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Generative Artificial Intelligence (GenAI) Adoption in Saudi Arabia: New Explored Dimension via Technology Acceptance Model (TAM)

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Abstract: The rapid advancement in Generative Artificial Intelligence (GenAI) technologies in Saudi Arabia has brought with it a transformative shift across various sectors and industries. As GenAI becomes increasingly integrated into the digital infrastructures of modern organizations, understanding the factors that influence its adoption, acceptance and use has become an important area of research beyond academia. Saudi Arabian GenAI adoption research focused primarily on educational institutions, and to gain a more comprehensive understanding of real-world implications, researchers must explore new territories to cover adoption across different industries. Accordingly, this research paper aims to provide a new prospect on GenAI adoption and use in Saudi Arabia by targeting 500 users working in a large Saudi energy organization capitalizing on the Technology Acceptance Model (TAM). A total of 104 users completed a survey questionnaire and included 87 males [83.7%] and 17 females [16.3%] with varying years of experience ranging from less than 5 years to over 20 years. Pearson correlation coefficients were calculated in addition to Structural Equation Modeling (SEM) to examine the hypothesized relationships among TAM's constructs. Pearson correlation showed stronger correlation between Perceived Usefulness (PU) and Attitude Toward Use (ATU) ($r = .680$, $p < .01$) compared to Perceived Ease of Use (PEOU) and ATU ($r = .327$, $p <.01$). Similarly, SEM revealed that PU had a significant influence on ATU ($\beta = .52$, $p < .001$) while PEOU influence was of non-significance on ATU ($\beta = .05$, $p > .05$). Findings revealed the implications of organizational strategies and users training prior to introducing GenAI for users with statistically significant association between ease of becoming skillful and understandability of GenAI tools ($r = .826$, $p <.01$).

Key Words: GenAI, Adoption, Saudi Arabia, Energy, TAM

I. Introduction:

The rapid advancement of Generative Artificial Intelligence (GenAI) technologies in Saudi Arabia has brought with it a transformative shift across various sectors and industries. As GenAI becomes increasingly integrated into the digital infrastructures of modern organizations, understanding the factors that influence its acceptance and use has become an important area of research. To investigate GenAI acceptance in Saudi Arabia, the Technology Acceptance Model (TAM) provided a foundational theoretical framework, offering insights into users' behavioral intentions to adopt technologies based on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). While recent research has applied TAM to investigate GenAI adoption in Saudi Arabia, most of it has focused on higher educational context. Therefore, broader organizational, cultural, and strategic dimensions remain unexplored. Given Saudi Arabia's digital transformation ambitions and the growing potential of GenAI in both the public and private sectors, there is a crucial need to understand how GenAI is adopted and utilized beyond the fences of academia. Accordingly, this research study aims to fill the gap in literature by applying the TAM model in organizational setting in order to explore GenAI adoption.

The study of GenAI acceptance and use in Saudi Arabia is considered relatively new (Aldossary et al., 2024), and most of previous work conducted in educational institutions (Al-Mamary and Abubakar, 2025). Accordingly, this research incorporates industry-based dimension to help Saudi organizations better understand, plan and mange GenAI development and deployment. The study provided insight into important factors that may require attention by organization in Saudi Arabia to foster better adoption including strategies and users training prior to GenAI deployment with understandability as a key factor to enhance adoption and use.

The literature review starts with background on TAM, its constructs and extensions (TAM-2 and TAM-3). A review of GenAI research in Saudi Arabia showed a considerable work done in academia with higher education institutes and universities as primary focus, leaving the majority of organizational and non-educational contexts unexplored. Fear of job displacement and lack of readiness to use GenAI were among the literature review themes attributed to less work done on GenAI adoption research in organizations, in addition to, privacy and data security (Sallam et al., 2025). Moreover, there is a lack of industry-based research in the Gulf Cooperation Council (GCC) in general (Almarzouq and Albashrawi, 2025) resulting in less work conducted in many areas including technology adoption. Due to its uniqueness, GenAI has a potential to significantly change the work activities within modern organizations and understanding how to successfully deploy and adopt it may produce opportunities for both academics and industries.

This study applied a quantitative research design to explore the factors that influence the adoption and use of GenAI with the TAM serving as the theoretical foundation. A survey-based approach was selected to obtain measurable insights from 500 users working in large energy company in Saudi Arabia. The questionnaire was taken from Davis, (1989) and modified for the purpose of this study. Non-probability sampling technique was applied, namely self-selection sampling to access the targeted population. A total of 104 users or 21.8% completed the survey questionnaire. Pearson correlation coefficients were calculated using Statistical Package for the Social Sciences (SPSS) in addition to Structural Equation Modeling (SEM) to examine the hypothesized relationships among TAM's constructs.

Unlike previous research (Ghimire and Edwards, 2024 and Baytak, 2023), PEOU was found to be of less significance for industry users compared to users in academia which may be attributed to fear of job replacement, trust or data privacy matters inside organizations (Sallam et al., 2025) in comparison to educational institutes in which users are primarily students or educators who are more likely to be exposed to training materials, books and keen to learn and explore new technologies. Industry users of GenAI may require more training and practice prior to deployment and use of these technologies in their organizations. This may explain the strong association found in this research between ease of becoming skillful and understandability of GenAI tools. The findings revealed the robustness of the TAM's model in predicting the adoption and use of GenAI technology. Both Pearson correlation and SEM revealed the significance of PU on GenAI adoption and use with implications discussed in details in the results discussion section of this research paper.

II. Literature Review:

The literature review is organized into four main sections. The first outline the theorical framework focused on Technology Acceptance Model (TAM) main constructs, development and evolvement. The second defines Generative Artificial Intelligence (GenAI) Technology. The third examines GenAI research in Saudi Arabia and the fourth section highlights gaps in the literature.

III. Theorical Framework

Information technology acceptance is an important area of research due to the evolving nature of people, processes and technology. In order to understand how people, accept and adopt information technology, several research paradigms and frameworks have been established in the field of information systems. One of the most predominant frameworks in this field is the Technology Acceptance Model or TAM (Hokroh and Green, 2018, Hokroh and Green, 2019, Hokroh et al., 2020 and Al-kfairy, 2024). The TAM was developed by Fred Davis in the year 1989 (Davis, 1989) to explain and predict users' acceptance of information systems. The framework has two main constructs which are Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), and both play a role in influencing users' intention to use information technology. PEOU refers to the degree to which users believe that using a system would be free of effort while PU refers to the degree to which users believe that using a system would enhance job performance. The TAM is considered a major theory of information technology due to its ease and high reliability of predicting users' acceptance (Al-Gahtani, 2001). The TAM framework was further extended in the year 2000 by Venkatesh and Davis who renamed it TAM-2 (Venkatesh and Davis, 2000). The extension of the framework provided a comprehensive view of the factors that influence users' acceptance of information technology by incorporating social and cognitive variables. In the year 2008, TAM-2 was extended by Venkatesh and Bala to produce TAM-3 which incorporated additional factors which included individual differences, system characteristics, social influence and facilitating conditions (Venkatesh and Davis, 2008). Despite the predominant use of the TAM framework, it has been extended or modified to test for several emerging variables within different contexts. According to Kruger and Steyn, (2024), the TAM served as the core model for more than 100 studies, 84% of which, have extended the model to fit for purpose. Furthermore, TAM has been combined with other models to cover wider range of factors to better understand factors influencing the adoption of information technology. This flexibility allows the TAM constructs to be adjusted to enhance the understanding of acceptance and use of emerging technologies (Mustafa et al., 2022). As a conceptual framework, TAM incorporates psychological and emotional factors like perception and intention and therefore it assumes that human factors such as trust, empowerment and learning play role in the acceptance and use of information systems. TAM is considered a fundamental framework to apply at different sittings to test the acceptance of various emerging technologies such as Generative Artificial Intelligence or GenAI.

IV. Generative Artificial Intelligence (GenAI) Technology

GenAI refers to different computational techniques that have the capabilities to generate seemingly new meaningful content such as images, texts or audio through searching and analyzing data (Feuerriegel et al., 2024). According to Feuerriegel et al., (2024), GenAI is becoming an integral part of the socio-technical components of information systems with transformative potential in business and engineering. As the GenAI technology is emerging in Saudi Arabian market, the call for research to understand acceptance and user is becoming imminent (Aldossary et al., 2024). According to Aldossary et al., (2024), the study of GenAI acceptance and use in Saudi Arabia is considered relatively new with promising prospect of its utilization in different fields. As pointed out by Al-Mamary and Abubakar, (2025), there is a need for further research in the area of GenAI application especially in Saudi Arabia in which most of the literature's attention was on educational setting. New research focus shall be able to offer new insights and opportunities to enhance the understanding of users' acceptance of such evolving technology (Al-Mamary and Abubakar, 2025). Saudi Arabian market has the potential and capacity to expand the use and adoption of GenAI to improve system processes and promote development in different areas (Al-Mamary and Abubakar, 2025). GenAI has the potential to change the way business is conducted offering more informed knowledge-based decision making by correlating, consolidating and synthesizing wide-areas of topics.

V. GenAI in Saudi Arabian Context

Recent research has used TAM to investigate the acceptance and use of GenAI in higher education (Al-Abdullatif, 2024). Al-Abdullatif, (2024) found that AI literacy and PEOU were the factors of most influence affecting teachers' acceptance of GenAI technology. Furthermore, Al-Abdullatif indicated that there is a need for specialized professional training programs for teachers to improve AI literacy. Other studies have shown strong correlation between PU and educators' acceptance of GenAI with PEOU as the most crucial factor in the acceptance of GenAI in educational setting (Ghimire and Edwards, 2024). According to Ghimire and Edwards, (2024), educators were found to have different attitudes towards GenAI ranging from strong enthusiasm to cautious skepticism. These variations highlight the important role of developing a tailored road map or strategies to address the distinct concerns and requirements of various educator groups. This point was also stressed by Setälä et al., (2025) who found that it is important for educational institutes to equip their teachers with the resources required to develop instructional approaches (pedagogical strategies) to boost student's enjoyment and PU of GenAI. A study by Baytak, (2023) aimed at reviewing the literature on the acceptance and adoption of Large Language Models (LLMs) such as ChatGPT and Google Bard in educational institutions found that users' acceptance of these technologies is often accompanied by reservations especially with regards to the reliability and ethical aspects of utilizing these tools in educational setting. Baytak found that PE, PEOU and trust were among the key factors influencing the adoption of GenAI technology. Baytak also highlighted that some educators were found to be early adopters, while some remained skeptical; and therefore, an organizational strategy is considered important in order to address diverse users' concerns. In Shata and Hartley, (2025) study of 294 higher education faculty members adoption and use of GenAI, it was found that PU has significantly influenced users' attitudes and intentions of use more than PEOU. Social influence from peers was found to be crucial in faculty decision to adopt and use GenAI. Trust in GenAI and moderated by peers influence impacted PU and thus willingness of adoption. With a focused attention on the mediating role of trust in technology, Alotaibi, (2025) surveyed a total of 365 students across five public Saudi universities to understand the factors influencing adoption and use of GenAI. The study concluded that students' technical knowledge significantly increased their trust in GenAI, which in turn was positively associated with improved academic performance. Additionally, both personal experience and perception were found to be positively related to increased trust in GenAI and enhanced academic outcomes.

Away from educational settings, the TAM combined with Technology-Organization Environment (TOE) (a framework used to understand how organizations adopt and implement innovative technology) showed that both PEOU and the positive attitude played significant role in influencing behavioral intention to use technology (Na et al., 2022). Conducted for a construction agency, Na et al., (2022) study findings revealed that there are key factors which influence use and utilization of innovative technologies which include organizational, environmental, individual, attitude and behavior. Another study of 100 software engineers, compatibility was one key driver for GenAI adoption followed by PU which was found to have lower impact on adoption compared to compatibility (Russo, 2024). Russo, (2024) attributed this result to the subject being studied (software engineers) values who called for AI tools that fit with existing workflows and practices. For software engineers this reflects easier system integrations with GenAI tools, reduced learning curve and gave them more assurance and trust.

VI. Literature Gaps and Research Directions

Most of the research on GenAI adoption in Saudi Arabi was conducted within the premises of higher educational institutions or universities (Al-Abdullatif, 2024, Ghimire & Edwards, 2024, Setälä et al., 2025 and

Baytak, 2023) and therefore the broader adoption and use landscape in Saudi Arabia remains unexplored, requiring more research to be conducted in non-educational sectors such as public and private organizations, healthcare providers and governmental institutions. There is limited empirical research on how organizational, cultural, ethical and social-technical aspects influence the adoption, acceptance and use of GenAI. In a study conducted to investigate the level of apprehension and concerns of GenAI use the Arab world, it was found that users exhibited concerns and mistrust in their acceptance (Sallam et al., 2025). Fear of job displacement and lack of readiness to use GenAI were also among the themes that were raised in the study in addition to ethical issues such as privacy and data security (Sallam et al., 2025) which may result in comparatively fewer empirical studies examining GenAI adoption in industry than in academia (Almarzouq and Albashrawi, 2025).

There is an opportunity gain for industries to conduct empirical-based studies to help organizations better understand GenAI adoption in order to facilitate better technologies deployment plans, manage users' resistance and reduce cost. GenAI differs from the traditional technology in terms of functionality, data analysis, interaction and user experience (Singh, 2024). On unique feature of GenAI is the ability to intelligently interact with users given them a personalized experience based on their interest by asking questions and simulated chatting in various languages (Al-Samarraie et al., 2024). This uniqueness may enable generating new areas of knowledge that may help advance technology adoption models and studies.

VII. Methodology:

This section outlines the research design, data collection procedure, including the sampling technique, sample size and survey instrument. It also describes the data analysis approach, in which two methods were employed, namely, Pearson correlation and Structural Equation Modeling (SEM).

VIII. Research Design

This study employed a quantitative research design to investigate the factors that influence the adoption and use of GenAI in large energy company in Saudi Arabia. The TAM serves as a theoretical foundation to investigate the objectives of this study. A survey-based approach was selected to obtain measurable insights from users while ensuring anonymity, flexibility and consistency.

The questionnaire was taken from Davis, (1989) and modified for the purpose of this study. The survey instrument consisted of six sections: (1) demographic information (4 items), (2) Perceived Usefulness (PU) (4 scaled items), (3) Perceived Ease of Use (PEOU) (4 scaled items), (4) Attitude Toward Use (ATU) (4 scaled items), (5) Behavioral Intention to Use (BIU) (4 scaled items) and (6) Actual Use (AU) (2 items, one of which was scaled items). All 17 scaled items were measured using five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The survey instrument demonstrated high internal consistency, with a Cronbach's Alpha coefficient of 0.936 for the 17 scalable items.

IX. Data Collection

This study employed non-probability sampling technique, namely self-selection sampling to access the targeted population. While convenience sampling is often recommended when participants are easily accessible and willing (Etikan et al., 2016), the nature of this study – where participation was open and voluntary – aligns more accurately with self-selection sampling technique. Accordingly, a structured online survey was distributed to 500 users in a large-scale energy company in Saudi Arabia between the month of June until August 2025. The participation was voluntary and informed consent was obtained prior to participation. A total of 121 users responded to the survey representing a response rate of 24.2%, of these 104 respondents have fully completed the survey, representing a rate 20.8% of the total surveyed sample.

X. Data Analysis

The respondents of 104 users, included 87 males (83.7%) and 17 females (16.3%) with varying years of professional experience, ranging from less than 5 years to over 20 years. The majority of respondents (61.5%) reported having between 1 and 5 years of experience, and most were under the age of 40. Regarding job roles, 25.9% held Chief Position Holder (CPH) roles, while the remaining 74.1% were individual contributors (employees). Table-2 shows the years of experience and age range of the respondents.

The majority of CPHs were males (96.3%) and one female (3.7%), similarly, males represented the majority of individual contributors (79%) followed by females (21%). Table-1 illustrates the gender distribution of CPHs and individual contributors (employees).

Category	**Females**	**Males**	**Total**
Chief Position Holders (CPHs)	1	26	27
Individual Contributors (Employees)	16	61	77
Total	**17**	**87**	**104**

Table-1

		Age Range							
		20-25	**25-30**	**30-35**	**35-40**	**40-45**	**45-50**	**> 50**	**Total**
	CPHs	**2**	**1**	**4**	**6**	**8**	**1**	**5**	**27**
	10-15			1		1			2
	1-5	1	1	2	5	3		4	16
	15-20				1	2			3
	5-10	1		1		1			3
Experience Years	> 20					1	1	1	3
	Employees	**16**	**29**	**14**	**6**	**6**	**2**	**4**	**77**
	10-15			2	1				3
	1-5	16	27	9	3	5	2	3	65
	15-20				2	1			3
	5-10		2	3					5
	> 20							1	1
	Total	**18**	**30**	**18**	**12**	**14**	**3**	**9**	**104**

Table-2

Pearson correlation coefficients were calculated, using SPSS, to test TAM's main constructs: PU, PEOU, ATU, BIU and AU. All correlation were positive and statistically significant at the 0.01 level (2-tailed). PU showed strong correlation with ATU ($r = .680$, $p < .01$) and BIU ($r = .665$, $p < .01$). PEOU was moderately correlated with BIU ($r = .430$, $p < .01$) and PU ($r = .401$, $p < .01$). ATU was strongly correlated with BIU ($r = .780$, $p < .01$) and PU ($r = .680$, $p < .01$). AU and BIU were moderately correlated with ($r = .386$, $p < .01$). All correlation were based on likewise deletion with N = 104 as shown in table-3

Correlations[b]

Pearson Correlation	PU	PEOU	ATU	BIU	AU
PU	1	.401**	.680**	.665**	.260**
PEOU	.401**	1	.327**	.430**	.330**
BIU	.665**	.430**	.780**	1	.386**
ATU	.680**	.327**	1	.780**	.353**
AU	.260**	.330**	.353**	.386**	1

**. Correlation is significant at the 0.01 level (2-tailed).

b. Listwise N=104

Table-3

A Structural Equation Model (SEM) was conducted via SPSS to examine the hypothesized relationships among the TAM constructs mainly PU, PEOU, ATU, BIU, and AU. Figure-1 presents the standardized path coefficients for the studied model. PU had a strong, positive, and statistically significant influence on ATU ($\beta = .52$, $p < .001$) and a smaller but significant direct effect on BIU ($\beta = .19$, $p < .05$). PEOU had a small, non-significant effect on ATU ($\beta = .05$, $p > .05$). ATU showed a substantial positive effect on BIU ($\beta = .59$, $p < .001$), and BIU strongly predicted AU ($\beta = .77$, $p < .001$).

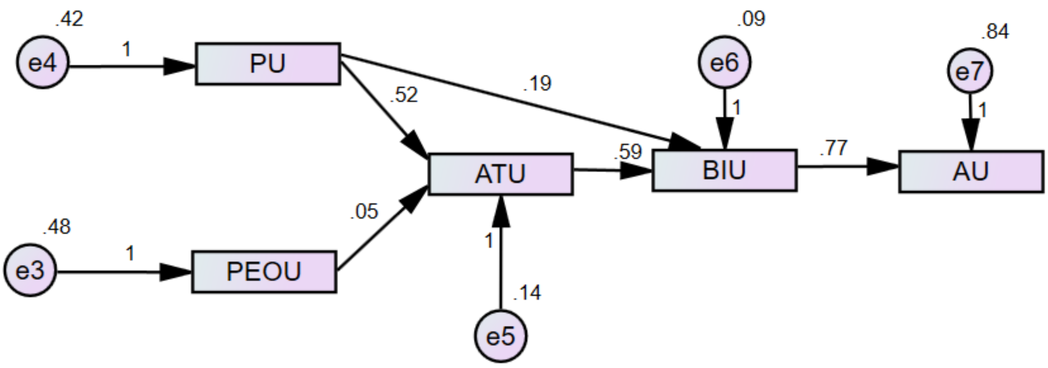

Figure-1

XI. Results Discussion:

PU was found to be a stronger predictor of both ATU and BIU than PEOU. More specifically, perceived improved productivity ($r = .642$, $p < .01$) and enhanced output quality ($r = .636$, $p < .01$) were the strongest predictors of ATU. Furthermore, these two factors were the strongest predictors of BIU ($r = .615$, $p < .01$ and $r = .620$, $p < .01$, respectively). Interestingly, speeding-up task completion exhibited a comparatively weaker influence on both ATU ($r = .580$, $p < .01$) and BIU ($r = .586$, $p < .01$) as shown in table-4.

Correlations[b]

Pearson Correlation	Improves Productivity	Enhances output quality	Speeds up task completion	Overall usefulness	ATU	BIU
Improves Productivity	1	.794**	.709**	.753**	.642**	.615**
Enhances output quality	.794**	1	.844**	.794**	.636**	.620**
Speeds up task completion	.709**	.844**	1	.755**	.580**	.586**
Overall usefulness	.753**	.794**	.755**	1	.624**	.607**
ATU	.642**	.636**	.580**	.624**	1	.780**
BIU	.615**	.620**	.586**	.607**	.780**	1

**. Correlation is significant at the 0.01 level (2-tailed).

b. Listwise N=104

Table-4

This finding maybe attributed to organizational setting in which users value accuracy, reliability and quality over task completion speed. Prior TAM-based research has shown similar results with users often prioritizing trust, reliability and accuracy over speed (Venkatesh and Davis, 2000 and Al-Abdullatif, 2024). For decision makers, investors or manager, GenAI quality (attribute and reliability) is suggested to be of critical importance when considering deployment of GenAI to ensure continued attention to use (Boakye et al., 2014). Organizations may establish, develop and implement a rigorous quality control process to ensure GenAI are accurate, consistent and reliable. This may include continuous testing, validation and improvement iterations of AI models to maintain it quality and reliability. Furthermore, establishment of GenAI performance indicators to measure and improve system quality and user experience maybe essential for organizations to sustain quality, reliability and accuracy.

In a study covered 406 university students in Malaysia, trust in GenAI negatively moderate the relationship with PU and PEOU (Masood et al., 2025). In order words, the influence of PU and PEOU is reduced when users trust the GenAI quality. This may explain the statistical significance between output quality and overall usefulness ($r = .794$, $p < .01$).

PEOU was found to be of lesser predictor of the ATU compared to PU, predominantly perceived easiness to use GenAI tools being the strongest factor ($r = .319$, $p < .01$) followed by learning to use the tool ($r = .308$, $p < .01$). Easiness to acquire skills and understand GenAI were of less predictability ($r = .292$, $p < .01$ and $r = .283$, $p < .01$, respectively) as detailed in table-5.

Correlations[b]

Pearson Correlation	ATU	Learning is easy	Easy to become skillful	Tools are easy to use	Understandable
ATU	1	.308**	.292**	.319**	.283**
Learning is easy	.308**	1	.796**	.765**	.771**
Easy to become skillful	.292**	.796**	1	.771**	.826**
Tools are easy to use	.319**	.765**	.771**	1	.802**
Understandable	.283**	.771**	.826**	.802**	1

**. Correlation is significant at the 0.01 level (2-tailed).

b. Listwise N=104

Table-5

The result opposed previous research (Ghimire and Edwards, 2024 and Baytak, 2023) in which PEOU was found to be a key predictor for GenAI use within the context of education. PEOU was found to be of less significance for industry users compared to users in academia which may be attributed to the workplace context.

The fear of job replacement, trust or data privacy issues within organizations (Sallam et al., 2025) are contributing factors to the less PEOU by users. Educational environment maybe more encouraging for users to promote new technology use, provide materials and training in addition to having keen users (students) who are willing to test and understand new technologies. This may explain the strong association found between ease of becoming skillful and understandability of GenAI tools (Table-5). Pearson correlation also showed a strong association between skillfulness and learning ($r = .796$, $p < .01$) and ease of use and learning ($r = .765$, $p < .01$)

indicating that training, ease of use and understandability are key enablers for successfully adoption and use. This may become more critical, especially, within organizational context, in which users are expected to understand tasks, processes and systems in order to perform their tasks correctly and maintain quality.

Previous research highlighted that PEOU is often dependent upon the availability of adequate training, user support and guidance (Venkatesh and Davis, 2000). Organizations may require to provide comprehensive training programs that not only focus on how to use GenAI but also explain GenAI capabilities and limitations to build users trust while deploying the technology.

Both positive attitude (r = .735, p < .01) and perceived benefits (r = .714, p < .01) were the strongest predictors of GenAI BIU followed likability (r = .683, p < .01) and ideology (r = .619, p < .01) as detailed in table-6.

Correlations[b]

Pearson Correlation	Using is a good idea	Liking the idea	Positive attitude	Perceived benefits	BIU
Using is a good idea	1	.876**	.796**	.589**	.619**
Liking the idea	.876**	1	.791**	.565**	.683**
Positive attitude	.796**	.791**	1	.617**	.735**
Perceived benefits	.589**	.565**	.617**	1	.714**
BIU	.619**	.683**	.735**	.714**	1

**. Correlation is significant at the 0.01 level (2-tailed).
b. Listwise N=104

Table-6

Positive attitude and perceived benefits could be attributed to PU and maybe improved by organizations focusing on creating awareness and training to showcase the benefits and applications of GenAI to build positive mindset for employees. This may include sharing of best practices, success stories and use cases to increase users' acceptance and reduce resistance. Likeability, on the other hand, might be attributed to users' system experience or user-interface. Organizations may invest in developing user-friendly interfaces and customized options to make GenAI systems more enjoyable and easier to use which can increase likability and users' engagement. Research showed that when GenAI is perceived as more human-like users tend to trust it more and have positive attitude toward its use (Polyportis and Pahos, 2024) and attitude played a major role in adoption and use of GenAI (Shata and Hartley, 2025).

Exploring more usage and utilization of GenAI was the stronger predicator of actual use (r = .412, p < .01) compared increased future usage (r = .394, p < .01) as per table-7.

Correlations[b]

Pearson Correlation	Intend to use regularly	Recommend to others	Explore more usage	Increase future usage	Actual Use
Intend to use regularly	1	.726**	.757**	.779**	.308**
Recommend to others	.726**	1	.783**	.772**	.295**
Explore more usage	.757**	.783**	1	.825**	.412**
Increase future usage	.779**	.772**	.825**	1	.394**
Actual Use	.308**	.295**	.412**	.394**	1

**. Correlation is significant at the 0.01 level (2-tailed).
b. Listwise N=104

Table-7

This may indicate that users who have used GenAI in the are more likely to actually use it, compared to those users who only have intentions or plans to use it in the future. Although the majority of the surveyed participants were young under the age of 40 years, the result may indicate that the majority lack familiarities with GenAI as it might be an emerging technology for organizations in Saudi Arabia. This result may also highlight the importance of helping users to explore and familiarize themselves with GenAI in order to increase their adoption and usage in the future. Users the unfamiliarity of systems or applications may lead to "belief trap" which results in lower adoption and use (Ma et al. ,2024). Therefore, organization introducing new systems or application may require to develop user acceptance testing, develop training sessions or engage users prior to deployment in order to increase future usage.

XII. Conclusion and Limitations:

This paper explored GenAI adoption in large-scale energy organization in Saudi Arabia, a new area that has not been widely explored as most of the previous work was done in the field of academia. The literature review outlined TAM main constructs and examined GenAI research in Saudi Arabia highlighting gaps in research with an opportunity gain for industries to conduct empirical-based studies to help organizations better understand GenAI adoption to facilitate better technologies deployment plans, manage users' resistance and reduce cost.

For the purpose of this study, a quantitative research design was applied to investigate the factors that influence the adoption and use of GenAI. A survey-based approach was selected to ensure anonymity, flexibility and consistency. The questionnaire was taken from Davis, (1989) and modified for the purpose of this study. Accordingly, a total of 104 users completed the survey and included 87 males (83.7%) and 17 females (16.3%) with varying years of experience ranging from less than 5 years to over 20 years.

PU was found to be a stronger predictor of both ATU and BIU than PEOU. More specifically, perceived improved productivity ($r = .642$, $p < .01$) and enhanced output quality ($r = .636$, $p < .01$) were the strongest predictors of ATU. Furthermore, these two factors were the strongest predictors of BIU ($r = .615$, $p < .01$ and $r = .620$, $p < .01$, respectively). Interestingly, speeding-up task completion exhibited a comparatively weaker influence on both ATU ($r = .580$, $p < .01$) and BIU ($r = .586$, $p < .01$).

Unlike previous research PEOU was found to be of lesser predictor of the ATU compared to PU, predominantly perceived easiness to use GenAI tools being the strongest factor ($r = .319$, $p < .01$) followed by learning to use the tool ($r = .308$, $p < .01$). Easiness to acquire skills and understand GenAI were of less predictability ($r = .292$, $p < .01$ and $r = .283$, $p < .01$, respectively).

Both positive attitude ($r = .735$, $p < .01$) and perceived benefits ($r = .714$, $p < .01$) were the strongest predictors of GenAI BIU followed likability ($r = .683$, $p < .01$) and ideology ($r = .619$, $p < .01$). Exploring more usage and utilization of GenAI was the stronger predicator of actual use ($r = .412$, $p < .01$) compared increased future usage ($r = .394$, $p < .01$).

Future studies may look at larger sample size and different business sectors other than energy. Comparing generation differences may help organizations customize GenAI development, deployment and adoption for different users. Gender difference o GenAI adoption maybe another perspective to explore.

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