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Technology Adoption and Economic Empowerment: An S–O–R Model Assessment of Chatgpt Utilisation among Self-Help Groups in Shravasti District, Uttar Pradesh

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Abstract

This study examines technology adoption and rural empowerment through the lens of the Stimulus–Organism–Response (S–O–R) framework, focusing on the use of ChatGPT by Self-Help Groups (SHGs) in Shravasti District, Uttar Pradesh. The research investigates how key technological and environmental stimuli, including perceived ease of use, perceived usefulness, institutional support, social influence, and perceived risk, shape individuals' internal psychological states, namely digital self-efficacy and perceived economic competence. These organismic factors subsequently influence technology adoption behaviour and contribute to economic empowerment outcomes among rural users. Employing a quantitative cross-sectional research design and Structural Equation Modelling (SEM), the study provides empirical support for the applicability of the S–O–R framework in understanding AI-enabled technology adoption in rural contexts. The findings indicate that perceived usefulness, institutional support, and social influence play significant roles in strengthening digital confidence and economic capability, while perceived risk negatively affects individuals' perceptions of their economic potential. Furthermore, enhanced digital self-efficacy and perceived economic competence promote greater adoption of ChatGPT, which, in turn, facilitates economic empowerment. The study contributes theoretically by integrating the S–O–R model, the Technology Acceptance Model (TAM), and empowerment theory to explain rural AI adoption. Methodologically, it demonstrates the value of SEM in rural development research, while practically highlighting the importance of institutional support, peer-driven diffusion mechanisms, and digital literacy initiatives in fostering sustainable rural economic empowerment through AI technologies.

Keywords: Technology Adoption, Rural Empowerment, S–O–R Model, Digital Self-Efficacy, Perceived Economic Capability, Social Influence, ChatGPT, Self-Help Groups, Structural Equation Modeling.

1- Introduction

The swift adoption of ChatGPT in India is emblematic of the growing acceptance of Artificial Intelligence (AI) in various industries, especially agriculture and rural development, where digital technologies are more and more making a contribution to socio-economic empowerment. The rapidly growing world of AI has contributed to the widespread adoption of generative AI technologies by micro-entrepreneurs, agribusinesses and rural institutions in India, alongside a rapidly expanding digital infrastructure, competitive technological innovation, and enabling policy frameworks (Malik et al., 2025). It is well-established that AI-driven applications can boost productivity, improve operational efficiency, and create job opportunities, particularly in the agricultural sector, which is a vital component of India's socio-economic development (Panigrahi, Ahirrao, & Patel, 2024). In this regard, ChatGPT proves itself to be a potential tool to share agronomic information, provide weather-based recommendations, aid in diagnosing crop diseases, and improve market information for farmers (Biswas, 2023). Moreover, AI-driven technologies have shown significant promise in supporting agricultural extension services, precision agriculture, sustainable farming, farm planning, pest management, and farmer education efforts, providing timely and valuable advice and guidance.

Artificial Intelligence (AI) technologies have contributed immensely to the improvement of agricultural extension services, precision farming, sustainable agriculture, pest control, farm planning, and capacity building of farmers by providing timely and context-specific information (Ray, 2023; Gaddikeri, Jatav & Rajput, 2023). At the same time, digitisation of rural India has broadened access to education, financial services, and livelihoods; promoting socio-economic participation and social mobility (Sindakis & Showkat, 2024). The role of the Self-Help Groups (SHGs) is of paramount importance in the field of financial inclusion and entrepreneurship of women (Tripathi et al., 2025; Kanjolia, 2025). While the possibilities of generative AI platforms like ChatGPT for improving decision-making, market engagement, income diversification, and sustainable rural empowerment are underutilized in SHG networks, there is little exploration of how they can help foster digital literacy.

The Stimulus–Organism–Response (S–O–R) model is used as a theoretical foundation to understand the adoption of technology because the model has a holistic perspective in explaining the influence of external stimuli on the cognitive and affective state of individuals, then on their behaviour or response. (Zhang & Zhang, 2025). The Technology Acceptance Model (TAM) has also been widely used to shed light on the adoption of technology, digital transformation, knowledge-sharing behaviour, and a wide range of socio-technical contexts (Zhang & Zhang, 2025). The move towards digitalization in the rural areas, supported by the Digital India initiative and rising smartphone usage, has boosted women's access to information, economic opportunities, and social engagement, contributing to their empowerment in India (Sindakis & Showkat, 2024). Further, the SHGs have emerged as crucial spaces for collective agency and financial resilience, with the financial inclusion, market access and organizational efficacy of rural women being further aided by digitalization (Tripathi et al., 2025).

Although AI technologies have been rapidly advancing and increasingly important in rural development, their potential for grassroots empowerment is under-theorized and under-investigated. AI literacy programs in rural areas offer insights into the growing developmental potential of generative AI technologies (Times of India, 2026; CXOtoday, 2026). In the context of this, and based on the S–O–R approach, the study explores the impact of AI-based stimuli (in this case, the use of ChatGPT) on the cognitive judgments and behavioral reactions of rural women engaged in SHG membership. Focusing on the impact of Chatgpt uses by members of SHGs in Shravasti District, Uttar Pradesh, this research paper aim at examining the role of technology adoption in promoting rural empowerment among Self-Help Group (SHG) members in Shravasti District, Uttar Pradesh, through the utilization of ChatGPT within the Stimulus–Organism–Response (S–O–R) framework. Another objective was to identify and analyze the key technological stimuli (perceived ease of use, perceived usefulness, accessibility, and organizational support) and organismic factors (digital self-efficacy, perceived economic capability, motivation, and awareness) influencing ChatGPT adoption among SHG members. And develop and validate an integrated S–O–R-based structural model explaining how ChatGPT adoption contributes to rural empowerment, and to propose policy and practical recommendations for strengthening AI-enabled SHG initiatives. The research addresses critical knowledge gaps in understanding generative AI adoption within marginalized communities.

2- Review of Related Literature

Stimulating Factors (S)

Perceived Ease of Use → Digital Self-Efficacy

Perceived Ease of Use (PEOU), derived from the Technology Acceptance Model (TAM), refers to the degree to which an individual believes that using a technology will be free of effort. Prior research consistently demonstrates that ease of use enhances users' confidence in their ability to operate digital systems, thereby strengthening digital self-efficacy (Venkatesh et al., 2012). In rural contexts, where digital literacy gaps are prevalent, simplified interfaces and vernacular accessibility significantly enhance users' belief in their technological competence. Studies on AI-based tools and mobile applications suggest that intuitive design reduces cognitive load and fosters mastery experiences, which are critical for self-efficacy development (Bandura, 1997; Dwivedi et al., 2023). For Self-Help Group (SHG) members in rural Uttar Pradesh, an accessible ChatGPT interface can lower psychological barriers and increase confidence in digital interaction. These arguments lead to the assumption of following hypothesis

H1: Perceived ease of use positively influences digital self-efficacy among SHG members.

Perceived Ease of Use → Perceived Economic Capability

Perceived ease of use also indirectly enhances economic perceptions by reducing operational barriers associated with digital entrepreneurship and information access. When technologies are easy to operate, rural users are more likely to explore digital marketplaces, government schemes, and financial literacy resources, strengthening their perceived economic capability (Venkatesh et al., 2012). Research in rural ICT adoption shows that user-friendly mobile applications facilitate income diversification and microenterprise management (Aker & Mbiti, 2010). In the context of ChatGPT, ease of generating business ideas, marketing content, and financial guidance can improve SHG members' perceptions of their ability to manage and enhance income-generating activities. These arguments lead to the assumption of following hypothesis

H2: Perceived ease of use positively influences perceived economic capability among SHG members.

Perceived Usefulness → Digital Self-Efficacy

Perceived Usefulness (PU) refers to the extent to which individuals believe that a technology enhances their performance. Empirical evidence suggests that when users recognize tangible benefits, they develop stronger confidence in their digital competencies (Davis, 1989; Venkatesh et al., 2012). AI-driven tools such as ChatGPT provide instant information, language assistance, and problem-solving support, which reinforce users' mastery experiences and strengthen digital self-efficacy (Dwivedi et al., 2023). In rural SHG settings, perceived utility in generating business communication or accessing government information can increase members' confidence in leveraging digital tools effectively. These arguments lead to the assumption of following hypothesis

H3: Perceived usefulness positively influences digital self-efficacy among SHG members.

Perceived Usefulness → Perceived Economic Capability

Perceived usefulness directly shapes individuals' assessment of economic empowerment potential. Studies on ICT4D (Information and Communication Technology for Development) show that technologies perceived as useful enhance productivity, market access, and financial inclusion (Heeks, 2018). AI-based conversational systems can provide tailored advice on pricing, savings, and government schemes, improving perceived economic capability. In rural India, digital tools linked to entrepreneurship training have shown positive associations with perceived income growth and financial confidence (Suri & Jack, 2016). These arguments lead to the assumption of following hypothesis

H4: Perceived usefulness positively influences perceived economic capability among SHG members.

Institutional Support → Digital Self-Efficacy

Institutional support, including training, digital infrastructure, and facilitation from government or NGOs, significantly enhances digital competence. According to UTAUT theory, facilitating conditions are crucial determinants of technology use (Venkatesh et al., 2012). Evidence from rural development programs in India indicates that structured digital literacy initiatives and SHG federations increase women's confidence in using mobile technologies (Gurumurthy & Chami, 2018). Institutional encouragement reduces uncertainty and strengthens self-efficacy beliefs. These arguments lead to the assumption of following hypothesis

H5: Institutional support positively influences digital self-efficacy among SHG members.

Institutional Support → Perceived Economic Capability

Beyond skill enhancement, institutional support strengthens perceptions of economic capacity by linking SHGs to financial schemes, digital banking, and entrepreneurship programs. Government initiatives such as Digital India and NRLM have demonstrated that institutional backing improves income prospects and economic agency (MeitY, Government of India, 2022). Institutional endorsement of AI tools like ChatGPT may further increase members' perception of their economic advancement potential. These arguments lead to the assumption of following hypothesis

H6: Institutional support positively influences perceived economic capability among SHG members.

Social Influence → Digital Self-Efficacy

Social influence refers to the degree to which individuals perceive that important others encourage technology use. In collectivist rural settings, peer endorsement and group norms significantly affect digital confidence (Venkatesh et al., 2012). Research on SHGs shows that peer learning and collective experimentation enhance digital literacy and self-efficacy (Gurumurthy & Chami, 2018). Observational learning within SHGs strengthens belief in one's ability to use digital platforms effectively. These arguments lead to the assumption of following hypothesis

H7: Social influence positively influences digital self-efficacy among SHG members.

Social Influence → Perceived Economic Capability

Social networks play a pivotal role in shaping individuals' economic perceptions by providing access to emotional support, information, and shared resources. Drawing upon Social Capital Theory, social interactions, mutual trust, and knowledge exchange enhance individuals' confidence in their financial capabilities and contribute to broader developmental outcomes (Putnam, 2000). Within Self-Help Groups (SHGs), regular interactions, collective decision-making, and the sharing of entrepreneurial and digital experiences strengthen members' perceptions of income generation and sustainable livelihood opportunities (Sanyal, 2009). Furthermore, socio-economic characteristics and capacity-building initiatives, particularly skill development programs, significantly improve SHG effectiveness, economic empowerment, financial self-confidence, and sustainable development outcomes among members (Krupa, 2017; Verma et al., 2024). These arguments lead to the assumption of following hypothesis

H8: Social influence positively influences perceived economic capability among SHG members.

Perceived Risk → Digital Self-Efficacy

Perceived risk- especially, privacy violation, misuse of data, misinformation, and uncertainty of technology- may drastically deter the digital confidence and intents to adopt among people. Prior research on artificial intelligence adoption highlights that concerns regarding data privacy, security, and the opacity of algorithmic decision-making significantly hinder users' willingness to embrace emerging technologies (Dwivedi et al., 2023). In rural contexts, where digital literacy levels are often limited, fears of online fraud and financial losses further restrict engagement with digital platforms, thereby reducing users' technological self-efficacy (Donner & Tellez, 2008). Similarly, Mugamba (2024) emphasizes that technological self-efficacy plays a crucial moderating role in fintech adoption and digital financial inclusion among marginalized women, while heightened perceived risk discourages technology usage. Research on Self-Help Groups (SHGs) also indicates that despite promoting empowerment and entrepreneurship, risk perceptions associated with digital technologies constrain members' adoption intentions (Bhaskar & Yadav, 2025). These arguments lead to the assumption of following hypothesis

H9: Perceived risk negatively influences digital self-efficacy among SHG members.

Perceived Risk → Perceived Economic Capability

The perceived risk is one of the most critical factors in influencing the economic expectations and financial choices of people on matters that concern technology. Uncertainty regarding digital transactions such as fears of fraud, privacy invasion and financial loss are likely to undermine the perception of the users of the possible economic gains and make them less ready to participate in digital financial sites. Empirical evidence indicates that perceived risk constitutes a significant barrier to financial inclusion and the adoption of mobile financial services. Furthermore, socio-economic vulnerabilities and risk perceptions influence the effectiveness of Self-Help Groups (SHGs) in achieving sustainable development outcomes. Financial and livelihood risks also affect women's participation in SHG-led microfinance initiatives, thereby limiting economic engagement, self-confidence, and empowerment. Consequently, perceived risk emerges as a critical determinant of inclusive financial participation and sustainable empowerment within SHG ecosystems.These arguments lead to the assumption of following hypothesis

H10: Perceived risk negatively influences perceived economic capability among SHG members.

Organism (O)

Digital Self-Efficacy and Perceived Economic Capability and Technology Adoption Behavior

In Stimulus-Organism-Response (S-O-R) model, the Organism (O) part represents the internal psychological state and transforms the external technological stimulus into responses from the organism. Self-efficacy in the use of digital technology and the perceived economic capability of the SHG members are conceptualized as key organismic factors that will affect technology adoption by the members of Self-Help Group (SHG). Based on Bandura's Social Cognitive Theory, digital self-efficacy is the belief that individual can effectively utilize digital technologies for the improvement of adoption intention and behavior. Previous research has shown that increased digital self-efficacy is a significant factor in sustaining technology and AI implementation (Compeau & Higgins, 1995; Dwivedi et al., 2023). Likewise, in the realm of digitization, digital confidence and perceived competence to use digital tools have been shown to positively affect digital engagement and business resilience for micro-entrepreneurs (Arifin et al., 2023; Hedau, 2025). The potential economic returns have been found to heavily shape technology continuance attitudes and Digital Platform usage in entrepreneurial settings (Venkatesh et al., 2012; Aker & Mbiti, 2010).All these results are consistent with the hypotheses

H11: Digital self-efficacy affects technology adoption behavior in SHG members positively,

H12: Perceived economic capability affects technology adoption behavior in SHG members positively.

Technology Adoption Behavior → Economic Empowerment

Literature provides a clear link between the use of technology, financial innovations and information systems and economic empowerment, with the use of these tools playing a clear role in enhancing the income generating potential and productivity of individuals and groups, and in giving them greater autonomy in making decisions, especially for marginalized groups. There is empirical evidence that the use of Information and Communication Technologies (ICTs) increases income diversification, productivity and the agency of women in rural and resource-constrained settings (Heeks, 2018; Suri & Jack, 2016). Adoption of technology enhances socio-economic participation, entrepreneurship skills, financial literacy, bargaining power, economic resilience, and operational efficiency in the Self-Help Groups (SHGs), which ultimately leads to women's empowerment (Sreeraj et al., 2020).Furthermore, the role of SHGs in promoting financial inclusion, sustainable livelihoods, and community development in the context of technology integration is significant (Kumar & Kumar, 2024). In this regard, ChatGPT can be a game-changer digital tool to unlock access to knowledge, business planning, marketing communication, and entrepreneurial innovation, and help increase the economic empowerment of SHG members. These arguments lead to the assumption of following hypothesis

H13: Technology adoption behavior positively influences economic empowerment among SHG members.

3- Theoretical Framework of the study

The present study is based on the concept of the Stimulus–Organism–Response (S – O – R) model which was put forward by Mehrabian and Russell (1974). The framework assumes that the external stimuli affect individuals' internal psychological states, such as thoughts and emotions, which in turn affect their behavior. Technological and contextual factors, such as perceived ease of use, perceived usefulness, digital literacy, training exposure, organizational supports within Self-Help Groups (SHGs) and infrastructural availability, are considered as stimuli in this study. These factors affect states of the organism, including self-efficacy using digital tools, trust in these tools and their capabilities, learning motivation, perceived economic capability, and perception of empowerment, and are in line with the Technology Acceptance Model (TAM) (Davis, 1989). The internal processes are the cognitive assessment and emotional involvement of the members with the AI based technologies (Dwivedi et al., 2023; Venkatesh et al., 2022). The response dimension is demonstrated in the behaviour of using ChatGPT, sharing knowledge, effective communication, entrepreneurial decision making, financial planning and socio-economic empowerment. Moreover, the framework builds on the innovation attributes of relative advantage, compatibility, and trialability from Rogers' Diffusion of Innovations theory (2003), offering a holistic understanding of the empowerment of rural and digitally under-reserved communities using AI. The model therefore contributes both theoretically and empirically by positioning ChatGPT adoption as a critical pathway linking technological stimuli to rural empowerment outcomes within SHG ecosystems in rural India.

4- Research Methodology

The present study employed a **quantitative research design** to assess the determinants and outcomes of ChatGPT adoption among Self-Help Group (SHG) members in Shravasti District using the Stimulus–Organism–Response (S–O–R) theoretical framework (Mehrabian & Russell, 1974), wherein **stimuli** were operationalized as technology attributes (e.g., perceived usefulness, ease of use), **organism** as psychological responses (e.g., attitude, empowerment), and **response** as behavioral outcomes (e.g., continued use intention and rural empowerment). A validated S-O-R construct and a modified scale were used to create a structured questionnaire with items being measure in a five-point Likert scale; content validity and contextual relevance were guaranteed by the expertise review of the researcher and pilot testing on 30 members of SHG. The entire SHG member in the district was the target population, and a sample size of 327 respondents was chosen using stratified random sampling to reflect the various blocks and SHG types to go to the adequate level of statistical power in structural equation modeling (Kline, 2016). To achieve consistency, Cronbach alpha and composite reliability were calculated on each construct, and values above 0.70 seem to be acceptable consistency (Nunnally and Bernstein, 1994), and convergent and discriminant validity were evaluated through average variance extracted (AVE) and Fornell-

Larcker scales in SmartPLS (Hair et al., 2022). Face-to-face and researcher assisted data gathering was done to ensure there was minimal response bias. The Common method bias (CMB) was analyzed with the help of Harman single factors test and further with the full variance inflation factor (VIF) to ensure that no one single factor resulted in majority of the variance (Podsakoff et al., 2003). Preliminary analyses (data analysis) involved descriptive statistics, reliability and validity measure, and structural model analysis (SPSS) via structural equation model (Partial Least Squares Structural Equation Modeling or PLS-SEM) path coefficients, effect sizes (f2), and predictive relevance (Q2). Table 1 indicate the demographic characteristics of respondents.

5- Results

Table 1 presents the demographic profile of 327 respondents based on age, gender, education, and period of using ChatGPT. As far as age is concerned, the biggest share of respondents is aged 31-40 years (111; 33.9%), 21-30 years (74; 22.6%), and 41-50 years (94; 28.7%), which speaks in favor of the fact that the sample composition is mostly represented by mature and middle-aged people. The proportion of those below 21 years is only 10.1 percent (33) and the proportion above 50 years is only 4.6 percent (15). Regarding the gender distribution, males have an insignificant larger proportion (180; 55.0%) than females (147; 45.0%), which indicates rather equal representation. In relation to educational attainment, the respondents are fairly distributed with the largest percentage of 90 (27.5-23.5) being graduates, 88 (26.9-22.0) undergraduates, 77 (23.5) postgraduates and 72(22.0) matric level. Regarding the amount of time using ChatGPT, most have been using it 1 to 2 years (101; 30.9%), 6 months to 1 year (81; 24.8%), last 3 years (73; 22.3%), and since the last 6 months (72; 22.0%), indicating that the majority of the participants have extensive and moderate experience with the platform..

Table1: Demographic Characteristics of Respondents

Characteristics	Description	Frequency	Percent
Age	Upto 21 Years	33	10.1
	21-30 Years	74	22.6
	31--40 Years	111	33.9
	241-to 50 Years	94	28.7
	above 50 years	15	4.6
Gender	Male	180	55.0
	Female	147	45.0
Education	Upto matric	72	22.0
	Under graduation	88	26.9
	Graduation	90	27.5
	Post Graduation	77	23.5
Period of Using Chatgpt	Since last six month	72	22.0
	6 month to 1 years	81	24.8
	1 to 2 years	101	30.9
	Last 3 years	73	22.3

The descriptive statistics and assessment of the measurement model in Table 2 indicate good psychometric properties for all the constructs of the study. The factor loadings of measurement items ranged from 0.673 to 0.940, which is above the 0.60 threshold recommended for indicators to be considered valid and reliable, showing good indicator reliability and construct representation. Institutional Support (IS5 = 0.940), Perceived Economic Capability (PEC2 = 0.907) and Economic Empowerment (EE5 = 0.909) had the highest loadings. Generally, respondents had favourable perceptions about technology adoption and the empowerment outcomes with mean scores between 3.2593 and 3.7486. Economic Empowerment reported the highest mean (M = 3.7486, SD = 0.6333), followed by Technology Adoption Behavior (M = 3.6430, SD = 0.5997) and Perceived Risk (M = 3.6126, SD = 0.6622). Social Influence had the lowest mean (M = 3.2593, SD = 0.8830) in contrast. The ranges of the standard deviation were between 0.5617 and 0.9465 with moderate response variability. The general results indicate positive perceptions of respondents, the coverage of the measures and their quality with respect to all constructs.

Table2: Stimulating factors of Technology Adoption, organism and Economic empowerment : A Descriptive Statistics(N=327)

	Factor loading	Mean	Std. Deviation	Variance
Perceived Ease of Use (PEOU)		**3.4495**	**.67160**	**.451**
PEOU1	0.908	3.5413	.78168	.611
PEOU2	0.783	3.4557	.71596	.513
PEOU3	0.811	3.4618	.74156	.550
PEOU4	0.872	3.3394	.92564	.857
Perceived Usefulness (PU)		**3.5229**	**.62096**	**.386**
PU1	0.690	3.3823	.62958	.396
PU2	0.883	3.5260	.75845	.575
PU3	0.863	3.5321	.82784	.685
PU4	0.850	3.6514	.77590	.602
Institutional Support(IS)		**3.3945**	**.94647**	**.896**
IS1	0.826	3.3028	1.13644	1.291
IS2	0.930	3.2446	1.11931	1.253
IS3	0.859	3.4801	1.01162	1.023
IS4	0.901	3.5015	1.01182	1.024
IS5	0.940	3.4434	1.03424	1.070
Social Influence(SI)		**3.2593**	**.88298**	**.780**
SI1	0.882	3.4709	.94556	.894
SI2	0.873	3.1131	1.00431	1.009
SI3	0.885	3.2997	.97928	.959
SI4	0.795	3.0765	1.16056	1.347
SI5	0.900	3.3425	.98398	.968

Perceived Risk (PR)		**3.6126**	**.66215**	**.438**
PR1	0.796	3.4954	.89261	.797
PR2	0.778	3.7095	.91912	.845
PR3	0.829	3.6330	.67370	.454
Digital Self-Efficacy(DSE)		**3.3619**	**.56167**	**.315**
DSE1	0.850	3.8654	.68301	.467
DSE2	0.784	2.6911	.70014	.490
DSE3	0.731	3.5291	.75020	.563
Perceived Economic Capability(PEC)		**3.4027**	**.91638**	**.840**
PEC1	0.889	3.5963	.96363	.929
PEC2	0.907	3.2630	1.04703	1.096
PEC3	0.904	3.3303	.99127	.983
PEC4	0.886	3.5688	.88996	.792
Technology Adoption Behavior.(TAB)		**3.6430**	**.59973**	**.360**
TAB1	0.853	3.6697	.66997	.449
TAB2	0.836	3.6300	.65116	.424
TAB3	0.824	3.5596	.84829	.720
TAB4	0.801	3.7125	.72843	.531
Economic Empowerment(EE)		**3.7486**	**.63327**	**.401**
EE1	0.796	3.7798	.64624	.418
EE2	0.881	3.7125	.73263	.537
EE3	0.870	3.8012	.83276	.693
EE4	0.673	3.5046	.92302	.852
EE5	0.909	3.9450	.72427	.525

Stimulating factors of Technology Adoption, organism and Economic empowerment: PLS SEM Modeling

Measurement Variable

Table 3 presents the assessment of construct reliability, convergent validity, and multicollinearity for the measurement model. The findings show that the constructs all have passed the recommended reliability levels. More precisely, the Cronbach alpha values are between 0.700 (Digital Self-Efficacy) and 0.935 (Institutional Support), which is more than the 0.70 minimum of internal consistency reliability recommended by Hair et al. (2019). The composite reliability coefficients (ρA and ρC) for all constructs are between 0.718 and 0.951, which is above the 0.70 threshold and below the Critical upper bound of 0.95, indicating good internal consistency and

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lack of indicator redundancy (Hair et al., 2019). The Average Variance Extracted (AVE) values are also considered in the range of 0.624 to 0.804, which is above the minimum criterion of 0.50 that is recommended by Fornell and Larcker (1981), meaning that more than 50% of the variance in each indicator is explained by each construct. In addition, the Variance Inflation Factor (VIF) values range from 1.090 to 2.496, which are below the conservative threshold of 3.30 (Kock, 2015) and the more liberal threshold of 5.00 (Hair et al., 2019), thereby indicating that there are no concerns of multicollinearity.

Table3: Construct reliability and validity

Constructs	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**	VIF
Digital Self-Efficacy	0.700	0.718	0.832	0.624	1.744
Economic Empowerment	0.884	0.883	0.917	0.690	2.496
Institutional Support	0.935	0.941	0.951	0.796	2.496
Perceived Ease of Use	0.870	0.919	0.909	0.714	2.146
Perceived Economic Capability	0.919	0.919	0.942	0.804	2.146
Perceived Risk	0.727	0.730	0.843	0.642	1.744
Perceived Usefulness	0.840	0.841	0.894	0.681	1.090
Social Influence	0.918	0.930	0.938	0.753	1.090
Technology Adoption Behavior	0.849	0.859	0.898	0.687	2.004

Table 4 shows the assessment of the discriminant validity based on the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratio. Discriminant validity is determined by the square root of the Average Variance Extracted (AVE) for each construct being greater than the correlations between each construct and other constructs (Fornell & Larcker, 1981). The results show that all the diagonal values of the Digital Self-Efficacy (0.790), Economic Empowerment (0.830), Institutional Support (0.892), Perceived Ease of Use (0.845), Perceived Economic Capability (0.897), Perceived Risk (0.801), and Perceived Usefulness (0.825) are higher than inter-construct correlations, which indicates good discriminant validity. In addition, the HTMT ratios are generally low, which is a good indicator of construct distinctiveness (Henseler et al., 2015). The few values out of the acceptable limit of 0.90 are in the acceptable range of 0.85.As such, results support the conceptual separation of constructs and the inclusion of various theoretical aspects in the proposed research model.

Table: Combined Discriminant Validity (Fornell–Larcker & HTMT)

Construct	**DSE**	**EE**	**IS**	**PEOU**	**PEC**	**PR**	**PU**	**SI**	**TAB**
Digital Self-Efficacy (DSE)	**0.790**	0.596	0.855	0.814	0.811	0.494	0.759	0.787	0.750
Economic Empowerment (EE)	0.481	**0.830**	0.589	0.650	0.726	0.173	0.745	0.670	0.689

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Institutional Support (IS)	0.704	0.543	**0.892**	0.715	0.742	0.319	0.682	0.725	0.585
Perceived Ease of Use (PEOU)	0.675	0.591	0.682	**0.845**	0.640	0.306	0.666	0.638	0.618
Perceived Economic Capability (PEC)	0.653	0.665	0.691	0.612	**0.897**	0.130	0.723	0.882	0.636
Perceived Risk (PR)	0.359	0.145	0.269	0.254	0.108	**0.801**	0.215	0.226	0.176
Perceived Usefulness (PU)	0.593	0.647	0.609	0.593	0.638	0.171	**0.825**	0.733	0.701

Structural Model and Path relationship

Table 5 shows that the explanatory power, predictive relevance, prediction accuracy and overall model fit were assessed in the structural model using the most important indicators of PLS-SEM, namely R^2, adjusted R^2, Q^2predict, RMSE, MAE, and model fit. The structural model has good explanatory and predictive ability. The R^2 values of the models reflect moderate to substantial explanatory power, with Digital Self-Efficacy ($R^2 = 0.620$) and Perceived Economic Capability ($R^2 = 0.723$) models demonstrating strong predictive capacities, whereas Technology Adoption Behavior ($R^2 = 0.407$) and Economic Empowerment ($R^2 = 0.375$) models display moderate explanatory strength (Hair et al., 2022). The R^2 and the adjusted R^2 values are very similar, which indicates stability of the model and the absence of overfitting. Furthermore, positive values of Q^2predict (between 0.348 and 0.713) indicated high values of predictive relevance, while low RMSE and MAE values showed high values of prediction accuracy. Model fit indices such as SRMR, dULS and dG indicate an acceptable fit and the NFI values are acceptable for exploratory PLS-SEM research (Hair et al., 2022; Henseler et al., 2016).

Table5: R -Square and Q square and Model Fit summary

	R-square	R-square adjusted	Q^2predict	RMSE	MAE
Digital Self-Efficacy	0.620	0.614	0.600	0.636	0.481
Economic Empowerment	0.375	0.373	0.713	0.539	0.391
Perceived Economic Capability	0.723	0.719	0.390	0.787	0.593
Technology Adoption Behavior	0.407	0.404	0.348	0.814	0.638
Model Fit Summary					
	Saturated model	Estimated model			
SRMR	0.091	0.100			
d_ULS	5.818	10.821			
d_G	2.127	2.295			
Chi-square	3436.412	3542.781			
NFI	0.702	0.692			

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The structural model results presented in Table 6 provide strong support for the proposed relationships among the stimulating factors, organism variables, and response outcomes. For DigSElfcap, Perceived Ease of Use is a significant stimulating factor, while for Perceived Economic Capability, it is not. For DigSElfcap, the hypothesis was accepted as the influence of Perceived Ease of Use was significant ($\beta = 0.255$, $t = 4.545$, $p < 0.001$); while for Perceived Economic Capability, the influence of Perceived Ease of Use was not significant ($\beta = 0.083$, $t = 1.584$, $p = 0.113$) and the hypothesis was rejected. The perceived Usefulness positively affects Digital Self-Efficacy ($\beta = 0.122$, $t = 2.186$, $p = 0.029$) and Perceived Economic Capability ($\beta = 0.105$, $t = 2.153$, $p = 0.031$) in support of the proposed hypotheses. Similarly, Institutional Support positively affects Digital Self-Efficacy ($\beta = 0.293$, $t = 5.093$, $p < 0.001$) and Perceived Economic Capability ($\beta = 0.193$, $t = 3.827$, $p < 0.001$). Social Influence has a significant positive influence on Digital Self-Efficacy ($\beta = 0.174$, $t = 3.019$, $p = 0.003$) and Perceived Economic Capability ($\beta = 0.588$, $t = 12.096$, $p < 0.001$) with the latter being the strongest among all the antecedents. Perceived Risk significantly influences Digital Self-Efficacy ($\beta = 0.160$, $t = 4.500$, $p < 0.001$) and negatively affects Perceived Economic Capability ($\beta = –0.097$, $t = 3.240$, $p = 0.001$). In addition, Digital Self-Efficacy ($\beta = 0.359$, $t = 6.119$, $p < 0.001$) and Perceived Economic Capability ($\beta = 0.343$, $t = 6.471$, $p < 0.001$) are significant factors that positively improve Technology Adoption Behavior. Lastly, Technology Adoption Behavior has a significant positive impact on Economic Empowerment ($\beta = 0.612$, $t = 14.849$, $p < 0.001$), supporting all hypotheses except that of Perceived Economic Capability and Perceived Ease of Use. The results validate the strength of the S–O–R framework to account for technology adoption and economic empowerment outcomes.

Table6: Structural Model and Path Coefficent (Path coefficients, Mean, STDEV, T values, p values)

	f-square	**Path Coefficient (β)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
Stimulating Factors					
Perceived Ease of Use -> Digital Self-Efficacy	0.080	0.255	0.056	4.545	0.000
Perceived Ease of Use -> Perceived Economic Capability	0.012	0.083	0.053	1.584	0.113
Perceived Usefulness -> Digital Self-Efficacy	0.020	0.122	0.056	2.186	0.029
Perceived Usefulness -> Perceived Economic Capability	0.020	0.105	0.049	2.153	0.031
Institutional Support -> Digital Self-Efficacy	0.091	0.293	0.058	5.093	0.000
Institutional Support -> Perceived Economic Capability	0.054	0.193	0.050	3.827	0.000
Social Influence -> Digital Self-Efficacy	0.034	0.174	0.058	3.019	0.003
Social Influence -> Perceived Economic Capability	0.538	0.588	0.049	12.096	0.000
Perceived Risk -> Digital Self-Efficacy	0.062	0.160	0.036	4.500	0.000
Perceived Risk -> Perceived Economic Capability	0.031	-0.097	0.030	3.240	0.001
Organisam					
Digital Self-Efficacy -> Technology Adoption Behavior	0.125	0.359	0.059	6.119	0.000
Perceived Economic Capability -> Technology Adoption Behavior	0.114	0.343	0.053	6.471	0.000

Response				
Technology Adoption Behavior -> Economic Empowerment	0.600 0.612	0.041	14.849	0.000

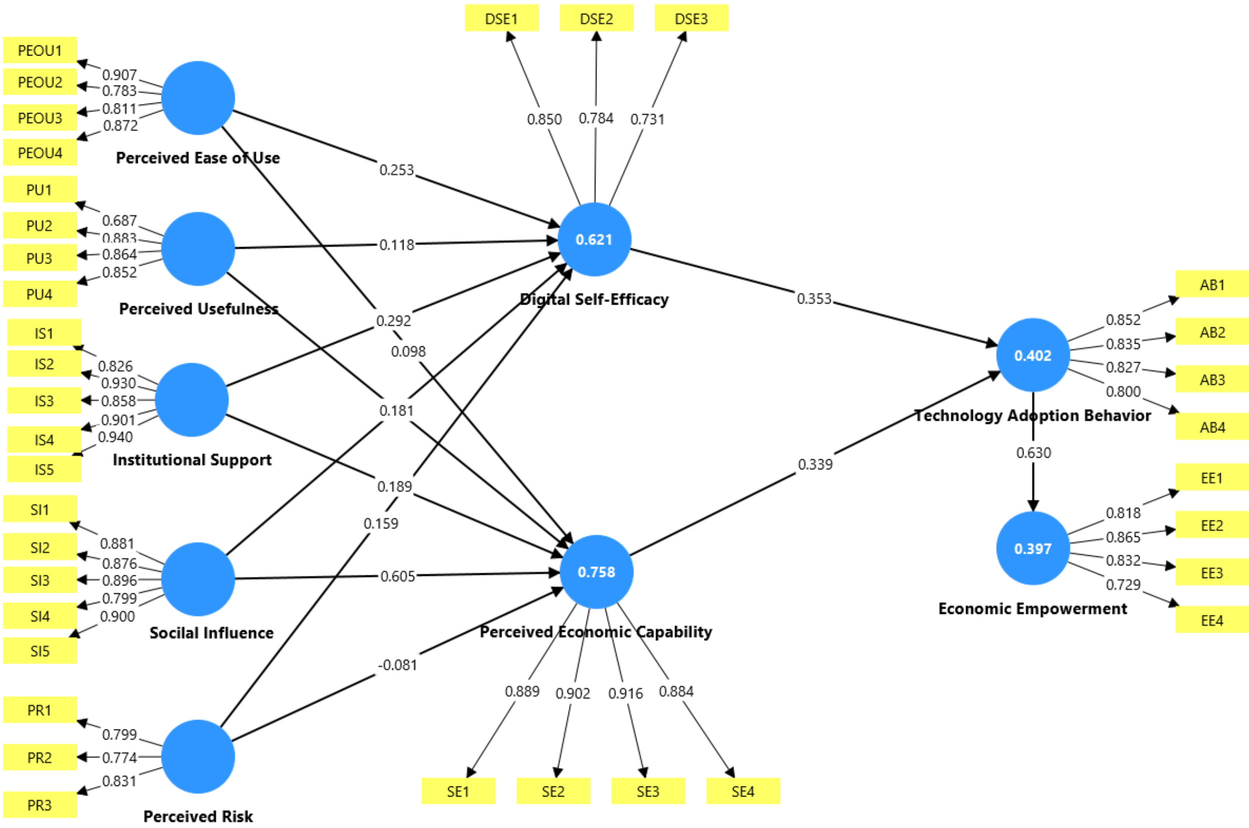

Figure1: Structural Model and outcome

Discussion

The present study examined the article Technology Adoption and Rural Empowerment: An S-O-R Model Evaluation of ChatGPT Use among Self-Help Groups in Shravasti District, Uttar Pradesh through the lens of the Stimulus–Organism–Response (S-O-R) framework to investigate how technological and social stimuli shape psychological states and behavioural intentions toward economic empowerment. The results are statistically significant and prove that the S-O-R model is applicable in the context of rural development, with significant implications for digital inclusion of Self-Help Groups (SHGs). In the stimulus dimension, it was determined that perceived ease of use significantly positively affected digital self-efficacy, while at the same time, perceived economic capability was shown to be no different. This discovery is consistent with the Technology Acceptance Model that recognizes ease of use as one of the influencing factors of the users' confidence and comfort with technology (Davis, 1989). Yet, perceptions of economic benefits seem to be related more to usefulness beliefs than usability (Venkatesh et al., 2003).

This finding corroborates the central tenets of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) models that argue that people are more likely to accept technology when they believe that it will have tangible effects on their performance and productivity (Davis, 1989; Venkatesh et al., 2003). The usefulness of ChatGPT in tasks like generating applications, obtaining market information, and communicating with members boosts the members' trust in their digital skills and economic prospects within the rural SHGs. In line with the empowerment theory, there is a strong link between perceived control, perceived competence, and socio-economic development (Zimmerman, 2000). Also, institutional support has a positive impact on digital self-efficacy and perceived economic capability which highlight the need for training, technical assistance and facilitation by government and non-governmental organisations. The results are consistent with the Social Cognitive Theory which focuses on environmental reinforcement as an important source of self-efficacy (Bandura, 1997), and with the diffusion research results pointing to institutional mechanisms as important factors to consider for technology adoption and capability enhancement in rural areas (Rogers, 2003).

Social influence was found to be the most influential stimulus that impacts on the perceived economic capability and reflects the collectivist and group orientation of Self-Help Groups (SHGs). Members' perceptions of the economic potential of ChatGPT are heavily influenced by peer validation, shared norms, and collective learning. The results confirmed Unified Theory of Acceptance and Use of Technology (UTAUT) model which states that social influence has a strong influence in behavioral intentions if the group norms are salient (Venkatesh et al., 2003). Moreover, the findings show a complex perception of risk. Perceived risk had a positive effect on digital self-efficacy by encouraging skill building and awareness of digital, but a negative effect on perceived economic capability. This could lessen the perceived value of an economic benefit while increasing a person's ability, but result in reduced trust in the competence due to issues with misinformation, financial fraud, or the misuse of AI (Bandura, 1997, Featherman & Pavlou, 2003). The results indicate the need to promote cybersecurity awareness and the ethical use of AI to maintain empowerment results.

In the organism component of S–O–R, the digital self-efficacy and perceived economic capability are significant predictors of technology adoption behavior, which aligns with the theory that external stimuli (behavioural) influence internal cognitive assessments (organism) before triggering behavioural outcomes (Mehrabian & Russell, 1974; Kala & Chaubey, 2023). In line with Social Cognitive Theory, it is suggested that self-efficacy increases the enactment of the behaviour in this instance, meaning that digitally confident and economically empowered SHG members are more likely to use ChatGPT for communication, information access and business planning.

The response component, which is technology adoption behavior, has a significant positive impact on women's economic empowerment. Results indicate that the successful implementation of the AI-powered tools like ChatGPT can improve the income-generating potential, financial independence, and decision-making power among rural women. This proof-based is in alignment with the digital empowerment theory (Hilbert, 2011; Kala & Chaubey, 2026) and the Capability Approach of Sen which emphasized technology's role in broadening the economic opportunities and freedoms of the people (Sen, 1999).

The results are favorable to the use of Stimulus–Organism–Response framework for understanding the adoption of AI-based technology by the rural, Self-Help Groups (SHGs). The findings suggest that the internal cognitive and psychological state of the users is influenced by technological characteristics, institutional support, and social influence, which then affects the economic empowerment and adoption of AI behaviour. Social influence plays a significant role, which emphasises the cultural embeddedness of technology diffusion in rural India. In addition, the findings indicate that digital self-efficacy and perceived economic capability mediate the relationship between the use of AI and the actual economic impact, highlighting the role of psychological empowerment as a key pathway between the two. These findings help in the theoretical integration of the S-O-R framework, Technology Acceptance Model (TAM) and Social Cognitive Theory and empowerment perspectives in the field of rural development research (Mehrabian & Russell, 1974; Davis, 1989; Bandura, 1986). Policy-wise, improving institutional support, leveraging SHG peer networks and raising awareness about AI, and digital literacy can enable inclusive digital transformation and sustainable rural development in Shravasti and similar districts.

6- Theoretical Contribution

The present research is highly theoretical because it applies the Stimulus-Organism-Response model to the rural digital empowerment, namely, to the use of ChatGPT among Self-Help Groups (SHGs) in the Shravasti District of Uttar Pradesh. Although the S-O-R paradigm has been used in consumer behavior and online setting (Mehrabian and Russell, 1974; Jacoby, 2002), this research setting extends the scope of digital innovation studies to the rural development grassroots literature by placing it in its rural setting. The study empirically proves the psychological mediation mechanism of digital transformation of rural areas by conceptualizing perceived ease of use, perceived usefulness, institutional support, social influence, and perceived risk as external stimuli; digital self-efficacy and perceived economic capability as internal organismic states; and the technology adoption behavior with economic empowerment as a response. The findings extend technology acceptance literature by demonstrating that social influence and institutional support are critical determinants of technology adoption in collectivist and resource-constrained rural settings, consistent with the Technology Acceptance Model (Davis, 1989) and Social Cognitive Theory (Bandura, 1986). Furthermore, the study advances empowerment theory by establishing technology adoption as a significant pathway to economic empowerment, supporting the argument that digital capabilities serve as strategic resources for socio-economic mobility and rural development (Kabeer, 1999).

7- Managerial Implications

Managerially and policy wise, the findings have some definite implications on the government agencies, non-governmental organizations, microfinance institutions and SHG federations working on the schemes like the National Rural Livelihoods Mission. To start with, the institutional support systems may be strengthened by using structured digital literacy programs, local training concerning AI tools such as ChatGPT, and ongoing mentoring to positively affect digital self-efficacy and economic perceived competence among members. Second, as the social influence became one of the key drivers, community-based diffusion strategies, peer learning circles, and SHG champions are to be used to increase the adoption rate. Third, the perceived risk should be met by the policymakers through enhancing digital awareness of security practices, ensuring there is clear usage rules and grievance redress to generate less fear and uncertainty. A combination of these strategies would help establish an enabling ecosystem that would make AI-based tools more of empowerment tools to rural women and marginalized groups than information resources.

8- Conclusion

To sum up, the paper establishes that the S-O-R framework is very strong when it comes to explaining rural empowerment, which is the case of technology empowerment. Technological and social stimulus conditions internal psychological resources, especially digital self-efficacy and perceived economic capability, the combination of which leads to the technology adoption behavior, which eventually results in better economic empowerment. The results underscore the fact that digital empowerment is not necessarily an activity that is mostly enforced by the availability of technology but it is entrenched in social networks, institutional support, and cognitive change in the individual. Therefore, AI-based systems like ChatGPT can have transformative potential when incorporated into supportive community systems.

9- Limitations and Future Research Directions

This study provides robust empirical support for the Stimulus–Organism–Response (S–O–R) framework in explaining ChatGPT adoption and its contribution to rural economic empowerment among Self-Help Group (SHG) members in Shravasti District, Uttar Pradesh. While this has been useful, there are some drawbacks that need to be addressed for future research. First, the cross sectional design impedes the capacity to draw causal inferences between changeable variables within a study. Longitudinal and/or panel studies might provide a more comprehensive understanding of the changing dynamics of digital self-efficacy, perceived economic capabilities, and the use of AI-touching technologies, and how these influence empowerment outcomes over time. Secondly, the geographical coverage of the study is limited to a single district, which limits the findings of the study to be generalized. External validity could be supported through future comparative research in different rural areas and states that would provide generalizable policy implications. Third, some of the measurement indicators had relatively low factor loadings, indicating conceptual problems and/or respondent interpretation. These measures could be further developed and expanded in future research to also include qualitative methods like interviews and focus group discussions in order to delve deeper into the perceptions of rural women on the use of AI for entrepreneurship, savings and value creation. Moreover, social factors are found to be a key influencers, underscoring the importance of the moderating factors: digital literacy, gender norms, institutional support, trust in AI systems, and training interventions. Finally, future research could expand the framework to other AI-powered digital platforms and incorporate economic performance measures. Integrating the S–O–R with capability and resource-based approaches can also contribute to theoretical progress, advancing the understanding of the process of rural transformation through AI and sustainable empowerment.

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