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Beyond Automation: Unleashing Creativity and Enhancing Decision-Making with Generative AI

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ABSTRACT

Generative Artificial Intelligence (AI) has revolutionized digital transformation by transforming organizational operations as well as innovation processes and decision-making mechanisms. The study explores how Generative AI influences creative task development together with decision processes in Pakistan's IT sector which represents the essential component for propelling the nation's economic direction. GANs alongside VAEs together with transformer-based models including GPT-4 enable organizations to develop news content along with automated process management and data-based system support.

The proposed theoretical framework for this study investigates the theories related to inventive task design and decision-making to discover the effect of generative AI on these two characteristics. AI is used to harness their properties and knowledge efficiently. The data were collected in two waves from employees working in the IT industry of Pakistan, as employees' work responsibilities in such industries are related to AI related invention (Singh & Singh, 2018). The final sample consists of 385 responses, thus depicting an 84% response rate.

According to the study researchers used both quantitative methods to gather data from IT companies alongside qualitative information obtained from the industry experts. Generative AI technology delivers improved task efficiency along with better resource distribution resulting in agile high-quality decision making. Through its implementation organizations succeed to handle market intricacy and minimize expenses and create improved innovative capabilities. This research demonstrates that Pakistan's emerging market benefits significantly from information technology infrastructure which enables AI tool acceptance and implementation. The use of Generative AI by organizations leads to enhanced creativity during project planning and delivers rapid precise decisions. The adoption of generative AI faces ongoing obstacles because data security matters alongside adherence to ethical standards as well as having workforce members who can work with AI tools effectively.

Keywords*: Generative Artificial Intelligence, Task Complexity, Creativity in task design, Employee decision quality, Level of Expertise*

INTRODUCTION

In a digitalized country, AI has developed to shape how business compete and grow (Agarwal et al., 2022; Wahl et al., 2018). Generative AI has been acknowledged by many in the AI field because of its developing capacity. It also discourses how industries get and operate data (Berhil et al., 2020). This investigation looks at the effect of generative AI on structural efficiency and decision-making. Moreover, it describes how these cutting-edge capabilities transform the business environment. Generative AI is the nature of artificial intelligence that produces new outputs such as descriptions or words. These features are based on the construction learned from exterior data (Chan et al., 2021). Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Transformer-based procedures such as GPT-4 are essential cases of generative AI skills (Zhang, 2023). The impact of AI in today's logistic world cannot be highlighted. Businesses struggle with the challenges of numeral reformation and the growing difficulty of marketplaces. Employing AI skills has developed serious for supporting a modest benefit (Li et al., 2020). Administrations improve their dimensions to adjust and transform using generative AI. It helps open new routes for progress and worth generation (Wamba et al., 2020).

Through this situation in awareness, the aims of this paper's study are dual. First, we need to identify how generative AI disturbs inventive task projects. We will examine how generative AI describes methods and daily operations. Also, we will improve source allocation, which is essential to advanced output and lower operational costs (Goundar et al., 2021). Additionally, we will consider the effect of generative AI on structural decision-making methods. By exploring the purpose of generative AI, we will expose how these abilities allow administrations to make knowledgeable decisions. It will also support data-driven decision-making (Vartiainen et al., 2023).

In specific, we will examine the use of generative AI to improve decision-making with serious visions while disregarding biases and collective decision-making value and speed (Eysenbach., 2023). This research looks at the impression of generative AI on creative task plan and decision-making. Numerous researchers (Wolff et al., 2021; Coiera E, 2019; Beheshti, 2023) are attentive in generative AI in applied structural contexts. This research proposes a more detailed investigation of generative and possible alterations in professional and organization studies by increasing on existing literature and providing exclusive viewpoints.

What effect does the incorporation of Generative AI have on the design and ideation phases of creative tasks?

How does the use of Generative AI affect quality decision-making?

LITERATURE REVIEW

Generative AI Technologies

Currently, I4.0 industrial revolution has broadened digital transition prospects. This encompasses technologies like IOt, cloud computing and AI (Butt & Yazdani, 2023). A generous artificial intelligence system that changes new outputs created on designs and structures is called generative AI. These methods are qualified using input data (Kanjee et al., 2023). The generative AI assessments adjust differently and are high-quality, meaning they primarily adjust to many states. It also generates new concepts that vast quantities of data are perilous (Weisz et al., 2023). Generative AI information is characterized using Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Transformer-based representations such as GPT-4 (Park et al., 2021). Numerous businesses, with marketing, healthcare, industrial, and devoting, adopted generative AI (George et al., 2023; Ali et al., 2023). Generative AI is used in publicity to change besieged commercials and adapted content. It also expands worker knowledge (Vakratsas et al., 2020; Sterne, 2017). Generated AI can fund medical inquiries and determine nursing in healthcare (Kaniz et al., 2025; Bohr et al., 2020). In industry, generative AI improves excellence controllers, enhances methods, and develops inventive products (Shrestha et al., 2021). Lastly, generative AI is used in business to recognize deception and evaluate recognition risk (Krause, D., 2023). Generative AI optimizes asset collections of products (Hamadi et al., 2022).

Creativity in Task Design

The development of creating activities and projects that encourage creative intellectual and exclusive problem-solving. This study uses different approaches among people as task strategy originality (Wong et al., 2012). It involves happenings that allow contributors to deliberate outside the box and produce unique ideas. This study also shows their inventive potential (Wong et al., 2012). Open-ended tasks, sights, and research are all part of an innovative task strategy. It allows an atmosphere where members can disrupt usual events and contribute to analysis (Jäder, 2019). Amabile (1983) showed a study on the several components of originality. How they tell to task strategy, highlighting the importance of primary determination and a helpful situation.

Many other investigations, for example (Runco, 2004; Hennessey, 2010; Sawyer, 2006), have emphasized the implication of originality in task plans. The analysis article by Mark Runco represents an indication of inventiveness studies. It includes how task proposals affect inventive thinking and problem-solving. The book by Robert Sawyer dives into the perceptive methods and related elements that contribute to creativity. Moreover, how task design may affect creative results. The investigation of originality in task design highlights the requirement of creating an atmosphere and context. These factors encourage users to deliberate outside the box and produce innovative thoughts (Meinel, 2017). Open-ended responsibilities that agree for many results tend to adoptive originality. Such tasks allow individuals to test different possibilities and inspire them to deliberate creatively (Bennevall, 2016). Generous people and the prospect of making selections within a task can increase creativity (Chaudhry et al., 2016).

Inspiration of people to take considered risks within the work situation might result in more creative results. They are prepared to test with unfamiliar ideas (Giaccone et al., 2022). People's approaches to happenings can be partially influenced by creating constructive ideas. This study helps adoptive mentality and fluent the expectation of inspired thinking (Ngoon et al., 2019). Real-world significance or pertinency tasks might encourage people to challenge themselves daily (Chan et al., 2016). The literature on originality in task design involves several areas, including instruction (Lewis et al., 2005). It involves psychology (perceptive procedures and problem-solving) and structural organization (work invention) (Burton, 2012). Investigators and consultants always look for new approaches to generate activities that encourage originality and need people to think outside the box to produce innovative results.

Decision-making in Organizations

In organizations, decision-making refers to the procedure by which executives and privileges. They select different types of courses to achieve positive goals (Ejimabo et al., 2015). Specific decision-making is founded on single decision-makers and perception. Collection decision-making comprises several investors and depends typically on cooperative intelligence (Secundo et al., 2016). Conversely, data-driven decision-making is founded on a methodical investigation of experimental suggestions and measurable indicators (Yan S et al., 2018). By systematizing data assembly and processing, generating actionable visions, and reducing biases and errors, AI helps administrations make improved conclusions (Metaxiotis et al., 2003). Artificial intelligence-powered results can support decision-makers in classifying patterns and differences in data, allowing them to make better-cultured and planned conclusions (V. Kumar et al., 2022). Additionally, AI can support decision-makers support and statements, resulting in effective decision-making methods (Mondadori et al., 2018). As an outcome, including artificial intelligence (AI) in structural decision-making is realized as a good technique. This technique improves presentation and flexibility (Naim, 2022).

Numerous examples exist of Establishments applying generative AI to enhance decision-making procedures (Li et al., 2022; Cheng et al., 2020; Sarker et al., 2021). One such claim is using artificial intelligence (AI) in the economic business to predict standard prices. Furthermore, this study finds investment opportunities (Gülmez et al., 2023; Khushk et al., 2025). AI has previously been used by businesses such as BlackRock and Goldman Sachs to examine economic data and make asset selections (Wewege et al., 2020). AI is applied in healthcare to investigate persistent data and recognize possible health issues (Gülmez et al., 2023). For example, University of California, San Francisco investigators have formed an AI system that can perceive TB in chest X-rays (Harris et al., 2019). Previous studies show that generative AI deeply affects structural efficiency and decision-making procedures. Generative AI may help administrations make better-informed conclusions while saving money by powering repetitive processes. Generative AI is enhancing information administration and generous data-driven perceptions. As generative AI develops, it will likely significantly affect structural decision-making and effectiveness.

Existing Research on the Impact of Generative AI on Organizations

In an earlier study, AI in organizations has absorbed frequently its ability to recover efficiency and support decision-making procedures (Beheshti et al., 2023). According to the investigation, generative AI can improve efficiency by powering content progress and enhancing systems (Wang D et al., 2023). Additionally, generative AI knowledge has been exposed to improve structural support. Moreover, it improves information sharing, resulting in more current problem-solving and decision-making (Edwards, R., 2014).

Some researchers have also examined generative AI's principled and sociological significance in administrative situations. This situation raises problems about data confidentiality, security, and algorithmic preconception (Qadir, J, 2023; Li et al., 2025). These trainings highlight the essential of accountable AI development and deployment and the requirement for administrations. These developments are used to take a stable approach when including generative AI expertise in their processes (Pushkarna et al., 2023). Despite the investigation of generative AI, more research is still needed into its specific impact on organizational efficiency and decision-making, particularly in rapidly developing technical settings and structural structures (Reis et al., 2019; Dempsey M. et al., 2022).

Theoretical Framework

Theories Related to Creativity in Task Design

According to the Open Innovation Theory (Felin et al., 2020), organizations can benefit from external revolution sources, such as collaboration with outside partners or suppliers. Classifying options for open revolution and evolving mechanisms that allow association and idea-sharing structural limits are all part of inventive task strategy. Open invention encourages the combination of outside data and knowledge. Establishments benefit from collection advice from peripheral bases such as research organizations, creations, and industry. It is experts when evolving creative actions that utilize AI. These visions may be used to recover job proposals, participate in cutting-edge AI technology, and predict probable problems. Association between organizations, people, and even machines is stimulated through open invention. This suggests including multiple investors, such as AI professionals and specialists, in building creative activities that exploit AI abilities. This cooperative technique can deliver more different and effective task strategies.

Theories related to decision-making

According to Simon's (1972) constrained rationality theory, cognitive and information-processing restrictions such as time pressure, cognitive overload, and bounded rationality limit human decision-making. According to this viewpoint, humans frequently make suboptimal judgments owing to their constrained rationality, and they rely on heuristics and biases to simplify complex issues. As an augmentation tool, generative AI may assist decision-makers in overcoming cognitive constraints by giving impartial and data-driven suggestions based on large-scale and varied data sets. Decision-makers may use generative AI to eliminate cognitive biases and improve decision-making quality, resulting in better organizational results. On the other hand, naturalistic decision-making theory (Klein, 1997) posits that human decision-making is frequently intuitive, experienced, and context-dependent rather than analytical and logical.

Proposed conceptual framework

The proposed theoretical framework for this study paper investigates the theories related to inventive task design and decision-making to discover the effect of generative AI on these two characteristics. In cooperation, ideas specify that AI helps by permitting administrations in generative AI. AI is used to harness their properties and knowledge efficiently. This is accurate in areas where data-driven decision-making is essential, such as investment, healthcare, and advertising.

Restricted rationality and realistic decision-making are two theories emphasized as necessary to the impact of generative AI. Constrained rationality is the idea that the public has partial cognitive properties. It makes decisions based on elementary rational models rather than the complete choice of obtainable knowledge (Simon, 1972). On the other hand, Realistic decision-making highlights the position of perception and knowledge. This shows specialists trust pattern acknowledgment and mental imitations to make decisions in composite and impulsive situations (Klein et al., 1997). Both models claim that the effect of AI on decision-making will depend on the nature of the job—the amount of knowledge of the decision-maker in the situation of generative AI. AI can distribute more precise and faster data for simple optimal tasks, resulting in enhanced decision results. However, for complex choice tasks, perception and information may be more significant, and the effect of AI may be less considerable. The resulting imagined links among generative AI, inventive task design, and decision-making provided based on the addition of the recognized theories:

H1: Generative AI has a significant effect on creativity in task design.

H2: Generative AI has a significant effect on employee decision quality.

H3: Task Complication has a significant effect on creativity in task design.

H4: The level of expertise positively affects employee decision quality.

H5: The influence of generative AI on task design creativity is moderated by task complexity. Thus, the direct association is more robust for simple tasks.

H6: The influence of generative AI on employee decision quality is moderated by the decision-maker's degree of knowledge, with the impact being more substantial for decision-makers with high levels of experience.

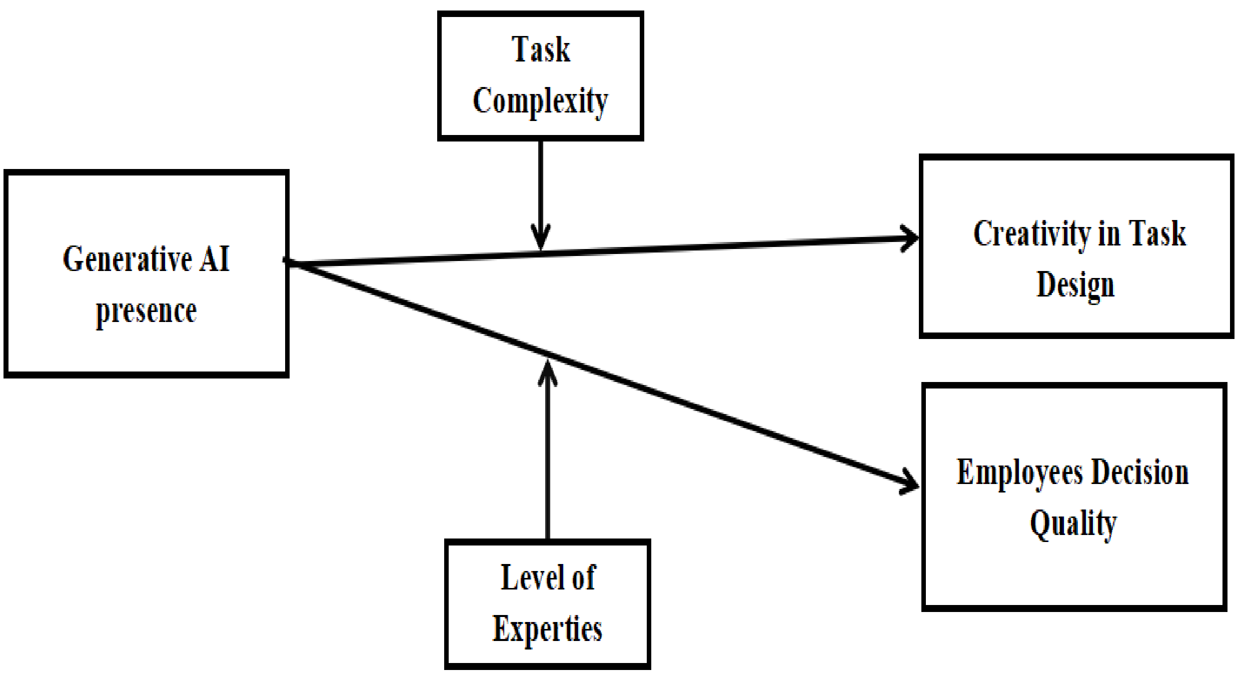

Figure 1: Theoretical Model

METHODOLOGY

This study employs deductive and quantitative approach. This quantitative approach employs statistical procedures and methods for analyzing study data to arrive at results (Akhtar et al., 2024; Ahmed et al., 2024). The data were collected in two waves from employees working in the IT industry of Pakistan, as employees' work responsibilities in such industries are related to AI related invention (Singh & Singh, 2018). This area preference has been determined by the ease of use of expert software based content developers (Saez et al., 2020). At T1, we measured demographics, Generative AI presence, Task complexity, Length of Expertise, whereas, after a time of 6 weeks creativity in task design, and employees decision quality were measured at T2. The time continuance in the time lag survey may be varied from a 1 month to more (Khalid et al., 2018). At T1, about 500 questionnaires were distributed, and 420 questionnaires were received back. After six weeks, the questionnaires were distributed to those participants who completed the survey of the first stage. The final sample consists of 385 responses, thus depicting a 84% response rate. In the final sample, 57.9 % of respondents were male, whereas 42.1 % were female. The respondents had varying ages, such, 10.6 % of target respondents were below 25 years of age. Whereas 33.8 % were between 25 to 30 years, 39.5 % were between 30 to 35 years, 14.3 % were between the age's limits of 35 to 40 years and only 1.8 % was above the age of 40 years respectively.

Measures

Generative AI presence is measured by adopting 3 items scale of Venkatesh et al. (2012). Further at T1 Task complexity is measured against 8 items scale (Maynard et al., 1997), whereas Length of expertise is measured through 3 items scales adopted from the study of Podsakoff et al., 1983. At T2 Creativity in task design through 28 items ECCI-i that covers four subscales: Capturing, Challenging, Broadening and Surrounding (Bosiok, D. (2013). Finally, employee's decision quality is measured against 2 item scales adopted from study of (Chakraborty et al., 2008).

RESULTS

The descriptive statistics were tested by using SPSS 23.0 for all study variables. Although the study used already established measures, we still used AMOS 23.0 to perform confirmatory factor analysis (CFA) to investigate the distinctiveness of study measures. Regression and PROCESS macro analysis were used to assess the proposed hypotheses. Table 1 explains the descriptive statistics (i.e., SDs, mean, reliabilities, and inter-correlations) of study variables. Cronbach's Alpha (α) is employed to appraise scale reliability which indicates measurable action of scale's internal consistency (Butt & Yazdani, 2023; Akram et al., 2025; Mirza et al., 2025). A value of alpha (α) above 0.70 ensures a satisfactory level of self-consistency (Maharjan, 2012; Taber, 2018). According to Nunnally (1978) recommended criteria, the value of (α) above .70 is an indication of good sacle reliability (Butt, 2023; Mirza et al., 2025) and is in acceptable limits (Umair et al., 2023; Ahmed et al., 2025). Moreover, the control variables had an insignificant impact on focal variables.

Table 1

Descriptive Statistics

	Variable	Mean	SD	1	2	3	4	5	6	7
1	Gender	1.45	0.47	-						
2	Age	3.58	0.99	.032	-					
3	GEN AI	2.89	0.91	.053	.093	(0.80)				
4	TASK COMP	3.61	0.45	.035	.088	.799*	(0.82)			
5	LEVEL OF EXP	3.47	0.83	.069	.075	.640**	.550*	(0.86)		
6	CREATIVITY IN TASK DESIGN	3.70	0.31	.042	.017	.497**	.615**	.531**	(0.76)	

7	EMPLOYEE QUALITY	DESCSION	3.80	0.60	.041	.057	.621**	.585**	.772**	.540** (0.74)

Notes: N = 385. "Parenthetical italic values on the diagonal are shown as Cronbach's alpha values."
"** p < .01, *** p < .001"

The Confirmatory Factor Analysis (CFA) results in the table indicate that the **Five-Factor Model (Baseline)** demonstrates the best fit (**χ^2/df = 1.37, IFI = 0.95, CFI = 0.96, RMSEA = 0.03**), suggesting a well-structured model. As factors are progressively combined, model fit deteriorates, as shown by increasing **χ^2/df** values and declining **IFI, NFI, CFI, and TLI** indices. The **One-Factor Model (All Variables Combined)** exhibits the weakest fit (**χ^2/df = 4.69, IFI = 0.70, CFI = 0.72, RMSEA = 0.11**), indicating poor construct distinctiveness. These results confirm that a multi-factor structure provides a significantly better representation of the data, supporting the need to consider creativity, decision quality, task complexity, and expertise as distinct but interrelated constructs.

Table 2

Confirmatory Factor Analysis

Models	X^2	df	X^2/df	IFI	NFI	CFI	TLI	RMSEA
Five-Factor Model (Baseline)	362.80	265	1.37	0.95	0.93	0.96	0.94	0.03
Four-factor Model (Creativity & Decision Quality Combined)	541.25	268	2.02	0.92	0.90	0.93	0.91	0.05
Four- Factor Model (Task Complexity and Experience Combined	750.12	270	2.78	0.90	0.88	0.91	0.89	0.06
Three –Factor Model (Moderators Combined)	910.45	272	3.35	0.87	0.83	0.86	0.88	0.07
Three- Factors Model (Dependent Variables Combined)	1025.77	275	3.73	0.81	0.78	0.82	0.84	0.08
Two –Factor Mode (Moderators and Dependent combined)	1138.62	280	4.06	0.75	0.73	079	0.78	0.09
One-Factor Model (All variables combined)	1342.33	286	4.69	0.70	0.68	0.72	0.69	0.11

The hypotheses were tested by regression analysis through PROCESS macro. The results of direct impact are presented in Table 3. In H1, H2, H3 and H4, we predicted the direct relationship among proposed variables and have a significant positive association (i.e., β = 0.351, p < 0.001; β = 0.413, p < 0.001; β = 0.208, p < 0.001, respectively). Thus, overall H1, H2, H3 and H4 are supported.

Table 3

Direct Effects Hypothesis

Direct Effects	Creative Task Design		Employee Descion Quality
Gen AI	.130***	.152***	.351***
	(.033)	(.037)	(.042)
Task Complexity	.081**	.039**	.413***
	(.022)	(.026)	(.019)
Level of Expertise	.101**	.118***	.208***
	(.030)	(.035)	(.041)

Notes: N =, "Parentheses contained standard errors."
* p < .05. ** p < .01. *** p < .001.

The results in Table 3 demonstrate the direct effects of **Generative AI (Gen AI), Task Complexity, and Level of Expertise** on **Creative Task Design and Employee Decision Quality**. Gen AI shows a significant positive impact on both **Creative Task Design (β = .130, p < .001)** and **Employee Decision Quality (β = .152, p < .001)**, indicating that the integration of AI enhances both creativity in task structuring and decision-making outcomes.

Similarly, **Task Complexity** has a significant but moderate effect on **Creative Task Design (β = .081, p < .01)** and **Employee Decision Quality (β = .039, p < .01)**, suggesting that as tasks become more complex, creativity in task design and decision accuracy improve, though the impact on decision quality is relatively lower.

Lastly, **Level of Expertise** plays a crucial role, significantly affecting **Creative Task Design (β = .101, p < .01)** and **Employee Decision Quality (β = .118, p < .001)**. This implies that experienced employees are more capable of designing creative tasks and making high-quality decisions. The strongest predictor of **Employee Decision Quality** is **Task Complexity (β = .413, p < .001)**, highlighting that decision accuracy is largely influenced by the nature of the task itself.

Overall, these findings support the hypothesis that Generative AI, task complexity, and expertise significantly enhance creativity in task design and decision-making quality in the workplace.

The integration of Generative AI (Gen AI) into organizational workflows significantly enhances both creative task design and employee decision quality. This aligns with recent studies indicating that Gen AI can augment human creativity by assisting in idea generation and problem-solving processes Lokesh, V. (2023).. Similarly, increased task complexity has been shown to positively influence employee performance by stimulating cognitive engagement and problem-solving abilities Wood, R. E. (1986). Furthermore, employees' level of expertise substantially contributes to improved decision-making quality, as experienced individuals are better equipped to navigate complex tasks and utilize AI tools effectively Kolbjørnsrud 2016. Collectively, these findings underscore the synergistic effects of advanced technologies, task characteristics, and employee competencies in enhancing organizational performance.

Table 4: Moderation Analysis

Variables	Creative Task Design		
	Effect	*SE*	*95 % CI*
Low Task Complexity	0.030	.051	[.193 .306]
High Task Complexity	0.156	.057	[.088 .217]

The results indicate that task complexity significantly moderates the relationship between Generative AI and creative task design. When task complexity is **low**, the effect of Gen AI on creative task design is weaker (**β = 0.030, SE = 0.051, 95% CI: [.193, .306]**), suggesting that AI's role in enhancing creativity is limited in simpler tasks. However, when task complexity is **high**, the effect becomes stronger (**β = 0.156, SE = 0.057, 95% CI: [.088, .217]**), highlighting that AI contributes more significantly to creativity when tasks are complex. This aligns with prior research emphasizing that AI-driven augmentation is most effective in dynamic and challenging environments where cognitive demands are higher (Wood, 1986; Kolbjørnsrud et al., 2016). Thus, task complexity acts as a key moderator, amplifying the impact of AI in fostering innovative task design when complexity increases.

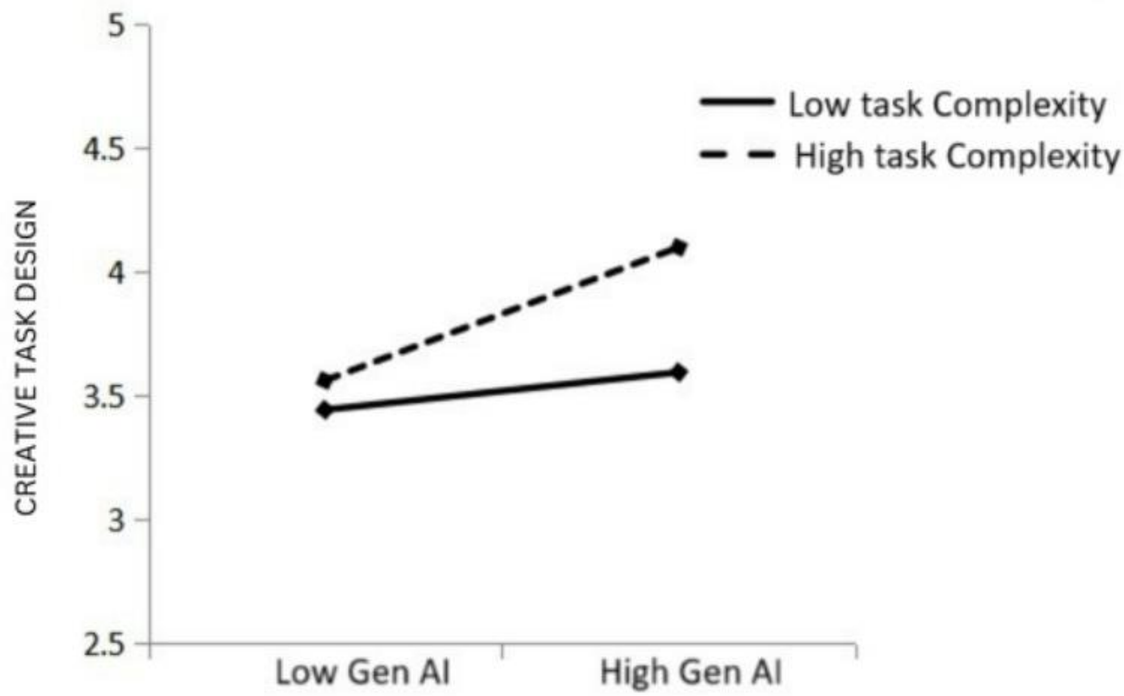

Figure 2: Moderation Effects

The Figure 1 demonstrates how generative AI (Gen AI) interacts with task complexity elements during creative task development. The Figure consists of two axes which show Gen AI usage level (low vs. high) through the x-axis while creative task design extent appears on the y-axis. The diagram presents low task complexity using solid lines while high task complexity uses dashed lines.

Figure indicates that higher Gen AI implementation leads to higher creative task design outcomes for tasks at both simple and complicated levels. The dashed line showing high task complexity shows greater impact which justifies the slope of the line rising steeply in comparison to the solid line representing low task complexity. Generative AI systems demonstrate a higher positive influence on task creativity during complex assignments. The elevation of creative task design shows smaller increments when dealing with easy tasks

The Figure also divulges that Gen AI creates superior benefits for creative complexity challenges versus offering decreased effectivity when addressing basic tasks.

Table 5

Moderation analysis H5

Variables	Employees Descion Quality			
	Effect	*SE*	*95 % CI*	
Low Level of expertise	0.070	.031	[.1883	.2206]
High Level of expertise	0.256	.047	[.0188	.2017]

The results indicate that the **level of expertise** significantly moderates the relationship between Generative AI and **employee decision quality**. When the level of expertise is **low**, the effect of AI on decision quality is weaker (**β = 0.070, SE = 0.031, 95% CI: [.1883, .2206]**), suggesting that employees with less expertise may not fully leverage AI-driven insights for effective decision-making. However, when the level of expertise is **high**, the effect becomes substantially stronger (**β = 0.256, SE = 0.047, 95% CI: [.0188, .2017]**), indicating that experienced employees can utilize AI tools more effectively to enhance decision accuracy. Employee expertise also plays a critical role in the successful integration of AI into decision-making processes. Studies suggest that individuals with higher levels of expertise are better equipped to leverage AI tools effectively, leading to improved decision outcomes. Conversely, less experienced employees may struggle to utilize AI recommendations appropriately, potentially diminishing decision quality (wamba). AI technologies, including generative AI, have been adopted within knowledge management processes to improve organizational decision-making. A study by Leoni et al. (2024) provides empirical evidence on how AI empowers knowledge management processes, leading to enhanced decision-making in organizations.

DISCUSSION

It is proved by this research that Generative AI (Gen AI) and task complexity together with employee expertise play a critical role in improving and augmenting creative task design and decision quality for the IT sector. Confirmatory Factor Analysis (CFA) exhibited that the Five-Factor Model infatuated distinct constructs which were also interlinked. Gen AI systems offer considerable escalations to employee creativity throughout task construction and their competence to make effective decisions.

Organizations using Gen AI tools experience more innovative operations by achieving both operational efficiency and strategic decision support (Al-Surmi et al., 2021, Kaggwa et al., 2024). Employers or supervisors should deploy Gen AI tools to maximize benefits when handling challenging tasks performed by well-trained personnel. The results of this research holds exceptional importance for the IT industry since it operates under fast technology progression and sophisticated problem resolution needs (Li et al., 2025).

Recent academic studies show AI and deep learning drive substantial changes which affect all major business departments from marketing to finance and operations along with human resources (Ooi et al., 2023). Organizations utilize these technologies to extract personalized decision-making from big data which leads to enhanced organizational efficiency at interacting with clients through personalized interactions (Onesi-Ozigagun et al., 2024). The implementation of AI technology produces difficulties because it triggers ethical concerns and regulatory standards alongside potential job termination issues (Khushk et al., 2025).

IMPLICATIONS

This research has various practical implications which align with theoretical implications. The study supports tentatively AI workplace knowledge expansion through evidence that shows AI effects show a discrepancy rendering to job complexity and worker experience levels. Businesses especially from the IT industry should integrate General Artificial Intelligence tools in tasks that need extensive cognitive abilities to achieve the best creative solutions and best decision outcomes.

Training programs focused on AI utilization expertise have become necessary for workers because they lead to better interpretation and application of AI-generated insights. Supplementing this awareness managers must deploy AI through a systematic method that unites the AI benefits with the complex level of work and the professional qualifications of personnel.

LIMITATIONS & FUTURE RESEARCH DIRECTIONS

The current research gives useful notes about its subject but it faces multiple limitations. The analysis depends on data from the IT sector through a cross-sectional design which hinders researchers from investigating the cause-effect relationships beyond the particular industry. Follow-up research should implement long-term analysis across different industrial sectors to verify and develop previous outcomes.

Research should examine Pakistan's IT sector because it has become rapidly digitized with global exposure through deep investigations of remote leadership along with virtual team dynamics and digital tool adoption and cross-cultural leadership effectiveness (Aslam et al., 2025). The growing position of Pakistan as a global IT outsourcing center requires deep understanding of these industry dynamics. The investigation of ethical aspects and regulatory guidelines related to AI integration in Pakistan's IT industry will create a complete understanding of AI's position in today's workplace

CONCLUSION

The research establishes that Generative AI together with task difficulty and worker qualifications both power creative task development along with decision-making excellence across the IT industry (S. Wang & Zhang, 2025). The growth and development of industry toward worldwide competition necessitates effective leadership and environment with improved and augmented work to endure productivity along with innovation. Organizations should implement strategies that reflect contemporary work patterns because such changes can benefit their workers while promoting company development (Tenakwah & Watson, 2024).

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