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Predicting Adoption of Artificial Intelligence Tools among the Researcher Scholars

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Abstract:

Purpose: *The research evaluates the predictors of Artificial Intelligence (AI) tool adoption among research scholars.*

Design/Methodology/Approach: *360 research scholars were chosen for the current study, and the Model was built using Multiple linear regression techniques.*

Findings: *Effort expectancy, Performance expectancy, and Personal Innovativeness significantly influence the research scholars' Intention to adopt AI tools.*

Practical Implication: *The researcher assists in evaluating predictors of adoption to use AI tools; thus, AI companies can use the antecedents to retain existing users and convert non-users into users.*

Originality/Values: *There are many studies conducted on the "Unified Theory of Acceptance and Use of Technology" (UTAUT) model & "Technical Opinion Leadership" (TOL). However, this study extends the literature by integrating two theories and building "Multiple Linear Regression" (MLR) in AI.*

Funding Statement: *No organisation or person has provided financial assistance or money for this study. Without outside funding, the study's research and analysis were carried out independently. The study was conducted entirely on an unsupported basis, including data collection, processing, and interpretation. The integrity and calibre of this study are entirely the result of the authors' time, labour, and resources. The lack of outside financing does not lessen the relevance of the findings reported here, and the study's results are exclusively the result of the author's painstaking work.*

Ethical Compliance: *Strict ethical standards were maintained throughout this investigation, and participants' anonymity and informed permission were guaranteed. It complies with pertinent laws and is sanctioned by the proper ethics board. The study upholds the rights of participants, conducts itself honestly, and is neutral while correctly presenting its findings.*

Keywords: *UTAUT, Technological Opinion Leadership, Artificial intelligence.*

1. Introduction:

The earliest instances of artificial intelligence (AI) appeared in the middle of the 1950s. It struggled despite its initial promise and seemed to end abruptly for several reasons, including technological limitations regarding data processing capability, handling different data types, and replicating the human mind. Technology's quick development has dramatically impacted the resurgence of AI technologies that solve past limitations. Never before have AI technologies matured so quickly and shown such promise for enterprises. For its benefits, a competitive edge, and improved performance, organisations are racing to invest in, develop, and employ AI technology in organisational activities [Venkatesh, V., 2022]. With the incorporation of several new and cutting-edge technologies and data sources, such as the Internet of Things and big data, the definition of AI tools and what they perform are continually expanding. An increasing mass of research is being done on many elements of AI tools, emphasising the design of these tools. These studies range from technical issues to needs elicitation. The supply chain, biomedicine, and intelligent healthcare in clinical settings are just a few areas where this research is being carried out. Observing how well these AI-based tools work compared to prior techniques and algorithms focuses on eliminating prejudices that could influence models, especially when learning comes from biased data, is fascinating. [Venkatesh, V., 2022] The reality frequently diverges significantly from the incredible promise of prior technologies like AI. Adopting and using any technology is a significant barrier to reaping advantages. The same is valid with AI tools, which will always be true. The typical suspects, such as the need for construction, the requirement for adequate teaching, the lack of a compelling argument in favour of adoption, and inadequate skills, to mention a few, are among the barriers that prevent implementation at the organisational level. These subjects have been covered in several pieces in the trade press. [Venkatesh, V., 2022]. The reality frequently diverges significantly from the incredible promise of prior technologies like AI. Adopting and using any technology is a significant barrier to reaping advantages. The same is valid with AI tools, which will always be true. The typical suspects, such as the need for construction, the requirement for adequate teaching, the lack of a compelling argument in favour of adoption, and inadequate skills,, to mention a few, are among the barriers preventing organisational implementation.

Artificial intelligence (AI) is increasingly being used on a large scale, and its uses are continually growing (Latinovic & Chatterjee, 2022). While AI has many advantages, it also raises several issues that require attention (Gevaert et al., 2021). For those interested in learning more, Natural Language Processing (NLP), a unique capability of AI, has several applications in management. NLP is a branch of AI that focuses on how computers and human language interact, allowing computational methods to understand, process, and produce human language. Numerous industries, including retail, operations, law, architecture, and transportation, use decision support systems, chatbots for customer relationship management, and other applications of this adaptable technology (Chowdhary, 2020). To create algorithms capable of processing, analysing, and producing natural language, NLP combines a variety of approaches, including statistical modelling, machine learning, and deep learning. Large language models (LLMs) are one of the developments in NLP that have drawn much attention. These AI models are equipped to produce human-like language and carry out a wide range of language-processing tasks since they are trained on enormous text datasets (Schwenk, 2007). LLMs, like ChatGPT by OpenAI and Bard by Google, are trained on enormous amounts of data without explicit programming, allowing them to respond to prompts with logical and contextually relevant language.

Artificial intelligence (AI) is now the driving force behind transformative advances in most industries. More and more industries are being impacted by the uses of artificial intelligence (AI), from the production of vehicles to the education of children to the detection of disease. The revolutionary nature of AI applications extends beyond performance metrics like productivity, accuracy, or job security to modifying the human component's function in the workforce. All possibilities are imaginable in the twenty-first century's new technology, big-data powered workplace, from AI supporting people to humans assisting AI to AI replacing humans. Self-driving cars, virtual shopping assistants, and social robots with human-like personalities are all applications of AI that excite and terrify people due to their potential to replace people in specific jobs. According to predictions, Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA) will replace a third of current jobs by 2025 [Thibodeau, 2014, Brougham & Haar, 2016]. According to the research of 702 professions, not just low-wage or low-skilled employment are at risk of being computerised, but also accounting, sales, customer service, commercial piloting, analysis, and office/administrative roles [(Frey & Osborne, 2017)]. These subjects have been covered in several pieces in the trade press. [Venkatesh, V., 2022]. This study uses two methods; the UTAUT model and Technical Opinion Leadership (TOL).

1.1 Theoretical Background

One of the most well-known theories, the unified theory of acceptance and use of technology (UTAUT) [Venkatesh et al., 2011], has been successfully duplicated several times and used to evaluate various technologies and circumstances other than employee adoption. It is acknowledged that the contextual elements and features unique to such technologies significantly impact how those technologies are adopted and used. As a result, this work focuses on assessing the factors indicating whether researcher academics would utilise AI techniques. This study expands on previous research by developing and testing a model of the factors that affect technical opinion leadership (TOL). This work makes three key contributions. First, it points out the importance of effort expectations, performance expectations, and individual inventiveness as indicators of research researchers' use of AI tools.

The fact that this study pinpoints the primary variables affecting research scholars' attitudes and intents towards AI makes it essential for promoting AI adoption in research practices. Academic institutions and politicians may apply focused methods to encourage AI integration, boosting efficiency and creativity in academic pursuits by comprehending the importance of human innovativeness and the effect of Technological Opinion Leaders. Additionally, by offering suggestions for evidence-based practises and regulations, the study supports academic technology management by building a collaborative environment that empowers researchers and raises overall research productivity and impact. The results guide attempts to foster an environment of creativity and research excellence by successfully integrating AI technology. They provide a starting point for a better understanding AI adoption in academia.

2.2 Adoption of AI

The literature review comprises a comprehensive analysis of AI adoption, drawing insights from various studies. Nazri, Ashaari, and Bakri (2022) investigated the factors influencing AI adoption in institutions of higher learning (IHLs), finding that the technological, organisational, and environmental contexts played crucial roles in determining adoption. Zawacki-Richter et al. (2019) systematically reviewed AI applications in higher education, revealing prevalent usage in STEM and computer science-related fields while highlighting the need for research on ethical and pedagogical aspects of integration. Thomas et al. (2023) surveyed perceptions of AI in academic publishing, finding plagiarism detection as the most widely known AI application and emphasising the importance of knowledge, expertise, and integration for unlocking AI's benefits. Shant Priya et al. (2023) explored AI adoption in Indian management colleges, identifying leadership support as critical to successful implementation, supported by the "Interpretive Structural Model" (ISM), "Cross-Impact Matrix Multiplication Applied to Classification" (MICMAC), and "Decision-making trial and evaluation laboratory" (DEMATEL) analyses. Horani et al. (2023) proposed a model for AI adoption intentions in Jordanian organisations, showing positive influences on adoption from relative advantage, support from senior management, "cost-effectiveness, competitive pressure, vendor support, compatibility, strategic alignment of AI, and resource availability", with the limited impact of market uncertainty and negative influence of complexity and governmental regulation. Kurup and Gupta (2022) developed a comprehensive model for AI adoption in businesses, emphasising leadership support, capacity for change, and influence from trading partners. Alhumaid et al. (2023) surveyed UAE users' attitudes towards AI in education, highlighting adoption characteristics and practical implications for educational authorities. The conceptual framework integrated personal and technological aspects, with diffusion theory factors outweighing others. Keles and Aydin (2021) assessed college students' perceptions of AI, finding more profound views among education students and recommending lectures on AI applications to improve perceptions. The literature review comprehensively understands AI adoption's transformative potential while acknowledging challenges and ethical considerations. Studies underscore the importance of leadership support, knowledge, and awareness in fostering successful AI adoption across different domains, offering valuable insights for educational authorities and businesses.

2. Literature Review of and Conceptual Framework:

2.1 Artificial Intelligence:

Adopting artificial intelligence (AI) technology has been a subject of interest in diverse fields, with researchers highlighting specific barriers to its widespread uptake. [Thakur et al. 2015] identify organisational concerns regarding their capacity to evaluate, develop, and effectively use AI technology. Despite recognising its significant benefits, the lack of top management support and unclear business cases hinder the deployment of AI solutions. In the academic sector, [Strzelecki, A., 2023] examines the usage of AI in university libraries in Southern Nigeria and finds that while security scanning devices are prevalent, more advanced AI features like chatbots, face and touch recognition, and AI classification tools still need to be included. On a broader scale, [Collins & Moons, 2019] conducted a bibliometric analysis and noted a considerable rise in AI-related research across various academic fields since the 1960s. They predict that applications of transdisciplinary AI are likely to continue in the future. [Haikowicz et al. 2023] focus on social development organisations in India and identify that employee adoption of AI-enabled technologies can be positively influenced by expected effort, performance, social influence, and enabling conditions. However, AI phobia may moderate these associations. [Strzelecki, A., 2023] reveal that gadget enthusiasm and technological inventiveness predict technical opinion leadership, and gadget aficionados mediate the association between personal innovativeness and technological creativity. Lastly, three crucial issues related were identified to AI tools, emphasising their general service, human interactions, and integration into operations management, and proposing an investigation of individual characteristics, technological factors, and environmental aspects to understand their influence on adopting AI technologies [Thakur et al. 2015].

2.2 Hypotheses Development for the Proposed Model

The UTAUT (Unified Theory of Acceptance and Use of Technology) model is a framework that explains users' acceptance and use of technology. It includes critical variables:

Performance Expectancy: Users' perception of how the technology enhances their performance. Facilitating Conditions: External factors that support or hinder technology use. Social Influence: The impact of social factors on technology adoption. Effort Expectancy: Users' belief in the ease of using the technology. The model helps understand user behaviour and informs technology design and implementation. [Venkatesh, 2022]

Technical Opinion Leadership (TOL) refers to a respected and influential expert in a specific technical field. It involves sharing insights, participating in industry events, and having a solid online presence to gain credibility and influence in the industry. TOL can lead to networking opportunities, business partnerships, and recognition as a thought leader in the field. An essential component of Technical Opinion Leadership (TOL) is individual innovation. It speaks to the capacity and desire to absorb cutting-edge concepts and new technology. High levels of personal innovation are exhibited by TOL persons who are early adopters of new technology, show proficiency in cutting-edge innovations, and motivate others to embrace change. They can promote industry developments and stay relevant in continually expanding areas because of their innovative problem-solving abilities and agility.[Agarwal & Prasad 1998] Technical Innovation: TOLs are generally the first to adopt new technologies and are at the forefront of technical development. Their desire to investigate and adopt technologies serves as an example for others and promotes an industry-wide culture of innovation. Personal Innovation: Individuals in TOLs' networks are encouraged to grow their personal innovation through their passion for new technology and openness to trying out creative solutions. The thought leadership and subject matter knowledge of TOLs inspire others to be adaptable and look for fresh chances for innovation in their work and initiatives.

2.2.1 Performance Expectancy

Performance Expectancy (PE) represents the predictors of adopting AIs (Artificial Intelligence) among researcher scholars. PE describes how people think utilising a specific technology, like AI, would make them more effective and efficient at their jobs [Venkatesh, 2022]. Extrinsic motivation, work fit, perceived utility, and result expectations are all included.

PE refers to the researcher researchers' belief that implementing AI will improve their productivity and efficacy in their research duties. According to previous studies, PE can significantly impact people's intentions to accept and utilise IT technology [Alamin et al. 2015, Almaiah et al. 2016, Tam et al. 2020, Venkatesh et al. 2011]. Thus, it is suggested that the following hypothesis be investigated:

Hypothesis 1 (H1): Performance Expectancy significantly and positively affects researcher scholars' intention to adopt AI technologies.

2.2.2 Facilitating Conditions

The term "facilitating conditions" (FC) refers to the extent to which someone thinks that the organisation has the resources required to promote system use, according to [Venkatesh et al. 2003]. According to [Thatcher et al. 2002], compatibility, perceived behavioural control, and objective characteristics that enable simple task completion are used to quantify FCs. [Thatcher et al. 2002] assert that offering users assistance and training is critical when they are having trouble utilising the system.

FCs refer to the perspective of research scholars on particular variables that either limit or support the acceptance and usage of AI technologies in the context of the current study on the adoption of AI by research scholars. According to prior research, the desire to accept and use IT technologies is highly influenced by FCs [Alamin et al., 2015, Almaiah et al., 2016, Strzelecki, A., 2023]. Thus, the following hypothesis is put forth:

Hypothesis 2 (H2): Facilitating conditions significantly and positively affect research scholars' intention to adopt AI technologies.

2.2.3 Social Influence

Social Influence (SI) is described by[Venkatesh et al. 2003] as the extent to which a person thinks influential people think they should use a new system. Images, arbitrary standards, and societal elements all contribute to SI. According to [Ajzen, 1991], subjective norms are the social pressure people experience that influences whether or not they engage in particular conduct.

SI refers to accountants' judgements of how important coworkers see their acceptance and usage of AIS (Accounting Information Systems) in the context of the present study on the adoption of AI by research researchers. According to prior research, SI substantially affects the desire to embrace and use IT technologies [Alamin et al. 2015, Almaiah et al. 2018, Mulhem et al. 2021, Tam et al. 2020]. Thus, the following hypothesis is put forth:

Hypothesis 3 (H3): Social Influence significantly and positively affects research scholars' intention to adopt AI technologies.

2.2.4 Effort Expectancy

Effort Expectancy (EE) refers to the following three essential ideas: complexity, usability, and perceived usability [Bani-Khalid et al. 2022]. In contrast to complexity, connected to users' beliefs that utilising technology is difficult to understand, ease of use refers to a person's opinion that utilising a system requires minimal physical and mental effort. [Alamin et al. 2015, Almaiah et al. 2016, Moore et al. 1991].

In this study, EE is directly connected to research scholars' perceptions of how simple it is to use AIs, affecting their skills at utilising AIS. AIS. Previous literature has indicated a significant effect of EE on the continuance intention to use AIS [Alaiah et al., 2016, Alsyouf, 2020, Venkatesh et al., 2011]. Thus, the following hypothesis is proposed for this study:

Hypothesis 4 (H4): Effort Expectancy significantly and positively predicts the adoption of Al's among the research scholars.

2.2.5 Personal Innovativeness

Personal Innovativeness is defined as the extent to which research academics embrace a specific invention early; that is, the extent to which people are willing to experiment with new products or services. High degrees of personal innovation in research academics make them more open to embracing technological breakthroughs and more likely to plan to use AI (Artificial Intelligence) favourably. They are less prone to perceive hazards because of their openness to innovation, making them more amenable to embracing AI technology.

[Adeiza et al. 2017] emphasised that innovation is an essential quality of people, demonstrating the level of interest research researchers have in discovering new areas of study. [Kim & Bipin, 2000]; their investigation on the adoption patterns of mobile payment users discovered that, as further evidenced by empirical study, personal inventiveness significantly and favourably influences users' intentions to embrace new technologies. Thus, the following hypothesis is proposed for this study:

Hypothesis 5 (H5): Personal innovativeness (PI) significantly impacts research scholars' attitudes (ATT) towards the adoption of AI technologies.

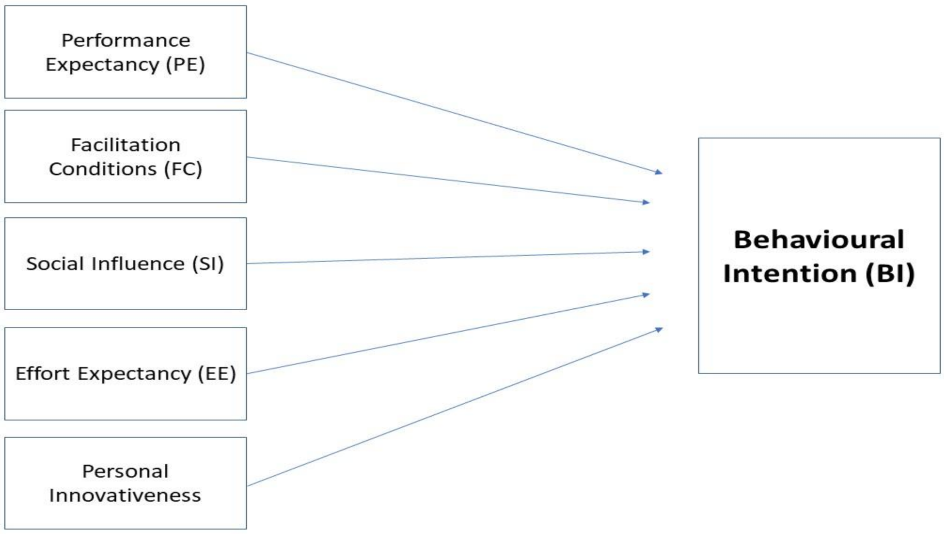

Figure No: 1 Conceptual Framework

3. Methodology:

3.1 Data Collection

The main goal of this study was to perform empirical research to understand the variables that significantly impact how research academics use AI (Artificial Intelligence) technology. The study aimed to comprehend the numerous factors influencing research academics' decisions to use AI in their scholarly endeavours. To comprehensively analyse research scholars' beliefs, attitudes, and behaviours about adopting AI, the study conducted empirical research to acquire actual data and observations from research scholars. The researchers hoped to get critical insights into the factors affecting research academics' decisions to use AI technology using this empirical technique. The study also examined research academics' behavioural goals about the use of AI. This meant evaluating the degree to which research scholars indicated a readiness to incorporate AI technology into their research practises and the extent to which they intended to use AI tools and applications in their academic endeavours. One hundred sixty research experts provided the data; 183 were male, and 177 were female. The majority of responders, 147 (25–35), 129 (45–55), and 84 (36–45), were between these ages. The 90 students were from the commerce, science, management, and banking departments.

Table No: 1 Demographic Profile

Variables	Category	Frequency
Gender	Male	183
	Female	177
Age Group	25 to 35 years	147
	36 years to 45 years	129
	45 years to 55 years	84
Department	Commerce	90
	Science	90
	Management	90
	Banking	90

3.2 Instrument Development

The scale had four externally impacting constructs, containing three to four measurement variables each. A five-point Linkert scale was used to describe each measurement variable's item. Participants were requested to share their ideas honestly. Respondents were asked to express their opinions as they truly felt them. The available choices were Highly disagree, disagree, uncertain, agree, and highly agree. The average was computed, and the ordinal data was converted into scale data to build MLR. This work employed the UTAUT model and the technology Opinion Leaders for data processing and analysis. The UTAUT paradigm integrates "Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions" to explain technological adoption. "Technological Opinion Leaders" are potent individuals who influence others' perceptions and advance technology acceptance through early adoption and subject-matter knowledge. Both concepts offer valuable insights for promoting successful technology integration.

Table No: 2 Measurement Instruments

Constructs	Measurement Items	Sources
Effort Expectancy	It is easy to interact with Artificial Intelligence. It is easy to become skilful at using Artificial Intelligence. Artificial Intelligence is user-friendly. (UI/UX is convenient)	Venkatesh et al. (2003)
Social Influence	Important individuals for me believe that I should employ artificial intelligence to carry out research work. My family and friends embrace the use of artificial intelligence. Those who have the power to affect my conduct believe that I should employ artificial intelligence to carry out research activities.	Venkatesh et al. (2003)
Facilitation Conditions	I have the tools to employ artificial intelligence, like a smartphone, a PC with an internet connection, etc. I am knowledgeable enough to employ artificial intelligence. (I find that using such AI technology is a superficial learning process. I may ask for assistance from others if I need it when employing artificial intelligence.	Venkatesh et al. (2003)
Performance Expectancy	Artificial Intelligence is useful for research purposes(I am satisfied with the solutions provided by Artificial Intelligence) Artificial Intelligence enables me to accomplish research tasks more quickly. (Artificial Intelligence saves much time, which is otherwise spent on doing tasks on my own). Artificial Intelligence increases my productivity in research.	Venkatesh et al. (2003)
Personal Innovativeness	I immediately looked for its possibilities when I heard about Artificial Intelligence. Among my friends, I frequently test out new applications first. I enjoy experimenting with cutting-edge technology.	Agarwal and Prasad, 1998
Intention to Use Artificial Intelligence (Behavioral Intention)	I also intend to use Artificial Intelligence to complete my research project shortly. I intend to engage in Artificial Intelligence routinely. I plan to use Artificial Intelligence frequently for my coursework and other research activities.	Venkatesh et al. (2003)

4. Results:

Table No: 3 Coefficients

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.142	.273		-.520	.604
	PE	.506	.086	.512	5.846	.000
	EE	.365	.096	.306	3.796	.000
	PI	.126	.053	.139	2.377	.019
	SI	-.012	.075	-.011	-.155	.877
	FC	.044	.063	.042	.700	.486
a. Dependent Variable: BI						

Subset model with three significant predictors and one dependent variable.

Table No: 4 Hypothesis Testing

Null hypothesis	P value	Result
Ho1 – There is no significant influence of performance expectancy on adoption to use AI tool.	0.000	Rejected
Ho2 – There is no significant influence of effort expectancy on adoption to use AI tool.	0.000	Rejected
Ho3 – There is no significant influence of personal innovativeness on adoption to use AI tool.	0.019	Rejected
Ho4: There is no significant influence of Social Influence AI tool.	.877	Accepted
Ho5: There is no significant influence of Facilitating Influence on adoption of AI tool.	.486	Accepted

Table No: 5 Unstandardized Coefficients

Model		Unstandardized Coefficients		t	Sig.
		B	Std. Error		
1	(Constant)	-.083	.236	-.354	.724
	PE	.512	.078	6.542	.000
	EE	.374	.094	3.967	.000
	SI	.129	.052	2.463	.015

It can be seen that Performance expectancy significantly influences intention to adopt AI tools among the research scholars with beta coefficient=0.512, t statistics=6.542 and p (value)=0.000.it is also seen that Effort expectancy significantly influences intention to adopt AI tools among the research scholars with beta coefficient=0.374,t statistics=3.967 and p (value)=0.000. Further, it can be concluded that personal innovativeness significantly intention to adopt AI tools among the research scholars with beta coefficient=0.129, t statistics=2.463 and p (value)=0.015.

Table No: 6 Hypothesis Testing

Null hypothesis	P value	Result
Ho1 – There is no significant influence of performance expectancy on adoption to use AI tool.	0.000	Rejected
Ho2 – There is no significant influence of effort expectancy on adoption to use AI tool.	0.000	Rejected
Ho3 – There is no significant influence of personal innovativeness on adoption to use AI tool.	0.015	Rejected

Assumption testing to build multiple linear Regression (MLR)

1. Lack of autocorrelation

Table No: 7 Model Summary

Model Summary										
					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.871[a]	.759	.751	.39606	.759	106.804	3	102	.000	2.174

Durbin-Watson should be between 1.5 to 2.5 for no autocorrelation among the error term. It is seen that Durbin-Watson =2.174, which means the error term is independent, or it can be said that residuals are not correlated with each other. Thus, it can be concluded that there is a Lack of autocorrelation between the error terms.

Ho: There is no correlation among the residuals

H1: There is a correlation among the residuals

P value = 0.37

P value > 0.05; therefore, Ho is accepted, and there is no autocorrelation among the residuals

2. Absence of multicollinearity

Table No: 8 Coefficients

Coefficients										
		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.083	.236		-.354	.724	-.551	.384		
	PE	.512	.078	.518	6.542	.000	.357	.667	.377	2.650
	EE	.374	.094	.313	3.967	.000	.187	.561	.381	2.627
	SI	.129	.052	.142	2.463	.015	.025	.233	.711	1.407

Variance inflation factor (VIF) is a measure to determine whether a predictor variable strongly correlates with other predictor variables. The cut-off criteria are that all the values of VIF for predictors must be less than 10, and tolerance values should be more than 0.10 to conclude the absence of multicollinearity. It can be seen from the above table that all the values of VIF are less than 10, and all the values of tolerance are above .10; therefore, all the predictors' variables are not highly correlated. There is the **absence of multicollinearity** as all the factors are independent of each other.

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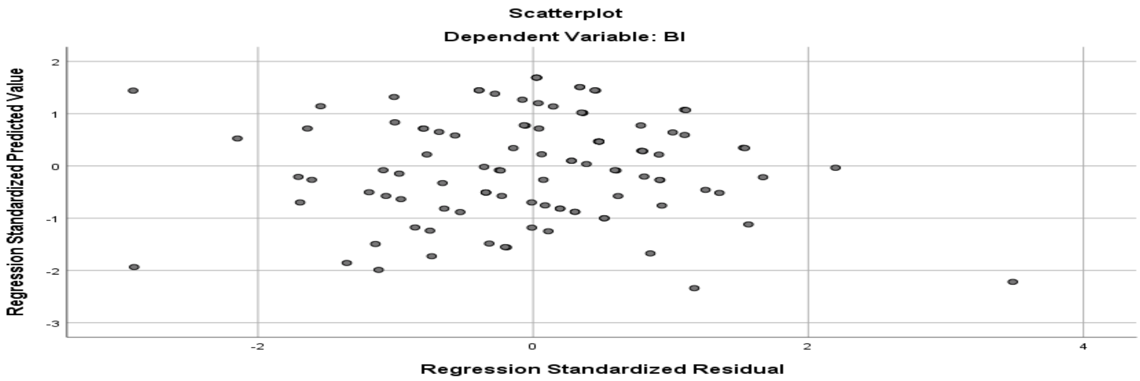
3. Homoscedasticity of Residuals

Figure No: 2 Scatterplot



It can be seen from the above figure that residuals are distributed uniformly on both sides as the distance is the same on both sides of the fit line, so there is an **adequate level of homoscedasticity.**

4. Normality of dependent variable (Intention to adopt AI tool)

Table No: 9 Tests of Normality

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BI	.357	106	.061	.493	106	.102

As p (value) of Kolmogorov-Smirnov=0.061 of dependent variable Intention to adopt AI tool thus it can be concluded that assumption of normality has been fulfilled.

Ho: Normality is present

H1: Normality is absent

P value = 0.61

P value > 0.05; therefore, Ho is accepted, and thus normality is present.

Table No: 10 Model fitness

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50.261	3	16.754	106.804	.000[b]
	Residual	16.000	102	.157		
	Total	66.261	105			
a. Dependent Variable: BI						
b. Predictors: (Constant), PI, EE, PE						

Table No: 11 Hypothesis Testing

Null hypothesis	P value	Result
Ho1: β1=β2=β3=0 (model is not overall fit)	**0.000**	**Rejected**

Regression model

$Y = \beta0 + \beta1X1 + \beta2X2 + \beta3X3$

Intention to use Artificial Intelligence = -0.083 + 0.512 x performance expectancy + 0.374 x effort expectancy + 0.129 x personal innovativeness

The overall model is fit as p (value) of ANOVA= 0.000 With R square=75%

5. Theoretical Implication

The study's theoretical contribution comes from its use of the UTAUT model and its acknowledgement of Technological Opinion Leadership as a driving force behind research academics' acceptance of AI. The UTAUT model is used in this study to expand on the existing theories of technology adoption and to provide a thorough framework for understanding the relationships between academics' attitudes and intentions regarding adopting AI and their expectations for performance and effort. These elements are combined to give academics and practitioners a comprehensive understanding of technology acceptance, enabling the development and use of successful methods to advance AI integration in academia.

Furthering our knowledge of social influence in the context of AI adoption is the identification of Technological Opinion Leaders as crucial influencers. The UTAUT model addresses social influence in general, but its application in academic contexts is improved by highlighting the unique function of technological opinion leaders. By highlighting the significance of opinion leaders in promoting technology acceptance in specialised fields like academia, this theoretical extension adds to the increasing body of knowledge on technology adoption.

6. Practical Implications

In the first place, knowing how vital Performance Expectancy, Effort Expectancy, and Personal Innovativeness are will help academic institutions and policymakers encourage the effective use of AI technology among research academics.

Secondly, since those academic institutions are aware of the impact of Performance Expectancy and Effort Expectancy, they may concentrate on demonstrating the practical advantages and simplicity of use that AI technologies provide to research researchers. Positive attitudes and desire towards using AI may be cultivated by offering training and resources to acquaint researchers with the tools and showcasing how AI can improve their research achievements. Institutions may help scholars more freely use new technologies by addressing concerns and emphasising the benefits of AI.

Moreover, discovering the significant influence of personal innovativeness highlights the significance of fostering an innovative culture in educational environments. In order to pique students' curiosity and inspire their enthusiasm for innovation, academic institutions might develop platforms for information exchange, teamwork, and exposure to cutting-edge technology. Research scholars' inventiveness and preparedness to use AI technologies in their research activity might be improved by encouraging them to investigate new technologies and keep current on AI developments.

In conclusion, the practical implications of this study highlight the significance of encouraging favourable attitudes towards the use of AI and building an innovative culture among research scientists. Academic institutions may help researchers integrate AI technology by addressing Performance Expectancy and Effort Expectancy issues and supporting their Personal Innovativeness. This will eventually improve academic research outputs' effectiveness, productivity, and calibre.

7. Discussion

The results of this study have significant ramifications for how academics use AI technology in their research processes. The importance of human traits in determining attitudes towards adopting AI is shown by identifying personal innovativeness as a significant influencing element. Higher degrees of individual inventiveness may make researchers more receptive to researching and using AI technologies, enhancing technology adoption and integration in their research processes. This is consistent with other research highlighting individual traits' significance in technological adoption.

Furthermore, it became clear that the impact of technological opinion leaders played a crucial role in encouraging research scientists to adopt AI. The results highlight the importance of thought leadership and expertise in encouraging other academics to use AI technology. Early adopters and critical players in the culture of innovation, technological opinion leaders inspire others to investigate the possible advantages of AI in their research projects—improved knowledge of the social dynamics involved in adopting technology results from identifying their effects.

8. Conclusion:

The results of this empirical study shed light on the crucial elements affecting research academics' adoption of AI technology. A thorough understanding of the connections between “Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Personal Innovativeness” and research researchers' views and intents towards AI adoption was made possible using the UTAUT model. According to the study, personal innovativeness among research academics is essential, and those more inclined to innovate are more likely to use AI technology. This result supports the idea that people more willing to test out novel items and technology are more inclined to adopt AI developments in their academic endeavours. The study supported the importance of personal innovativeness among research researchers, showing that individuals with a higher propensity for creativity are more open to using AI technology. This result supports the idea that people are more inclined to adopt AI developments in their academic endeavours if they are more willing to test new items and technology. Furthermore, it became clear that the impact of technological opinion leaders played a crucial role in encouraging research scientists to adopt AI. Other academics were greatly influenced to adopt AI technology by these opinion leaders' early acceptance and shown skill. This emphasises how crucial thought leadership and knowledge are to building an innovative culture and supporting the adoption of AI in academia.

As a result, our empirical investigation using the UTAUT model and examining Technological Opinion Leadership has shed important light on how academic researchers are embracing AI technology. The results highlight the significance of individual inventiveness, favourable circumstances, and societal influence in determining research academics' views and intentions towards adopting AI. Although the study has highlighted the difficulties associated with AI adoption in academia, it is essential to understand its limits. In the future, overcoming these restrictions and considering new avenues can help us better understand the integration of AI in academics. Researchers and institutions may support technical innovation and research excellence in the constantly changing field of artificial intelligence by considering various academic environments, monitoring the dynamic nature of AI adoption, and addressing ethical considerations.

9. Limitations and Future Directions

It is essential to recognise this study's shortcomings. Because the study was carried out in a single academic context, there may be restrictions on how widely the results may be applied. Furthermore, self-reported data may induce response biases, which should be considered when interpreting the findings. Numerous exciting new avenues are suggested based on the knowledge gathered from this investigation. Future studies should include other academic institutions and research sectors to increase the external validity of the findings and provide a more thorough knowledge of the adoption of AI among research researchers. Studies that follow the uptake of AI through time and account for its dynamic character may shed light on how it may eventually affect academic practice and results. To help academics embrace AI technology, looking at the efficacy of training programmes designed to improve researchers' AI literacy would also be helpful. Future studies should also pay attention to ethical issues surrounding the use of AI. Ensuring data privacy, addressing algorithmic biases, and advancing ethical AI practices in academia may be achieved by investigating AI use's ethical implications in research.

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