanced countries, finer skill-building can go hand in hand with natural productivity improvements, in South Asian countries, the realities are a bit more worrying as labor markets are constrained, and if training possibilities do not improve, the risk of employment polarization may persist, consistent with recent evidence emphasizing that AI opportunities are distributed unevenly at various skill levels (Goos et al., 2014; Lane et al., 2023).

Institutionally, capacity is a notable factor that influences how artificial intelligence will influence jobs. For instance, under weak labor institution settings, informality, and weak enforcement of regulations, there may be a buffering effect on the application of artificial intelligence in influencing employment. Artificial intelligence may be gradually embedded into prevailing employment arrangements, forming a blend of employment structures. This is with regard to theories that emphasize a socio-institutional approach to influencing how technological processes influence employment (Rodrik, 2018). Pursuant to the traditional perspective offered by Zaheer, Sadiq, and Safi (2025a), there is a critical point that institutional preparedness is important in actualizing technological capabilities into employment issues.

Some additional information on these mediated processes can be obtained from the service industry with the help of AI technologies. Previous research has proven that the overall performance and satisfaction are improved by mediating factors, such as the service quality and the nature of interaction between individuals and AI technologies, and not necessarily through the actual usage of AI technologies themselves (Zaheer et al., 2025b). The implications for work can similarly mean that, in the presence of AI technologies, the outcomes for labor will depend on more than simple substitution effects. Thus, it seems that the changes in employment patterns due to AI in South Asia follow a context-specific process that is gradual in nature and corresponds to the underlying structures. Hence, the region fundamentally differs from other developed economies in this aspect.

A. Policy Implications

The study's findings indicate a number of policy options that are relevant and useful for South Asian governments, schools, and labor groups. In one instance, one of the key policy options that can be derived from the study's findings is that the South Asian governments, schools, and labor groups would need to focus on facilitating workers in handling and coping with changes in tasks and jobs, rather than simply preventing job loss. Instead, governments, schools, and labor groups ought not to refer to AI as an unemployed maker.

Second, investing significantly in education and retraining programs is vital. Additionally, since adaptive leadership techniques can increase employee resilience during technology transformation, organizational leadership and employee motivation should be included in workforce transition plans (Zaheer & Barakzai, 2026). For instance, since AI influences labor indirectly, addressing this can serve as a guide for policymakers. Investing more in programs to enhance digital literacy can strengthen workers' ability to cope with the displacements that AI programs bring. In service economies, where AI alters workers' activities without eliminating human engagement, this is significant.

Thirdly, institutions have to be strong to facilitate inclusive employment transformation. Technological change structures have to be enhanced, and work regulations/social protection schemes need to be improved in line with technological advancements. Many countries with high rates of unofficial workforces need to adopt a more formal work force, enhancing worker benefits. It has been documented in international literature that strong structures can ease the transition in cases of technology-induced disruptions (Choi et al., 2024).

Fourth, a tailored governance approach should be used depending on the sectors being governed. The labor impact of AI changes a lot depending on the sector's circumstances, especially for the services sector due to its differences in quality perception, trust, and emotions.

Lastly, regional cooperation and experiment-based research can help improve the potency of AI-related policies. Generally, South Asia harbors economies which have comparable work conditions and obstacles; therefore, the door for cooperation and policy adoption or sharing is wide open. Regional readiness for technological changes would be enhanced by the creation of a shared strategy for AI ethics and workforces.

B. Theoretical and Practical Contributions

By expanding upon established theoretical concepts on the labor market, applying it to an unexplored context, and providing a mediated, institutional perspective on the impacts of artificial intelligence on employment, this research is groundbreaking. At the same time, it offers practical implications for policymakers who seek to effectively navigate the expected change by focusing on adjustment rather than resisting it.

VI. CONCLUSION

The goal of the current study is to contribute to a theory-informed context-sensitive understanding of the impact of AI on South Asian countries' employment markets. By integrating task-based models of employment, skill-biased technological change, and socio-institutionalist approaches, the current research will attempt to expand upon the theoretical background of the relationship between artificial intelligence and employment trends in the field. The current study employed secondary data sources in order to demonstrate the mediating role of tasks, skills, and institutional forces in the relationship between artificial intelligence and employment, thus expanding upon simplistic understandings of the impacts of technology on the labor market.

The above analysis suggests that the employment transformation in South Asia can neither be sudden nor linear. It will continuously depend on the local conditions prevailing in South Asia. Since the introduction of AI has major implications for the nature and structure of work, we can see a distinction in the labor markets in South Asia from those existing in advanced nations.

Furthermore, in terms of theory, by developing an integrated framework, it can enable theory-building by extending conventional perspectives regarding labor markets into underdeveloped regions that have remained poorly explored in such study. Moreover, it can also spell out the indirect effects of AI in employment; thus, policymakers can have a clear understanding of deciphering disparate available data. Moreover, on the practical level, policymakers can have this initiative as one that promotes interventions in workforce development, enhancing institutions, and inclusive skills development, as opposed to addressing issues of technology threats.

A. Future Research Directions

Although this theoretical framework is comprehensive, more empirical studies need to be conducted that utilize firm-level, occupation, or longitudinal-level data collected from countries in South Asia to test the propositions suggested in this paper. Furthermore, it would be useful to collect data using sector-specific data (especially in service industries) to better understand how human–AI interaction has affected employment outcomes, such as redesigning jobs, providing emotional labor, and creating more skilled jobs. Building on the evidence regarding the effect of service quality perceptions and trust in AI on mediating factors (Zaheer, Sadiq, & Safi 2025b), longitudinal cross-country studies comparing countries in South Asia would provide insights into how differences in the institutions' capabilities to govern, the types of educational systems, and the regulatory framework of the labor market augment the transformation of employment outcomes due to AI. Lastly, integrating economic, mental, and ethical perspectives into longitudinal and interdisciplinary research would provide additional insights into how AI will affect the long-term quality of jobs, employment stability, and sustainable development in the labor market.

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