AI Tech International Journal, **ISSN: 3079-4749**
Vol. 4, No. 1, January-June, 2026,
Journal homepage: https://techaijournal.com

Exploring Diffusion of Innovation in AI Adoption for Rural Healthcare: An Overview in Daily Work Management for ASHA Workers

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Article Info

Article history:
Received January 01, 2026
Revised January 15, 2026
Accepted January 27, 2026
Published February 08, 2026

Keywords: artificial intelligence, rural healthcare, diffusion of innovation, work management

ABSTRACT

This study explores the diffusion of Innovation theory to map the adoption of artificial intelligence among the Accredited-Social-Health Activists (ASHA) workers in rural Bengal, explicitly focusing on daily work management practices of rural healthcare. Developed by Everett Rogers, this theory provides a framework for understanding how new technologies spread within a management system. Further, the study delineated the innovative attributes and key elements for such motivational adoption, from initial awareness to full implementation. The study is conducted over three months to get an overview of management in six villages by ASHA workers under the Gangmuri-joypur panchayat in Birbhum district of West-Bengal.

Methodologically, the study employs a mixed-methods approach, including qualitative data from semi-structured interviews with working ASHA workers and quantitative data from surveys of fellow professionals vis-à-vis AI integration in their daily work management. Data analysis comprises thematic analysis of qualitative data to identify recurring themes, codes, and patterns, including comparative analysis of quantitative data in mean and median sheets to identify the stages of adoption techniques in organizational scenarios.

Additionally, this will contribute to determining the lagging factors and possibilities to amalgamate such innovation to function better in rural health care and meet daily targets in information data base within villages. Indeed, it also contributes to policy formation and innovative practices by aligning external and internal symmetry. It includes a conducive managerial system in rural healthcare that is within the shortest possible efficacy despite having less digital orientation and network accessibility within the village community.

INTRODUCTION

The rapid integration of Artificial Intelligence (AI) into various sectors has redefined conventional practices and amplified efficiency (Barua, Sami , & Barua , 2025). However, the diffusion of AI-driven innovations in rural healthcare remains a unique challenge, warranting a nuanced understanding of its adoption and implementation dynamics (Kerketta & Sathiyaseelan, 2024). Accredited Social Health Activists (ASHAs), the cornerstone of India's rural healthcare delivery system, play a pivotal role in bridging the gap between communities and healthcare services (Uteng, 2011). Their daily work management, characterized by multifaceted responsibilities such as maternal care, immunization tracking, and health data collection, stands to be significantly enhanced by AI-enabled mobile tools. The adoption of AI in workload management for ASHAs is an opportunity to improve service delivery and a critical case for studying the diffusion of innovation in low-resource settings. Drawing from Everett Rogers' Diffusion of Innovation

Theory, this article explores the stages of AI adoption among ASHAs, categorizing them as innovators, early adopters, early majority, late majority, and laggards. By analyzing adoption trends and identifying barriers to integration, this research sheds light on how AI can be effectively diffused to improve healthcare outcomes in underserved communities.

This study further examines the practical implications of AI tools in managing ASHA workers daily tasks, evaluating their potential to optimize scheduling, monitor health data, and provide decision support. It also delves into the socio-cultural, infrastructural, and technological factors influencing adoption, offering a comprehensive overview of challenges and opportunities. Understanding these dynamics is pivotal for tailoring interventions and ensuring equitable access to AI-driven healthcare innovations. This research contributes to the evolving discourse on leveraging AI to strengthen India's last mile of healthcare delivery by unraveling the interplay between technology, adoption behavior, and rural healthcare systems.

LITERATURE REVIEW

In bringing global sustainability towards maintaining equilibrium in every division of performing human excellence, the United Nations also involves healthcare among its important goals in its declaration towards viable achievement (Goal 3: Ensure healthy lives and promote well-being for all at all ages). Despite advances and efforts to bridge healthcare gaps in developing countries, it is imperative to note that public healthcare is still grappling to eliminate many demanding and deeply rooted factors. For instance, India still faces challenges in the rural half, where infrastructural, socio-cultural, economic, and digital accessibility are among the few that need efficient care management (MoHFW, 2017). Artificial Intelligence, being in the new domain of adaptability, provides grounds for supplementary advantages and technological vision; it enhances healthcare management by raising standard care and supporting rural healthcare (How AI can transform rural healthcare in India, 2019). Various factors, such as inadequate healthcare personnel, distance from nearby health centers, and low accessibility and awareness among rural locales, bring discrepancies in rural healthcare (Julianna Schantz-Dunn, 2011). However, studies confirm that recent advances in artificial Intelligence offered assurance in narrowing the healthcare divide in rural regions by delivering prompt and precise medical care through tools like telemedicine, chat bots and AI algorithms. (Hollander & Carr, 2020), opine that telemedicine is an effective alternative in providing exceptional care to rural patients by limiting time and cost for healthcare availability. Despite efforts to meet the deficits resulting from divergent sources, the report from the National Health Profile is not favorable, where successive convergence of low health equities is challenging the persistence of rural healthcare, resulting in higher infant mortality, maternal mortality, malnutrition, and communicable diseases including tuberculosis and malaria among rural communities (https://www.who.int/data).

To meet the same, the Government of India time to time also tried alternatives with the best suitable way to bridge the gap through technology-mediated tools, such as e-Sanjeevani, e-Hospital, e-Blood Bank, Online Registration System, Services e-Health Assistance and Tele-consultation, e-Raktkosh, and telemedicine, all implemented as part of the National Health Mission to enhance healthcare access in rural regions (MoHFW). Nevertheless, the acceptance that these initiatives could contribute to rural locals accessing healthcare is still underutilized at the regional level (Sharma, 2014). Studies reported that outcomes of amalgamation are aligned with different geographical settings, confirming how AI applications enhanced the accessibility of quality healthcare in rural areas. Further, the significance of AI solutions in limited-resourced contexts hinges on understanding local dynamics, defining precise usability standards, and accessing practicum through field trials.

Besides, while implementing AI in low-resource settings, it is most reasonable to use iterative, field-based methods that are assembled into existing systems and institutions rather than initiating from scraping or replacing existing systems; however, broken- institutions that cannot fix itself is likely to be able to support and use a complex technology properly through identification and evaluation of diverse AI applications customized for rural healthcare settings (Nadarzynski et al., 2019). Again, applications such as remote patient monitoring and operational efficiency tools have the potential to enhance access to and the quality of healthcare delivery in rural areas. The same applies to AI implementation, which provides guidance and recommendations to nurses and paramedical staff. The study also showed that the overall consistency rate between the early detection and prevention system and physicians was 94%, indicating that patient responses were positive following the implementation of such technology. As a result, village health workers were interested in using electronic devices such as mobile phones, laptops, and other wearable devices, which enabled healthcare workers to improve the quality of healthcare delivery in rural settings. One of the healthcare centers in Bangalore, India, has employed cloud computing medical services and extended its reach to remote areas in northern Indian states where nurses and paramedical staff stationed in rural areas received comprehensive training to manage medical assistance effectively. Meanwhile, skilled and qualified physicians remotely monitor the operations from the center. Despite bearing the possibility, scholars in their respective studies researched the impact of AI fusion on rural healthcare through different methodological approaches. They emphasized the need for comprehensive training of healthcare workers with better infrastructures and government support on such partnerships for favorable outputs.

Statement of Problem

The literature shows that barriers resulting from sources of limited trials, varied geographical settings, socio-cultural acceptability, and adaptability of technology within the healthcare staff are crucial areas to gear upon. Further, the acceptance of this proliferation contributing to rural dynamicity in accessing healthcare is underutilized at the restricted level, which needs a more profound understanding of the composite managing of AI and the daily routine of healthcare workers, especially ASHA, in rural healthcare and hence it is well evident to address that whether in the grassroots management such progress of innovation is feasible whether does it have any capability of bringing new advent to the rural healthcare or in a layman mapping this has no hereafter prospects as such, merely a hype creation with indefinite connotations juxtaposing in an obscure domain. Besides, the rural economy is mainly thriving on beneficiary credits to meet daily needs, and healthcare, being at utmost care, needs special attention from government agencies, significantly when the physician-to-patient ratio lags the threshold limit where AI can bridge the gap potently through grassroots health workers which nonetheless needs baseline data generation to target the groups in an achievable identified and well-planned way.

Hence, this justifies working on the underlying and identifying the extent of daily work management, where, with attainable resources, the best can be accomplished. Besides, the efficiency in utilizing the revamped applications of technology is a climactic area to chart for a more reasonable understanding of its acceptability for the concrete direction towards explanation. Since the beginning of amalgamating technology in communicating information, the technology mediated information dissemination prioritizes every sector. Indeed, healthcare is also witnessing the same. For instance, the emergence of mobile phone communication provides many options for the public in availing healthcare choices, which are earlier distance constraints; however, the same may vary upon the acceptance and availability for the public domain, which varies upon assorted facets. Therefore, the availability of artificial intelligence in a better sense should be studied to better coincide with the desired proliferation.

Objectives of the study

The researcher has undertaken the objectives to understand the scenario in a rural setting within the specified time. In doing so, the researchers have specifically limited the study's general objective to: firstly, identifying the stage of adoption among ASHA workers; secondly, determining AI adoption among ASHA workers; and thirdly, analyzing the influencing factors in their work management. Secondly, the study focuses on evaluating the impact of such AI integration, identifying potential changes, barriers, and overall effectiveness. Lastly, the study provides recommendations based on its short-term evaluation, which foster AI with the present system management, which may provide actionable outcomes.

Table 1: Objectives Mapping Table

SL. No.	Objectives	Specific Objectives
1.	Identification of the stage in adoption	a. To determine the stage of AI adoption among ASHA workers of selected villages.
		b. Analyse the factors influencing or restraining AI adoption in their work management.
2.	Evaluation of AI impact on daily work management	a. To evaluate the influence of AI integration on ASHA workers' daily work management practices if any.
		b. Identifying changes in efficacy, effectiveness, and overall job performance.
3.	Recommendation over Policy and Integration Enhancement	a. To provide actionable recommendations for healthcare administrators.
		b. Fostering AI adoption in rural healthcare system settings to achieve more efficiency in best possible time.

THEORETICAL FRAMEWORK

Over the years, Diffusion of Innovation has seen a recent broad application in healthcare technology, especially with the dynamicity of advancing technical elevation. Several studies have been conducted to understand how the audience adopts a particular intervention through several stages. The adoption process depends on innovation, communication channels, time and the social system (Wani & Ali, 2015). However, in health, this theory aims to highlight potential improvement areas and doubts concerning such new behaviors, which nevertheless help policymakers, draft effective initiatives to overcome the doubts and ensure complete adoption. This shows the effectiveness of the diffusion of innovations theory in analyzing, promoting, and adopting new behaviors in the system and the public.

Earlier studies assess the probability of acceptance of health-related technological initiatives like m-Health and e-Health by identifying loopholes. (Jilani et al., 2022), conducted a study to understand the *'trialability'* of m-Health apps and behavioral traits to adopt the apps during COVID-19 found that these apps gained more popularity during this pandemic period due to the introduction of social distancing. This shows that social distancing has stimulated the public process of the newly introduced apps. Another study on mothers of newborns aligned on technological adoption model (TAM) found that most relied on the Internet as the primary source of any health question (Sundstrom, 2015). The research confirmed that the Internet has been able to diffuse into society such that mothers tend to search every health-related question on Google.

Besides assessing the success of interventions, this theory is also used to identify loopholes in new health policies, such as the reasons behind the low adoption of e-health services found that ineffective communication had led to less development of the value of the new service among the people (Greenhalgh et al., 2004). The study's results confirmed that healthcare providers must create health interventions considering Roger's four success determinants and effective communication strategies. The diffusion of innovations theory is, therefore, one of the most popular theories in health communication, and it is used to analyze and stimulate the adoption of new interventions within a community. However, with the new synchronization of artificial intelligence in the internet formatting of the virtual majority urges for new dimensions, finding out whether the performing task within the healthcare system has a similar influence to Rogers's assertion is an area to explore. Further, the technological penetration with network disparities concerning digital gap and divide henceforth brings hindrances that align with other extraneous factors of availing services. Therefore, the theory needs attention to rural health and those of ASHA workers in healthcare management to understand a clear note of their adoption tone.

METHODOLOGY

The researcher attempted to complete the research within three months; accordingly, the choice of the studied area and selected villages within the gram panchayat under a considered block were crucial for the validity of the results. Considering the demographic and the health profile of Rajnagar block among all other listed blocks in the Birbhum district of West Bengal, the researcher at the first level of selection considers Rajnagar block to be fit for the study within this constraint. As comprehended by early works, the Rajnanagr block and Birbhum district, compared to the other blocks and districts in West Bengal, is comparatively a little behind in its progress towards healthcare (Mukherjee & Ghosh, 2009; Mondal, Ghosh, & Sutradhar, 2018); however, the steady growth in healthcare awareness is also noticeable during the study. In the second level of selection, the researcher was assisted by the ASHA Coordinator in Block Primary Health Centre to select the number of villages that would best cover the maximum rural population and their engagement with ASHA workers during their field visits in daily routine work management. Consequently, six villages with their respective ASHA workers were selected.

The rationale of the study demands a comprehensive approach. Accordingly, the researcher uses a mixed-method approach, applying qualitative and quantitative procedures. To map the current state of integrating AI adoption and its rate of diffusion for work management among ASHA workers, the researchers approach a descriptive cross-sectional study to gauge data at a single point in time. Further, a questionnaire set of structured questions was provided to the ASHA workers selected purposively from the respective studied villages, which includes seeking information on the demographic health profile of the village, knowledge and technological availability, awareness towards artificial intelligence, inbuilt system elevation on mobile software system integration AI based responses of similar prompts, their work management routine, benefits and challenges, their current mobile phone usage pattern.

Additionally, in-depth interviews were conducted to gain insights from ASHA workers, and a focused group discussion was held among them to identify recurring codes and patterns during the discussions. Data analysis follows descriptive statistics over inferential on a mean, median sheet considering limitations in number over targeted villages. Again, the interviews and the focused group data were transcribed and categorized under constructs in a broader range to gain a significant understanding of the related factors. To meet ethical adherence, the researcher chose to stick only the public information questions on the daily work management of ASHA workers and artificial intelligence and not to enquire more on confidential grounds unless required to collect baseline data or case history.

Findings and Analysis

The researcher summarizes the generalization based on the quantitative values through the questionnaire set employed over the ASHA workers based on the outcome score over the mean and median. The mean and median statistics are often considered to measure the central tendencies over the new innovation adoption rate, performance metrics and segmentation of the adopters (https://open.umn.edu/opentextbooks/textbooks/1191). Further, summation of the calculated values of associations provides us with the justification for the stage of the adopters. In categorizing the stages of adoption, the researcher defines the threshold for adoption score for ingraining artificial intelligence in daily work management in five categories of 1 to 10-point scale vis-à-vis grading in each category for the observed score in the data set for their specific outline. In doing so, below are mentioned stages with their threshold AI adoption score:

Table 2: Adoption stage with score range

Stages	**Score Range**		**Description**
	Mean	**Median**	
Innovators	9-10	9-10	Early experimenters instantly adopting new innovations
Early Adopters	7-8	7-8	Individuals adopting the new innovation based on potential before the early majority
Early Majority	5-6	5-6	Individuals having slower and cautious integration with the work flow
Late Majority	3-4	3-4	Individuals adopting innovation by evaluating prospects and with social pressure
Laggards	1-2	1-2	Individuals with rigid scepticism and resistance towards new shift

The above score range is arranged over different dimensions such as sources of knowledge in new technology, level of awareness, working routine and implementation, related queries in healthcare, benefits and challenges, usage of mobile and AI in work management, familiarity level with AI software, ability in use and decision making, influence on job performance, encouragement towards healthcare administration, shared experience and perceived beliefs in the rate of adoption based on questions in the questionnaire set over each response from the ASHA workers.

With the observed values based on the equations below, the results are interpreted in cross-sectional data at a single point in time, using the stage of artificial intelligence adoption in rural grassroots healthcare management by ASHA workers.

$$\text{Mean} = \frac{\sum (x_1+x_2+x_3+x_4+x_5+x_6)}{n}$$

Where $(x_1+x_2+x_3+x_4+x_5+x_6)$, is the sum of all obtained data points and *n* is the number of all data points.

$$\text{Median} = \frac{\frac{n}{2} + (\frac{n}{2} + 1)}{2}$$

Where $\frac{n}{2}$ and $\frac{n}{2}+1$ are the value positions of data in even case

Here, after compilation and calculation from the data set, the observed values correspond to a mean score of *4.33* with a median of *4*, which implies the stage of shifting from the late majority to the early majority. In other words, data observes the shift in perspective of ASHA workers in adopting artificial intelligence innovations in their daily work. However, the score indicates the practice of most ASHA workers in rural healthcare in the late majority stage, where successive stimulation may act as a catalyst in the fast-shifting of the stage in the adoption of artificial intelligence. Further insights into qualitative data provide a more in-depth understanding of such rooted correlations and the cause of initial shifting in more detail.

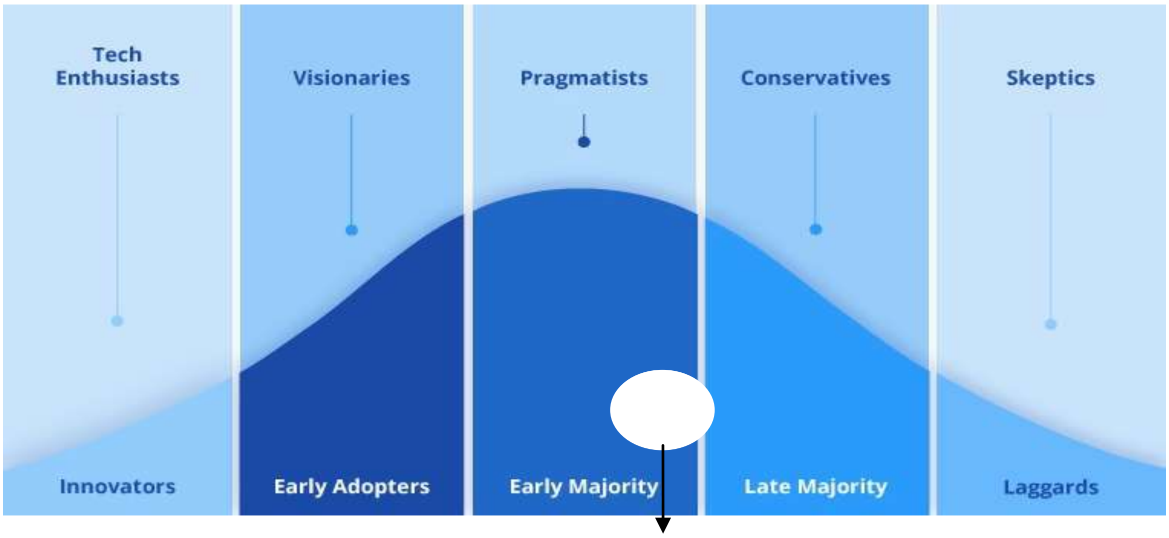

Figure 1: Diagrammatic representation of AI diffusion stage in daily work management

Thematic Analysis of Focused-Group Discussion

Thematic analysis of unstructured data becomes critical to bring the actual feasible conditions in the ground level management of populations by healthcare workers. Thematic analysis is the method used for interpreting collated qualitative data (Kiger & Varpio, 2020). Spreading this sequence additionally, the preference of this research is to bring out all factors from the focused group discussion among the ASHA workers with the possibility of properly sketching the workload management at the grass root level and to stretch the dimensions to which such base level execution and supervision by nullifying the covert matters so that the overall process thoroughly aid the rural healthcare delivery system with the AI adaptability. Since details from ASHA workers on their AI awareness and the work management will help the researcher's perception and provides a direction in shaping the analysis, inductive thematic analysis was supposed to be an additional fit.

The researcher developed codes from similar pattern from focused group discussions with the ASHA workers, after grouping them, a few meaningful themes were developed, and the codes were placed as per their themes for a better understanding and interpretation of the obtained data (Table 3).

Table 3: Themes and Codes from Qualitative data

Sl. No.	Themes	Codes	Findings
1.	Infrastructural attainability	Data management, Resource allocation, Access barrier	Perspective Shifting
2.	Comprehension in elevation	Field Practice, Group training, System awareness	
3.	Behavioural readiness	System adaptability, Domain knowledge	

Precise interaction and observations during the focused group discussion reveal emphasis upon attributes as described by (Feder et al., 1982) in adopting artificial intelligence-enabled services for workload management, which becomes a prerequisite for any innovation to integrate with the system and simplifies the 'uncertainty reduction process'. As identified during the qualitative coding, three themes have emerged: *infrastructural attainability*, *comprehension in elevation* and *behavioral readiness*, which closely resemble the attributes with *relative advantage*, *compatibility*, *complexity*, *observability*, and *triability*, *respectively*. Further, it is very much evident to note that daily work routine as data management of the rural population mainly targeted rural women with maternity care and related awareness, allocation of the available resources with proper information such as medicines, medical kits, and telephonic consultation during urgencies have a prospect with AI integration where system assisted AI prompts such as meaningful translation of medical terms in regional layperson verbal ability including the compilation of grass root baseline healthcare data for block level requirement and automated text messages for frequently asked questions from the village area population have meaningful advantages in daily routine work for ASHA workers which makes the *relative advantage* attribute more consequential in terms of adopting AI prompts for workload management. However, barriers such as network availability, geographical reach, familiarity with the technology, and low-grade data-enabled systems such as poor mobile phone handsets and limited access confer the attribute of complexity, which in turn results in the frequency of diffusion in lesser terms by increasing the possibilities of the uncertainty reduction process.

Such attributes of complexities can be negotiated with comprehension in the elevation process as decoded in the qualitative theme by providing sufficient training to ASHA workers involving system awareness and field trials of integrating artificial intelligence to reduce time by managing work in the shortest possible time. The researcher, during his observation of the discussion, identifies an additional new attribute of '*inducibility'* as a compensating factor in reducing complexities under this theme where inducibility to a specific stimulus such as providing guidance and proper training to ASHA workers by equipping them with updated mobile handsets, more specifically AI-enabled 5G handsets preferably postpaid services with better network availability by government agencies providing an alternative for better results in innovation adoption. Further, with the enhancement of inducibility, there are very few chances of complexities in the innovation adoption process as it simplifies the readiness of the ASHA workers to accept or refute innovation with their timely knowledge establishment of the expected operational benefits; this intensifies their behavioral readiness towards the use of artificial intelligence by exploring their new realms of the domain knowledge by acquainting with the upgraded system through innovative adaptability as specified under the theme behavioral readiness, such behavioral inclination closely resembles compatibility, observability, and trialability. Additionally, scholars in the same line of research in their subsequent work edify these essential attributes to the innovation model with better assumptions; however, the central aspect holding the key implication remains the same in the above. The researcher in this work opines that despite modifying the existing attributes, the scholars in their practice should skim into the prospect of comparative and negotiating attributes to confine the adverse consequences of the belittling potential of innovation adoptions, as in the above case of *inducibility* with the attribute of *complexity*.

CONCLUSION

The study comes with many ground realities in the diffusion of artificial intelligence and the factors of adoption among Accredited-Social-Health Activists (ASHA) workers in their routine work management. Although the outcome is too early to be defined in the universal generalization, a preliminary idea can be drawn from the discussion of the outcome. Here, the researcher identifies the diffusion rate of artificial intelligence in daily work management among ASHA workers at a late majority stage, which is perceived towards the early majority. However, a number of factors play a crucial role in such progress towards adoption, including the potential barriers to such diffusion. In addition to the innovation model's existing attributes, the researcher argues with '*inducibility*' as a compensating attribute as a new addition in reducing attributes of complexities. Further, the study also noted the possibilities for efficacy and the potential of AI integration if induced correctly in a system with continuous upgrading and training of ASHA workers with new technology. The results strongly recommend implementing government initiatives to equip ASHA workers with updated systems and mobile handsets; this will bring transformation and efficacy in the smooth performance of their daily tasks only when the system completely diffuses new innovations such as artificial intelligence and AI prompts.

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