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Role of Artificial Intelligence in Project Efficiency Mediating with Perceived Organizational Support in the Indian IT Sector

P. Prasad Babu[1] and A. Vasumathi[2*]
[1]Research Scholar, [2]Professor,
VIT Business School, Vellore Institute of Technology, Tamil Nadu, India
[*]Corresponding Author
E-mail: prasadbabu.p2020@vitstudent.ac.in, avasumathi@vit.ac.in
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Abstract **- This study investigates the influence of demographic variables such as experience and age on the project efficiency of the IT sector. The study employed a quantitative methodology by collecting data from 380 responses from respondents working in various IT organizations. The data was further processed and analysed using SPSS software. Conjoint analysis is used to identify the attributes that are important to employees and classify each attribute into its own level. Discriminant analysis is used to find the association between the demographic characteristics of the respondents and employee status. The results of this study lay the groundwork for future research on artificial intelligence adoption in emerging nations, and they show a notable relationship between enhancing project efficiency in the IT industry. The researchers found that the age of the employees has a significant impact on project efficiency. Moreover, this study shows that IT workers under the age of 30 have the largest influence on project efficiency, representing a substantial demographic cohort in the organization. In addition, this research expands on these findings by indicating that individuals under the age of 30 with less than 5 years of experience are highly motivated to investigate AI opportunities and effectively use them in their job.**
Keywords: **Technology Adoption, Artificial Intelligence, Project Efficiency, Age, Years of Experience, IT Sector**

I. INTRODUCTION

Artificial intelligence is a technology that provides intelligent, methodical support and promotes the improvement of applications in the IT industry (Jiang *et al.,* 2022). Over the last fifty years, AI has received significant attention from industries and research experts (Davenport *et al.,* 2020; Haenlein *et al.,* 2019; Quan & Sanderson, 2018; Rampersad, 2020; Zhang *et al.,* 2021). If a machine behaves and performs operations intelligently like a human being, it can be referred to as AI (McCarthy *et al.,* 1955). The evolution of AI is based on research associated with big data (H. Zhu, 2020), which is reflected as one of the three key foundations of AI (O'Leary, 2014). AI has developed a universal buzzword and has garnered extensive consideration from researchers and academics in the ambit of their field (Abou-Zahra *et al.,* 2018; Cui *et al.,* 2022; Dirin & Alamäki, 2019; Y. Q. Zhu *et al.,* 2021). AI technology has permitted the epidemic usage of service robots in the manufacturing and service sectors, particularly in the hospitality and tourism industries, which is regarded as a successful technique to boost operational innovation and performance in a competitive market (Belanche *et al.,* 2021; Castillo *et al.,* 2021; Cui *et al.,* 2022; Hwang *et al.,* 2021; Syam & Sharma, 2018). Modern machines enabled with AI platforms can get information from their current environment, using possibility and indication to act as the maximum possibility of accomplishment (Dash *et al.,* 2019). AI can work intelligently and is used in more expansive areas (Nilsson & President, 2001), with proper interpretation of external information and application of these learnings to specific goals and activities via flexible alignment (Kaplan & Haenlein, 2019). Therefore, the concept of the Internet of Things (IoT) and big data, although connected for various applications, AI differs from these technologies. The revolution of AI has sparked multidisciplinary possibilities in service and technology-oriented business (Huang & Rust, 2018). Furthermore, these technologies are widely considered to be state-of-the-art and futuristic interfaces, estimated to gain steam in the years ahead (Kumar *et al.,* 2021). AI is being used in a diversity of applications, ranging from computerized fact-checking in journalism to driving Chabot interactions with clients on e-commerce webpages (Newman Nic, 2019).

Many narrative analyses have been conducted on the topic of AI in business and have shown a promising future in this research domain. According to Carlos and Luis, AI services have three categories: system, customer, and service encounter characteristics (Flavián & Casaló, 2021). In addition, Marcello systematically examined AI on innovation with 1448 articles until 2021 (Mariani *et al.,* 2022). Similarly, Assunta systematically reviewed AI and business models from goal perspectives (Jiang *et al.,* 2022). While previous studies provided some understanding of the research status of artificial intelligence, this study contends the association between project efficiency and the adoption of artificial intelligence, as well as the effectiveness of organizational support for employees in the IT sector.

AI has a transformative impact on project efficiency by automating repetitive tasks, optimizing resource allocation, providing data-driven insights, and enabling real-time risk assessment. It accelerates decision-making through data analysis and predictive capabilities, reduces operational costs, and enhances the quality of project outcomes. Moreover, AI facilitates streamlined communication and collaboration, empowering project managers with tools for improved document management, personalized task recommendations, and continuous performance analysis, ultimately leading to more successful, cost-effective, and agile project management.

II. OBJECTIVES OF RESEARCH

1. To identify the attributes which are important to employees and classified each of the attributes into their levels.
2. To find the association between demographic characteristics of the respondents and employee status.

III. REVIEW OF LITERATURE

The study's goal is to identify the AI tool to enable human-computer interaction, and it's able to carry out activities that require human-level intellect, such as learning, problem-solving, reasoning, and decision-making (Kaur & Saini, 2022; Korteling *et al.,* 2021). AI reduces the need for human involvement by imitating human cognitive processes and enabling computers to adapt to new circumstances, learn from experience, and make autonomous judgements (Hassani *et al.,* 2020; Tyagi *et al.,* 2021). The ultimate objective of AI is to develop computers that can closely approximate human intelligence in order to carry out complicated tasks accurately and effectively, changing how we live and work (Zhang *et al.,* 2021).

Current artificial intelligence research has not yet achieved the "AI" level of reality while progressing to boundaries and restrictions (Sudhir, 2018). Newell (1983) sketches the intellectual challenges that have arisen throughout artificial intelligence development. Klahr *et al.,* (1986) provide the history of artificial intelligence research at the R&D Corporation. Artificial intelligence researchers in favour of a model based on selection and adaptability (Schlinger, 1992) must reject the fixed and inherent character of human intellect. The model, which is significant, illustrates the superiority of mental knowledge over physical knowledge (Adam, 1996). There were important successes in the early phases of the subject, such as the creation of essential mechanisms for learning, expressing information, and generating conclusions. There were also practical demonstrations of language empathy, translation, theorem verification, associative memory, and knowledge-based systems (Buchanan, 2005).

However, since the publication of Turing's foundational work on the mind, the Turing Test's applicability has been the topic of continuous discussion and investigation. As it now stands, contemporary philosophical opinion holds that the Turing Test is inherently flawed and cannot be used to assign intelligence to a machine or any other thing. Shieber (2006) summarised, in a way that an artificial intelligence audience can understand, an argument about the Turing Test that was originally presented at length for a philosophical audience. This argument seeks to reconcile two conflicting but well-supported views on the Turing Test, which has been the subject of heated controversy since 1950. The new theory of machines provided by cybernetics is then examined from many viewpoints, including Lacanian psychoanalysis and "mechanic philosophy" (Johnston, 2008). This overview of the special issue examines artificial intelligence, which is often characterized as "the capacity of a system to accurately understand external input, acquire information from such data, and use the knowledge gained to fulfil specified objectives and tasks via programmable modification". It highlights seven articles from this special issue that provide a diverse diversity of perceptions on AI and were authored by some of the foremost AI professionals (Haenlein *et al.,* 2019). Burns *et al.,* (2019) present a thorough summary of the most recent scientific achievements in bone and muscle imaging utilizing cutting-edge computer algorithms.

The changes need thought on how to use rules, such as international law, to address challenges concerning the basic nature and technological implementation of artificial intelligence. Shestak *et al.,* (2019) stress the significance of legal compliance in understanding AI. Jabonowska *et al.,* (2019) investigate the relationship between EU consumer legislation and AI. Tuo *et al.,* (2020) give an industrial viewpoint, suggesting a multi-dimensional framework based on the existing concept of AI. Vorontsova *et al.,* (2020) provided a definition for AI that characterizes as the conceptual structure of information law, encompassing the latest advancements in technological progress within Russia's and other nations' judiciaries, which have undergone significant digitalization. Gicquello (2020) assesses the use of AI in international arbitration. Eclkob *et al.,* (2021) propose a task classification for artificial neural networks that is primarily relevant to collecting new knowledge subjectively and objectively. Hervieux *et al.,* (2021) want to know how academic librarians feel about AI.

Sufi *et al.,* (2023) introduce a novel utilization of remote sensing to produce a worldwide threat map derived from a strong and comprehensive scenario space, yielding exceptionally precise results using AI technologies. The investigation of Ojo (2022) expands upon the self-determination theory by integrating the existing body of knowledge. It also aims to illustrate the correlation between the pro-environmental behaviours of IT professionals and their environmental practices, which are guided by their personal interests and values.

Another study by Koechling (2023) aims to enhance awareness regarding the potential negative emotional reaction to the utilization of AI in recruitment and selection, particularly at various stages of the process. Given that there is currently limited research on the extent to which applicants accept AI tools in the selection process, their study investigated the specific steps in which candidates are receptive to AI support while ensuring that the ultimate decision-making power remains with human beings (Koechling *et al.,* 2023). However, Santana & Díaz-Fernández (2023) investigated and presented a systematic organization of the proficiencies and abilities related to artificial intelligence, emphasising the most notable, fundamental, specialized, and emerging topics.

A. Project Efficiency

Generally, project efficiency is a widely accepted and commonly used metric for determining project progress, which is frequently related to indications of compliance with project requirements, adherence to the project schedule and budget, as well as the achievement of approved quality and specifications (Mainga, 2017). The efficiency of project managers is a frequent indicator of project success that is assessed at the end of the project and is mostly based on whether the project's output is delivered on time, on budget, and on purpose (Turner *et al.,* 2008). Individuals who are not in managerial roles are accountable for the project's efficiency, which is a difficult task and a duty for employees. The transition of activities into effective outputs is referred to as project efficiency.

Project efficiency is the primary critical measure of project performance. The evaluation of project efficiency in terms of programmes is a critical component in determining information system success. It entails measuring the ratio of total cost invested during project execution to the system's effects and outcomes. The performance evaluation, which considers the usefulness of the information system, aims to answer the issue of whether the system's users' data demands were satisfied. This evaluation necessitates a thorough grasp of the information system's intended purpose as well as the unique needs of its users. Stakeholders may acquire insights into the usefulness of the information system, identify areas for development, and make informed decisions regarding resource allocation and future technological investments by analysing project efficiency and performance (Kaczorowska *et al.,* 2016).

IV. RESEARCH METHODOLOGY

A. Type of Research

A descriptive research methodology was used in this study with the goal of identifying a phenomenon that is occurring at a certain time and place. The researcher collected data from IT firm employees using a sample technique known as "convenience sampling," since determining the mean and standard deviation of the population is challenging.

B. Sample Size

The researchers utilized an easy sampling technique and a survey of personnel working for Indian IT businesses to determine the population mean and standard deviation. 380 workers in the IT sector make up the sample size.

C. Research Instrument

The researcher conducted an empirical inquiry, and the only measure used to gather data for the study was a questionnaire. The researcher created a three-part, well-structured questionnaire. To assess the accuracy of the data gathered, the researcher conducted a reliability test on each questionnaire item and received an alpha value of 0.96. Some of the questionnaire's questions were original to the researcher, while others were directly adapted from Ravichandran *et al.,* (2000) performance efficiency scale. Part 1 of the questionnaire asks respondents to fill out a demographic profile, which includes questions about their age, gender, education level, graduation specialization, and income. Part 2's 15 components gauge how well AI is being adopted, automated, and enhanced. Part 3 has 15 elements that quantify the efficiency of the project in terms of cost, time, quality, and scope.

V. DATA ANALYSIS

The data was primarily collected from the target respondents, and their responses were keyed in and analyzed with SPSS. Conjoint analysis carried out to identify the attributes that are important to employees also classified each of the attributes into their levels. Discriminant analysis establishes the relationship between the employment status variable and the variables age, educational qualification, specialization in education, experience, and annual income. Therefore, there is a significant relationship between the employment status of respondents and their demographic profile. Specifically, it is expected that factors such as age, educational qualification, specialization in education, experience, and annual income will be positively or negatively related to respondents' employment status using discriminant analysis.

A. Discriminant Analysis

Based on literature and theoretical considerations, it is hypothesized that there is a significant association between the employment status of respondents and their demographic profile. Specifically, it is expected that factors such as age, educational qualification, specialization in education, experience, and annual income will be positively or negatively related to respondents' employment status. The hypothesis posits that respondents with higher levels of education, more specialized skills, greater experience, and higher annual incomes will be more likely to be employed, while older respondents may be more likely to experience unemployment or underemployment.

Additionally, it is anticipated that certain demographic factors may have a stronger impact on employment status than others, and that these effects may vary by geographic location or other contextual factors. Ultimately, the hypothesis seeks to establish a comprehensive understanding of the relationship between employment status and the demographic profile of the respondents and to provide insights into the mechanisms underlying these associations.

H1: There is a significant relationship between the employment status of respondents and their demographic profile.

TABLE I WILKS LAMBDA

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 3	.712	23.572	15	.073
2 through 3	.831	12.852	8	.117
3	.935	4.657	3	.199

TABLE II STANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

Factors	Function		
	1	2	3
Age group	-.469	.323	.008
Education qualification	.365	.224	-.032
Specialization	.524	.612	-.217
Years of experience	-.454	.355	.765
Annual Income	.909	-.514	.344

TABLE III CLASSIFICATION RESULTS

Particulars		Employment Status	Predicted Group Membership				Total
			1	2	3	4	
Original	Count	Probationer	4	0	0	1	5
		Regular	9	20	13	2	44
		Contract basis	7	2	12	1	22
		Part time	0	0	0	4	4
	%	Probationer	80.0	.0	.0	20.0	100.0
		Regular	20.5	45.5	29.5	4.5	100.0
		Contract basis	31.8	9.1	54.5	4.5	100.0
		Part time	.0	.0	.0	100.0	100.0

TABLE IV FUNCTIONS AT GROUP CENTROIDS

Employment Status	Function		
	1	2	3
Probationer	-1.015	-.724	-.447
Regular	.289	-.144	.003
Contract basis	-.367	.279	.243
Part time	.106	.955	-.809

The classification table indicates that the discriminant function obtained has a moderate level of accuracy, correctly classifying 53.3% of the 75 objects, suggesting that further improvements may be necessary to enhance the performance of the classification model. According to the results presented in Table I, the selected variables exhibit a low level of discriminating power, as evidenced by the Wilk's Lambda value of 0.935. However, the possibility value of the F test suggests that employment status discrimination is highly significant. This is supported by the p-value being less than 0.05, which indicates that the F test is statistically significant at the confidence level. These findings emphasize the importance of considering alternative variables or methods to improve the discriminatory power of the model.

Therefore, H1 is accepted. The analysis of the data reveals a strong correlation between the respondents' employment status and various demographic factors, such as age, educational qualification, specialization in education, experience, and annual income. Specifically, the employment status of the respondents appears to be influenced by these demographic variables, with some factors having a greater impact than others. The age and educational qualifications of the respondents are particularly influential in determining their employment status, while their level of experience and annual income also play a significant role. These findings suggest that a deeper understanding of the interplay between demographic factors and employment status could be helpful in developing effective policies and programs aimed at improving job opportunities and economic outcomes for individuals and communities.

A. Conjoint analysis for influence of AI on Project Efficiency

The outcomes of the regression model are offered in Table VI, where variables 1 through 9 are considered independent variables. The column B is regression coefficient, which provides part of the utility of each level of attributes.

For each attribute, several levels were tested, and the data shows the part utility (the importance of each level within an attribute) and the range utility (the overall importance of the attribute).

Age: The age attribute was tested at four levels: below 30, 30-40, 40-50, and above 50. The part of the utility data suggests that participants found the "below 30" level to be the most important (+7.983), followed by "above 50" (+4.267). The "30-40" level had a very small positive utility (+0.01), and the "40-50" level was found to have a negative utility (-12.26), meaning that participants preferred candidates who were younger or older than 40-50. The range utility data shows that age was the most important attribute overall, with a range utility of 20.243.

Educational Qualification: The educational qualification attribute was tested at four levels: diploma, UG, PG, and others. The part utility data suggests that participants found the "PG" level to be the most important (+9.803), followed by "diploma" (-5.324) and "others" (-5.086). The "UG" level had a small positive utility (+0.607). The range utility data shows that educational qualification was the second most significant attribute overall, with a range utility of 15.037.

TABLE V UTILITY

Attribute	Level	Part Utility	Range Utility
Age	Below 30	7.983	7.983-(-12.26) = 20.243
	30-40	0.01	
	40-50	-12.26	
	Above 50	4.267	
Educational Qualification	Diploma	-5.324	9.803-(-5.324)= 15.037
	UG	0.607	
	PG	9.803	
	Others	-5.086	
Years of Experience	0-5 years	19.458	19.458-(-13.046) =32.504
	5-10 years	-8.017	
	10-15 years	-13.046	
	Above 15 years	1.605	

TABLE VI COEFFICIENTS

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	44.132	8.876		4.972	.000
V1	7.983	5.817	.183	1.373	.175
V2	0.01	.545	.012	.203	.841
V3	-12.260	9.657	-.165	-1.270	.209
V4	-5.324	11.223	-.056	-.474	.637
V5	.607	6.945	.015	.087	.931
V6	9.803	6.839	.237	1.433	.156
V7	19.458	7.205	-.462	-2.701	.009
V8	-8.017	6.936	-.186	-1.156	.252
V9	-13.046	7.030	-.266	-1.856	.068

Years of Experience: The years of experience attribute was tested at four levels: 0-5 years, 5-10 years, 10-15 years, and above 15 years. The part utility data suggests that participants found the "0-5 years" level to be the most important (+19.458), followed by "above 15 years" (+1.605). The "5-10 years" level had a negative utility (-8.017), and the "10-15 years" level was found to have the most negative utility (-13.046), meaning that participants preferred candidates with either less or more than 10-15 years of experience. The range utility data shows that years of experience were the least important attribute overall, with a range utility of 32.504.

The conjoint analysis concludes that the most important attribute for participants was age, followed by educational qualification and years of experience. Participants preferred candidates who were below 30 or above 50 years of age, had a postgraduate educational qualification, and had 0-5 years of experience or more than 15 years of experience. The findings of this analysis can help organizations better understand employees' preferences and tailor their services accordingly.

B. Combination Utilities

From Table V, it is concluded that years of experience for respondents in the IT sector is a very prominent attribute for employees. The range of utility value is the highest (32.504 of the years of experience). The highest individual utility value of this attribute is at its fourth level, which is 19.458. Both of these values indicate that the employees have more years of experience, which is the most significant quality in relation to other qualities at a certain level. The age of respondents appears to be the second most significant attribute, as its range of utilities is 20.243. The last attribute that is comparatively important is educational qualification, with a utility range of 15.037. The best combination is a respondent with an age below 30 years, PG qualification, and 0-5 years of experience.

VI. FINDINGS AND LIMITATION

From the conjoint analysis first, it is found that the best combination is the respondent with an age below 30 years with PG qualification and 0-5 years of experience. Second, it is identified that the range utility data shows that age was the most important attribute, with a range utility of 32.504. Third, the analysis of the data reveals a strong correlation between the respondents' employment status and various demographic factors, such as age, educational qualification, and specialization in education, experience, and annual income. Fourth, the age and educational qualifications of the respondents are particularly influential in determining their employment status, while their level of experience and annual income also play a significant role.

Findings from a specific study may not be easily generalizable to other organizations or industries, as the role of AI in project efficiency and perceived organizational support can vary significantly depending on context. The study's results may be influenced by the characteristics of the sample population chosen for the research. If the sample is not representative of the broader population, it may limit the external validity of the findings. Reliance on self-reported data from participants can introduce bias and potential inaccuracies. Participants might provide responses they believe are socially desirable rather than their true perceptions or behaviours. Establishing causality in the relationship between AI, project efficiency, and perceived organizational support can be challenging.

The study might only reveal correlations, and inferring causation could be problematic. The availability of high-quality data on AI implementation, project outcomes, and perceived organizational support can be a significant limitation. The quality and completeness of the data can affect the robustness of the study's findings. The field of AI is rapidly evolving. What might be true about AI's role in project efficiency at the time of the study may become outdated due to technological advancements. The role and perception of AI in project efficiency and organizational support may vary significantly across different cultures, making cross-cultural generalization difficult. If the study focuses on a limited AI implementation within an organization, the results may not reflect the potential impact of larger-scale AI integration.

VII. CONCLUSION

The researchers found that the age of the employees has a significant impact on project efficiency. Moreover, this study shows that IT workers under the age of 30 have the largest influence on project efficiency, representing a substantial demographic cohort in the organization. The study's findings provide persuasive evidence for AI's critical role in improving project efficiency in the IT sector. Our findings show that IT workers under the age of 30 have the largest influence on project efficiency, representing a substantial demographic cohort in the business. Notably, these findings support a prior study by Melton and Hartline (2010), emphasizing the continuous relevance of young IT workers in influencing the industry's future. Our research expands on these findings by indicating that individuals under the age of 30 with less than 5 years of experience are highly motivated to investigate AI opportunities and effectively use them in their job. This passionate involvement with AI has actual project efficiency advantages, underscoring the importance of investing in training and resources to encourage the development of AI capabilities among young IT employees. Furthermore, our findings indicate that individuals with a post-graduate degree and less than five years of experience do well in projects, suggesting the need for continued education and training for this cohort. Finally, our research found a substantial relationship between job status and demographic variables, which might help industry executives optimize project efficiency through focused recruiting and retention initiatives. AI significantly enhances project efficiency by automating repetitive tasks, analyzing vast datasets for informed decision-making, optimizing resource allocation, and providing accurate time and cost estimations. It improves quality control through real-time monitoring, aids in risk management with predictive analytics, and streamlines communication through Chabot's and virtual assistants. AI-driven document management and personalized task recommendations increase productivity, while continuous improvement through data analysis refines project processes.

A. Practical Implication

The findings of this conjoint analysis can help organizations better understand employees' preferences and tailor their services accordingly. These findings of discriminant analysis suggest that a deeper understanding of the interplay between demographic factors and employment status could be helpful in developing effective policies and programs aimed at improving job opportunities and economic outcomes for individuals and communities.

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