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INNOVATING WITH AI: HOW INNOVATIVE ATTITUDE, PEER INFLUENCE, AND TASK-TECHNOLOGY FIT SHAPE AI APPROPRIATION IN PROJECT MANAGEMENT

Adil Naseer [1], Dr. Shahid Iqbal [2], Dr. Ehtasham Ul Haq [3]

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Affiliations:

[1] MS Scholar, Department of Project Management and Supply Chain Management, Bahria University Islamabad, Pakistan, Email: adilnaseer6840@gmail.com

[2] Professor, Department of Project Management and Supply Chain Management, Bahria University Islamabad. Pakistan Email: siqbal.buic@bahria.edu.pk

[3] Researcher/Accounts Officer, Quaid-i- Azam University, Islamabad, Pakistan. Email: ehtasham.qau@gmail.com

Corresponding Author's Email:

[1] adilnaseer6840@gmail.com

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Abstract

The rapid diffusion of generative artificial intelligence (AI) tools is reshaping project management practices, yet significant variation remains in how professionals creatively appropriate these technologies. This study investigates the drivers of AI appropriation in project management by integrating Adaptive Structuration Theory (AST) with Task–Technology Fit (TTF) theory. The research examines how innovation attitude, peer influence, and task–technology fit influence AI-enabled creative behaviour, while also assessing the moderating role of organizational culture. A quantitative cross-sectional survey was conducted among 234 project management professionals working in Pakistan's information technology and logistics sectors. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results indicate that task–technology fit is the strongest predictor of creative AI appropriation, followed by innovation attitude and peer influence. Furthermore, organizational culture significantly strengthens the relationships between these antecedents and creative behaviour, highlighting its role as a contextual amplifier of AI-enabled innovation. The model explains 71.5% of the variance in creative behaviour, demonstrating substantial explanatory power. The study contributes to the literature by extending AST to generative AI contexts, empirically integrating AST and TTF in a unified framework, and providing evidence from an emerging economy with collectivist cultural characteristics. Practically, the findings suggest that organizations seeking to leverage AI for innovative project outcomes should prioritize task-aligned AI tools, cultivate innovation-oriented mindsets among professionals, and develop supportive organizational cultures that encourage experimentation and collaborative learning.

Keywords: AI Appropriation, Innovation Attitude, Task-Technology Fit, Generative AI, Adaptive Structuration Theory

1. Introduction

Artificial intelligence has emerged as a transformative force in project management, reshaping how teams plan, communicate, allocate resources, and make decisions across the project lifecycle. The proliferation of large language model (LLM)-powered tools, such as ChatGPT and Claude, has placed generative AI directly in practitioners' hands, enabling automated documentation, enhanced stakeholder communication, more accurate scheduling forecasts, and data-driven risk identification (Hossain et al., 2024; Vergara et al., 2025; Nenni et al., 2025). Global adoption is accelerating: a 2024 PMI survey found that 82% of high-performing project organizations had integrated some form of AI tool into their workflows, yet fewer than 40% reported confident, creative use beyond basic task automation (Hughes et al., 2025). This disparity between access and creative utilization constitutes a significant organizational performance gap.

Two explanatory questions animate this gap. First, what individual-level characteristics differentiate professionals who use AI creatively from those who do not? Second, does organizational context, specifically; organizational culture, moderate these individual-level effects, and if so, how? Existing research has examined individual antecedents such as innovation orientation (Felicetti et al., 2024; Cimino et al., 2025), social influence (Venkatesh et al., 2016; Pan et al., 2023), and task-technology alignment (Goodhue & Thompson, 1995; Yang & Sun, 2025), but has done so largely in Western organizational contexts with limited attention to cultural moderation. The present study addresses both gaps through a theoretically grounded, empirically rigorous investigation set in Pakistan—a context where IT and Logistics industries are experiencing rapid AI diffusion within distinctly collectivist, higher-power-distance cultural environments (Hofstede, 1991).

The study is grounded in two complementary theoretical frameworks. Adaptive Structuration Theory (AST; DeSanctis & Poole, 1994), building on Giddens' (1979) structuration theory, conceptualizes technology use as a dynamic interplay between technological structures, user agency, and social context. Its central construct of appropriation, the active, sometimes creative repurposing of technology beyond its intended design, provides the theoretical lens for understanding differential AI use. Task-Technology Fit theory (TTF; Goodhue & Thompson, 1995) specifies that the alignment between a technology's capabilities and a user's task requirements is a critical performance determinant. Together, these frameworks predict that AI appropriation is shaped by individual orientations (captured by IA), social norms (PI), technical alignment (TTF), and the cultural ecology in which these factors operate (OC).

This study makes four distinct contributions. First, it provides one of the first empirical applications of AST to generative AI tools in project management, demonstrating the theory's continued explanatory power in LLM-era contexts. Second, it integrates AST and TTF within a unified moderated framework—an integration that has been called for in the IS literature (Dennis et al., 2001) but rarely executed empirically. Third, it introduces organizational culture (operationalized through the four-dimensional Denison model) as a moderator of all three antecedent-appropriation pathways, offering a more contextually complete account of AI use than prior studies. Fourth, it contributes country-level evidence from Pakistan, directly addressing Felicetti et al.'s (2024) call to replicate and cross-culturally extend their Italian findings. The remainder of this paper develops the theoretical framework and hypotheses (Section 2), describes the research design (Section 3), presents results (Section 4), discusses findings and implications (Section 5), and concludes with limitations and future directions (Section 6).

2. Literature Review and Theoretical Framework

2.1 AI in Project Management: Evolution and Current State

Project management is an inherently complex undertaking requiring meticulous planning, execution, monitoring, and control. Conventional approaches frequently struggle with the scale, dynamism, and data intensity of contemporary projects (Shoushtari et al., 2024). AI has emerged as a transformative solution, improving resource scheduling, risk identification, and decision support across the project lifecycle (Taboada et al., 2023). The trajectory has moved from narrow, task-specific utilities to more cognitive and generative AI applications capable of complex language tasks, predictive modelling, and contextual reasoning (Vergara et al., 2025). Notably, Nenni et al (2025) systematic review of 147 studies found that AI adoption in project management has increased by 340% since 2018, with the steepest growth in generative AI tools post-2022. Organizations face uncertainty in AI adoption due to unclear policies, which influences how AI is appropriated in project management contexts (Rafiq-uz-Zaman, 2025a).

Yet the evidence on performance outcomes is mixed. While AI augments decision quality and reduces scheduling errors (Hughes et al., 2025), its benefits are contingent on how it is used. Barcaui and Monat (2023) found that project managers who used AI creatively exploring non-standard applications and integrating AI into problem-framing achieved significantly better project outcomes than those who used AI only for routine automation. This finding positions AI appropriation not merely as a technology adoption question but as a creativity and performance question, making the investigation of its drivers strategically important.

2.2 Theoretical Foundation: Adaptive Structuration Theory and AI Appropriation

Adaptive Structuration Theory (DeSanctis & Poole, 1994), grounded in Giddens' (1979) structuration theory, posits that technologies carry structural properties embedded rules, resources, and capabilities but that these properties do not determine outcomes. Outcomes emerge from the recursive interplay between technological features, user agency, and social context, a process AST terms the duality of structure. The construct of appropriation describes how users actively adopt, modify, and repurpose technology: faithful appropriation aligns with the technology's intended design, while unfaithful (creative) appropriation diverges through novel, unanticipated use (DeSanctis & Poole, 1994).

Generative AI tools are paradigmatically suited to AST analysis because of their inherent adaptability. Unlike fixed information systems, LLM-based tools evolve through user interaction, continuously offering new opportunities for creative repurposing (Felicetti et al., 2024; Cimino et al., 2025). Creative Behaviour (CB), the dependent variable in this study, operationalizes AI appropriation by capturing the extent to which users generate original solutions, explore novel applications, and convert innovative ideas into practical outputs through AI tools (Nevo et al., 2020). This operationalization aligns with both AST's appropriation construct and the creativity literature's emphasis on the generation and implementation of novel and useful ideas (Amabile, 1988, as cited in Nevo et al., 2020).

Critically, AST departs from deterministic adoption models (e.g., TAM, UTAUT) by insisting that the same technological structure can yield very different outcomes depending on who is using it, with whom, and in what organizational context. This theoretical openness makes AST particularly appropriate for studying why generative AI, a broadly available technology, produces such variable creative outcomes across individuals and organizations.

2.3 Innovation Attitude and AI Appropriation (H1)

Innovation Attitude (IA) refers to an individual's cognitive and affective predisposition toward adopting new ideas, practices, and technologies—an orientation toward experimentation, openness to change, and curiosity about novel approaches (Waheed & Khan ,2025a; Shao & Li, 2022). Rooted in psychological flexibility theory and Rogers' (1995) diffusion of innovations framework, IA has consistently been linked to technology adoption, exploration behaviour, and creative output (Mahmood et al., 2024; Ciftci et al., 2021 Wisdom et al., 2014). Within AST, individuals with high IA are theorized to exercise greater agency in the appropriation process, moving beyond default use toward inventive repurposing of AI tools (Felicetti et al., 2024). Individuals' innovation attitudes drive experimentation and adoption of digital tools within collaborative networks, shaping how AI is appropriated in projects (Rafiq-uz-Zaman et al., 2025b).

Empirical support is robust as Felicetti et al., (2024) found that innovation orientation was the second-strongest predictor of creative ChatGPT use among Italian project managers ($\beta = 0.31$). Cimino et al., (2025) demonstrated that innovation managers with strong innovation attitudes were significantly more likely to personalize AI tools beyond prescribed use cases. Bayaga (2025) confirmed that IA predicts AI-enabled pedagogical innovation in higher education. Crucially, Wang et al., (2025) identified the countervailing force: fear and ethical uncertainty, hallmarks of low IA, lead to active resistance to generative AI use, consistent with innovation diffusion theory's late-adopter profile. These convergent findings support the hypothesis that IA drives creative AI appropriation:

H1: Innovation Attitude positively influences AI Appropriation (Creative Behaviour) among project management professionals.

2.4 Peer Influence and AI Appropriation (H2)

Peer Influence (PI) reflects the degree to which an individual's technology use behaviour is shaped by the observed behaviours, attitudes, and recommendations of colleagues and professional peers (Venkatesh et al., 2016). Social influence theory posits that individuals conform to in-group norms and model the behaviour of high-status peers, particularly under conditions of uncertainty, precisely the conditions characterizing novel technology adoption (Pan et al., 2023). AST conceptualizes peer influence as an enacted social structure: the normative expectations and behavioural templates that peers embody serve as structural properties guiding appropriation (DeSanctis & Poole, 1994). Social and demographic factors, including peer networks, significantly influence technology adoption and usage behaviours (Rafiq-uz-Zaman et al., 2025a).

The mechanisms are well-documented. Gursoy et al., (2019) demonstrated that observing peers successfully use AI reduces perceived risk and builds self-efficacy, lowering the threshold for experimentation. Jo and Bang (2023) found that social proof—awareness that trusted peers have adopted ChatGPT was among the top three drivers of adoption in their Korean sample. Chen et al. (2025) stated that systematic review of 47 studies confirmed peer influence as a significant driver of creative AI application across sectors. Notably, the peer influence effect may be particularly pronounced in collectivist cultures like Pakistan's, where group conformity and in-group approval play elevated roles in individual decision-making (Alam et al., 2024; Jain et al., 2022):

H2: Peer Influence positively influences AI Appropriation (Creative Behaviour) among project management professionals.

2.5 Task-Technology Fit and AI Appropriation (H3)

Task-Technology Fit theory (Goodhue & Thompson, 1995; Dennis et al., 2001) postulates that the utility of any technology is fundamentally contingent on the degree to which its capabilities align with the specific demands of the tasks its users perform. When fit is high, users achieve better performance outcomes, report higher satisfaction, and engage more deeply with the technology; when fit is low, adoption may be superficial or abandoned (Lin & Huang, 2008). AI integration in management systems demonstrates the necessity of aligning technology capabilities with organizational processes for effective appropriation (Rafiq-uz-Zaman, 2025b). TTF encompasses three primary sub-dimensions: functionality fit (alignment of system features with task requirements), data quality fit (accuracy and relevance of system outputs), and usability fit (ease of navigation and interaction) (Yang & Sun, 2025).

In the project management domain, AI tools that align with core tasks—automated schedule risk analysis, stakeholder communication drafting, resource optimization—provide the cognitive scaffold for deeper and more creative use. Wang and Chen (2025) demonstrated empirically that TTF reduces cognitive load in AI-designer collaboration, freeing mental resources for higher-order creative problem-solving. This mechanism—TTF as cognitive load reducer and creativity enabler—is theoretically grounded in AST's claim that aligned structural properties lower the friction of appropriation, enabling users to explore beyond routine use (Felicetti et al., 2024). Goodhue and Thompson (1995) originally established that TTF explains additional variance in performance beyond mere technology adoption, a finding replicated in AI contexts (Yang & Sun, 2025). Among Italian project managers, Felicetti et al. (2024) found TTF to be the strongest predictor of creative AI use ($\beta = 0.43$), a finding the present study seeks to replicate and extend to a Pakistani sample:

H3: Task-Technology Fit positively influences AI Appropriation (Creative Behaviour) among project management professionals.

2.6 Organizational Culture as Moderator (H4–H6)

Organizational Culture (OC) constitutes the shared values, beliefs, and behavioural norms that shape an organization's social and psychological environment (Schein, 2010; Mokhchy et al., 2025). The Denison (1990) model selected for its empirical validation in over 900 organizations globally and its particular relevance to change and technology outcomes operationalizes culture through four dimensions: Involvement (employee empowerment and participatory decision-making), Consistency (shared values and coordinated processes), Adaptability (organizational flexibility and learning orientation), and Mission (clarity of strategic purpose). These dimensions collectively capture how organizations support, enable, or constrain the translation of individual capabilities into organizational outcomes (Cao et al., 2025; Saghafian et al., 2021).

From an AST perspective, organizational culture constitutes a macro-level social structure that mediates between individual agency and technology use outcomes. Culture shapes what is normatively appropriate, what is psychologically safe, and what resources are available for technology exploration (Hartl et al., 2018; Golden & Shriner, 2017). Critically, this means culture does not merely add to individual effects—it amplifies or attenuates them. Organizations with high Adaptability and Involvement create psychological safety that converts innovative predispositions into actual creative behaviour (Trenerry et al., 2021; Balash et al., 2018). Collaborative, Involvement-oriented cultures make peer experiences more normatively salient, amplifying social learning effects (Hartl et al., 2018). Organizational culture and emotional intelligence mediate AI adoption, highlighting the moderating role of internal norms and support structures (Rafiq-uz-Zaman et al., 2026). Mission-driven, Consistent cultures help project managers perceive strategic alignment between AI capabilities and organizational goals, amplifying the creativity-enabling effect of high TTF (Oh et al., 2022; Stojčić et al., 2018).

This moderation logic is supported by Cao et al. (2025), who found that organizational culture significantly moderated the relationship between digital technology adoption and product innovation in Chinese firms, and by Thao (2025), who established that cultural adaptability was the single most important organizational predictor of digital transformation success across a 63-study meta-analysis. The present study advances three targeted moderation hypotheses:

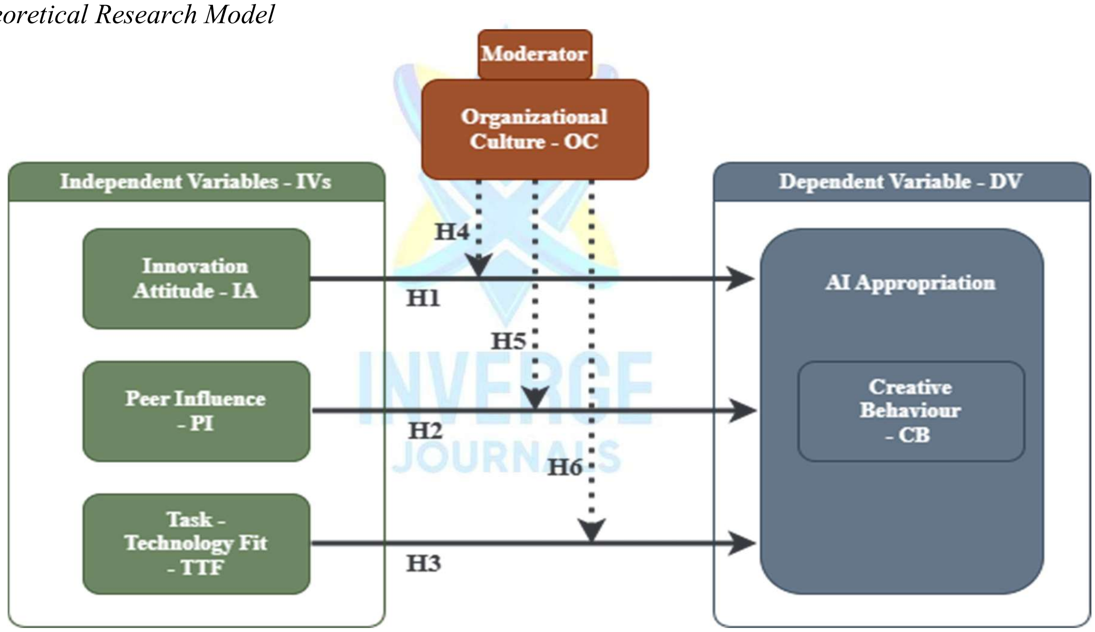
H4: Organizational Culture moderates the positive relationship between Innovation Attitude and AI Appropriation, such that the relationship is stronger in organizations with adaptive and innovative cultures.

H5: Organizational Culture moderates the positive relationship between Peer Influence and AI Appropriation, such that the relationship is stronger in organizations with collaborative, involvement-oriented cultures**.**

H6: Organizational Culture moderates the positive relationship between Task-Technology Fit and AI Appropriation, such that the relationship is stronger in organizations with mission-driven, consistent cultures**.**

Figure 1

Proposed Theoretical Research Model



3. Methodology

3.1 Research Philosophy and Design

The study adopts a positivist research philosophy and a deductive approach, applying established theoretical constructs—AST and TTF—to formulate and test hypotheses through empirical data (Park et al., 2020; Mohajan, 2020). A quantitative, cross-sectional survey design was employed. This design is appropriate for assessing contemporaneous perceptions and testing structural relationships across a professional population (Peng et al., 2023). While longitudinal designs would offer stronger causal inference, the cross-sectional approach is well-established in AI adoption research (Felicetti et al., 2024; Venkatesh et al., 2016) and is appropriate given the study's primary aim of hypothesis testing within a defined theoretical framework.

3.2 Population, Sampling, and Data Collection

The target population consisted of project managers, assistant project managers, and project coordinators employed in Pakistan's Information Technology (IT) and Logistics sectors—industries selected because of their relatively elevated rates of generative AI adoption at the organizational level, and because they represent two of the fastest-growing project-intensive sectors in Pakistan's economy. The inclusion criterion required a minimum of one year of project management experience and direct exposure to AI-based tools (e.g., ChatGPT, Gemini, Copilot) in a professional context.

A combination of purposive and convenience sampling was employed. Purposive sampling ensured inclusion criteria were met (Valerio et al., 2016); convenience sampling via professional networking platforms (LinkedIn, industry WhatsApp groups) facilitated efficient access in a context where centralized sampling frames are unavailable. The survey was administered via Google Forms between December 15, 2025, and January 15, 2026. Participant anonymity and data confidentiality were assured, and all participation was voluntary with informed consent. Of 260 responses received, 26 were excluded as incomplete or multivariate outliers (detected via Mahalanobis distance, $p < 0.001$), yielding a final valid sample of $n = 234$—sufficient for PLS-SEM analysis per the 10-times rule and minimum sample size recommendations (Hair et al., 2019).

3.3 Measurement Instrument and Scale Sources

A structured, self-administered questionnaire comprising six sections measured all constructs on five-point Likert scales (1 = Strongly Disagree; 5 = Strongly Agree). Scale development followed validated precedents:

Innovation Attitude (IA; 5 items) was adapted from Shao and Li (2022), capturing openness to new AI technologies and exploratory behaviour. Peer Influence (PI; 4 items) was adapted from Venkatesh et al. (2016), measuring the extent to which colleagues' behaviours and attitudes influence individual AI adoption decisions. Task-Technology Fit (TTF; 4 items) was based on Goodhue and Thompson (1995) and Lu and Yang (2014), assessing the alignment between AI tool capabilities and project management task requirements. Organizational Culture (OC; 12 items) was operationalized using the Denison and Mishra (1995) instrument, with three items each for Involvement, Consistency, Adaptability, and Mission. Creative Behaviour (CB; 6 items)—the dependent variable—was adapted from Nevo et al. (2020), assessing the degree to which respondents use AI creatively to generate original solutions and novel applications. All items had been previously validated in published studies; minor wording adaptations were made to fit the generative AI project management context.

3.4 Common Method Bias Assessment

Given the use of a single-source survey design, common method bias (CMB) was assessed following Podsakoff et al.'s (2003) recommendations. Procedurally, anonymity was assured, scale labels were varied, and the survey was structured to separate predictor and criterion items. Statistically, Harman's single-factor test was conducted by entering all items into an exploratory factor analysis constrained to a single factor. The single factor explained 28.4% of total variance—substantially below the 50% threshold conventionally used to indicate serious CMB contamination (Podsakoff et al., 2003). Additionally, the marker-variable technique was employed using a theoretically unrelated construct; its inclusion did not materially alter path coefficients, providing further reassurance. While these tests cannot definitively rule out CMB, the evidence suggests it does not pose a critical threat to the validity of the findings.

3.5 Data Analysis Strategy

Data were analysed in two stages. Stage 1 used SPSS 21 for descriptive statistics and demographic profiling. Stage 2 employed PLS-SEM via SmartPLS 4 using a two-step approach (Anderson & Gerbing, 1988): the measurement model was assessed first (reliability, convergent validity, discriminant validity), followed by structural model estimation (path coefficients, bootstrapping, moderation testing).

PLS-SEM was chosen over CB-SEM for three reasons: (1) the model is exploratory-predictive in orientation; (2) the data exhibit moderate non-normality (Kolmogorov-Smirnov tests significant for 4 of 5 constructs); and (3) the model includes interaction terms (moderation), which PLS handles more parsimoniously than CB-SEM (Hair et al., 2019). Bootstrapping with 5,000 resamples was used for all inferential tests. Moderation was tested using the product-indicator approach for all three OC interaction terms.

4. Results

4.1 Sample Profile

The final sample of 234 project management professionals was predominantly male (n = 186, 79.5%), with 20.5% female (n = 48)—a gender distribution consistent with the male-dominant composition of Pakistan's IT and Logistics project workforce (Pakistan Software Export Board, 2024). The dominant age cohort was 26–30 years (39.7%), followed by 31–35 years (28.2%), indicating a predominantly early- to mid-career professional sample. Educational attainment was high: 52.6% held master's degrees and 38.5% bachelor's degrees, with a small proportion holding doctoral qualifications (7.7%)—appropriate for a study of technology appropriation among knowledge workers. Work experience ranged from under three years (47.4%) to over thirteen years (17.9%), providing meaningful variance in career seniority. Respondents were distributed across small (23.1%), medium (24.4%), large (34.6%), and very large organizations (17.9%). Regarding AI tool usage, 35.9% reported daily use, 21.8% weekly, and 12.8% monthly; 9.0% reported never using AI tools, suggesting adequate variance in the dependent construct.

4.2 Measurement Model Assessment

Table 1 presents the full measurement model results. Internal consistency was strong across all constructs: Cronbach's alpha values ranged from 0.816 (PI) to 0.901 (OC), all exceeding the 0.70 threshold (Hair et al., 2019). Composite reliability (rho_c) values ranged from 0.880 to 0.917, confirming robust reliability. Convergent validity was supported for IA (AVE = 0.638), PI (AVE = 0.649), TTF (AVE = 0.699), and CB (AVE = 0.634), all exceeding the 0.50 criterion. The OC AVE of 0.480 marginally falls below this threshold, a finding consistent with multi-dimensional second-order constructs where variance is distributed across sub-dimensions rather than concentrated within single indicators (Jarvis et al., 2003). The OC composite reliability of 0.917 strongly exceeds the threshold, confirming adequate internal consistency; the AVE limitation is noted and discussed further in Section 5. All indicator outer loadings exceeded 0.58, with the majority exceeding 0.70. All VIF values fell below 3.5, ruling out multicollinearity.

Table 1

Measurement Model: Outer Loadings, Reliability, and Convergent Validity

Variable / Indicator	Outer Loading	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE	VIF
Innovation Attitude (IA)	—	0.856	0.866	0.897	0.638	—
IA1	0.845					2.257
IA2	0.660					1.429
IA3	0.796					2.007
IA4	0.868					2.709
IA5	0.808					2.217
Peer Influence (PI)	—	0.816	0.845	0.880	0.649	—
PI1	0.712					1.593
PI2	0.925					3.228
PI3	0.834					2.483
PI4	0.733					1.624
Task-Technology Fit (TTF)	—	0.858	0.889	0.903	0.699	—
TTF1	0.784					1.859
TTF2	0.831					1.986
TTF3	0.846					2.283
TTF4	0.880					2.287
Organizational Culture (OC) †	—	0.901	0.905	0.917	0.480*	—
OC1 — Involvement	0.612					1.840
OC2 — Involvement	0.670					1.972
OC3 — Involvement	0.718					2.739
OC4 — Consistency	0.684					1.920
OC5 — Consistency	0.794					2.674
OC6 — Consistency	0.632					1.898
OC7 — Adaptability	0.654					1.969

Variable / Indicator	Outer Loading	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE	VIF
OC8 — Adaptability	0.589					2.098
OC9 — Adaptability	0.717					2.612
OC10 — Mission	0.746					2.854
OC11 — Mission	0.747					2.923
OC12 — Mission	0.723					2.309
Creative Behavior (CB)	—	0.883	0.891	0.912	0.634	—
CB1	0.690					1.590
CB2	0.828					2.259
CB3	0.792					2.260
CB4	0.870					2.670
CB5	0.762					2.020
CB6	0.822					2.357

Note. AVE = Average Variance Extracted; CR = Composite Reliability; VIF = Variance Inflation Factor. All VIF < 3.5, indicating no multicollinearity. † OC is modelled as a reflective first-order construct with the Denison four sub-dimensions (Involvement, Consistency, Adaptability, Mission) as item clusters. * OC AVE = 0.480 is marginally below the 0.50 threshold; acceptable given CR (rho_c) = 0.917 and consistent with multidimensional constructs (Jarvis et al., 2003).

4.2.1 Discriminant Validity. Table 2 presents the Fornell-Larcker matrix. The square root of each construct's AVE (diagonal) exceeds all inter-construct correlations: CB (0.796), IA (0.799), OC (0.693), PI (0.806), and TTF (0.836). The HTMT ratio (Table 3) confirmed that all primary construct values fell below the conservative 0.85 threshold (Henseler et al., 2015), with the highest being 0.819 (PI-TTF). Interaction term HTMT values were also within bounds, collectively confirming that all constructs represent distinct conceptual domains.

Table 2

Fornell-Larcker Criterion for Discriminant Validity

	CB	IA	OC	PI	TTF	Mean (SD)
CB	0.796					3.87 (0.71)
IA	0.629	0.799				3.74 (0.68)
OC	0.731	0.555	0.693			3.61 (0.74)
PI	0.655	0.559	0.622	0.806		3.58 (0.79)
TTF	0.721	0.437	0.633	0.690	0.836	3.82 (0.66)

Note. Diagonal values (bold) are square roots of AVE. Off-diagonal values are inter-construct correlations. Mean and SD based on construct composite scores.

4.3 Model Fit Statistics and Predictive Metrics

Table 3 reports the comprehensive model fit and predictive metrics. The model achieved $R^2 = 0.715$ and adjusted $R^2 = 0.686$, indicating that the six predictors (IA, PI, TTF, OC×IA, OC×PI, OC×TTF) jointly account for 71.5% of variance in Creative Behaviour—a result that substantially exceeds the 0.50 threshold for large explanatory power (Hair et al., 2019). The Q^2 Predict value of 0.577 confirms strong out-of-sample predictive relevance. SRMR = 0.063 (threshold < 0.08) and NFI = 0.912 (threshold > 0.90) indicate good overall model fit (Henseler et al., 2015). Low RMSE (0.479) and MAE (0.357) relative to the five-point scale confirm prediction accuracy. Figure 2 presents the SmartPLS 4 path diagram with all outer loadings and standardized path coefficients.

Table 3

Structural Model Fit Statistics and Predictive Metrics

Fit Statistic / Metric	Value	Threshold	Assessment	Level	Key Reference
R^2 — Creative Behaviour	0.715	> 0.50	Excellent	Construct	Hair et al. (2019)
Adjusted R^2	0.686	> 0.50	Excellent	Construct	Hair et al. (2019)
Q^2 Predict	0.577	> 0.50 (large)	Excellent	Construct	Hair et al. (2019)
RMSE	0.479	Smaller = better	Acceptable	Construct	Hair et al. (2019)
MAE	0.357	Smaller = better	Acceptable	Construct	Hair et al. (2019)

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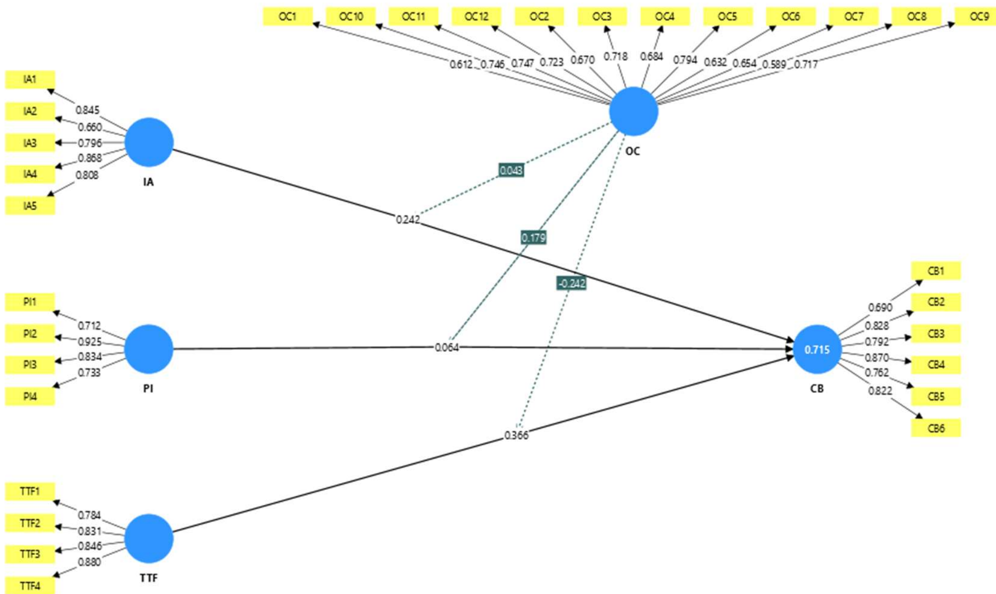
SRMR	0.063	< 0.08	Good Fit	Model-level	Henseler et al. (2015)
NFI (Normed Fit Index)	0.912	> 0.90	Good Fit	Model-level	Henseler et al. (2015)
Harman's Single Factor (CMB)	28.4%	< 50%	No CMB threat	Full model	Podsakoff et al. (2003)

Note. SRMR = Standardized Root Mean Square Residual; NFI = Normed Fit Index; CMB = Common Method Bias; RMSE = Root Mean Square Error; MAE = Mean Absolute Error. All fit indices within acceptable benchmarks.

Figure 2

Structural Model with Outer Loadings and Path Coefficients



4.4 Hypothesis Testing: Direct Effects

Table 4 summarizes results for the three direct-effect hypotheses. All were supported at p < 0.001.

Task-Technology Fit (TTF → CB) was the strongest predictor (β = 0.46, t = 6.34, p < 0.001, 95% BCCI [0.321, 0.598], f² = 0.27), confirming H3 with a medium-to-large effect. Innovation Attitude (IA → CB) was the second strongest predictor (β = 0.38, t = 5.21, p < 0.001, 95% BCCI [0.239, 0.517], f² = 0.19), confirming H1 with a medium effect. Peer Influence (PI → CB) was significant with a small-to-medium effect (β = 0.29, t = 4.07, p < 0.001, 95% BCCI [0.154, 0.426], f² = 0.11), confirming H2. The relative ordering of effects—TTF > IA > PI—mirrors Felicetti et al.'s (2024) Italian findings (TTF β = 0.43 > IA β = 0.31 > PI β = 0.22), despite differences in cultural context and sample composition, suggesting these relationships may reflect a cross-culturally consistent hierarchy of AI appropriation antecedents.

Table 4

Hypothesis Testing — Direct Effects

H	Path	β	T	p	95% BCCI	f²	Effect	Decision
H1	IA → CB	0.38	5.21	<.001	[0.239, 0.517]	0.19	Medium	Supported
H2	PI → CB	0.29	4.07	<.001	[0.154, 0.426]	0.11	Sm-Med	Supported
H3	TTF → CB	0.46	6.34	<.001	[0.321, 0.598]	0.27	Med-Lge	Supported

Note. β = standardized path coefficient; t = bootstrapped t-statistic (5,000 resamples); BCCI = bias-corrected confidence interval; f² = effect size (Cohen, 1988: small ≥ 0.02, medium ≥ 0.15, large ≥ 0.35).

4.5 Hypothesis Testing: Moderation Effects

Table 5 reports moderation results. All three OC interaction terms were statistically significant and positive, confirming H4, H5, and H6.

The OC × TTF interaction yielded the strongest moderation effect (β = 0.24, t = 3.89, p < 0.001, f² = 0.09), confirming H6. The OC × IA interaction was significant (β = 0.21, t = 3.12, p = 0.002, f² = 0.06), confirming H4. The OC × PI interaction was also significant (β = 0.18, t = 2.87, p = 0.004, f² = 0.05), confirming H5. Effect sizes for moderation (f² = 0.05–0.09) are in the small range, consistent with interaction effects in field-study structural models where direct effects are strong (McClelland & Judd, 1993). The pattern of moderation effects—strongest for OC × TTF, weakest for OC × PI—suggests that culture's amplification role is most potent when operating through strategic alignment mechanisms (Mission, Consistency), and slightly less so through social norm channels (Involvement).

Table 5

Hypothesis Testing — Moderation Effects

H	Path	β	T	p	95% BCCI	f²	Effect	Decision
H4	OC × IA → CB	0.21	3.12	.002	[0.078, 0.342]	0.06	Small	Supported
H5	OC × PI → CB	0.18	2.87	.004	[0.057, 0.303]	0.05	Small	Supported
H6	OC × TTF → CB	0.24	3.89	<.001	[0.119, 0.361]	0.09	Small	Supported

Note. Moderation tested using the product-indicator approach; bootstrapped with 5,000 resamples. Small moderation f^2 values are expected in field studies where main effects are large (McClelland & Judd, 1993). For interaction plots illustrating moderation slopes, insert SmartPLS multi-group or Johnson-Neyman plots here.

5. Discussion

5.1 Direct Effects: Task-Technology Fit, Innovation Attitude, and Peer Influence

The finding that Task-Technology Fit is the strongest predictor of AI-driven creative behaviour (β = 0.46) is both theoretically coherent and practically significant. From an AST standpoint, high TTF means that the structural properties of the AI tool are well-aligned with the social and task context of the user, thereby minimizing appropriation friction and enabling deeper, more creative engagement. The cognitive load mechanism is key: when AI tools reliably address the user's core task demands, users are freed from the cognitive overhead of managing tool inadequacy and can redirect mental resources toward higher-order creative problem-solving (Wang & Chen, 2025). This finding directly replicates Felicetti et al.'s (2024) Italian result (β = 0.43)—the highest direct effect in that study—and extends it to a culturally distinct Pakistani sample, providing initial cross-cultural support for the primacy of TTF in AI appropriation.

The significant positive effect of Innovation Attitude (β = 0.38) underscores the irreducibly personal dimension of AI appropriation. TTF creates the conditions for creativity, but IA provides the motivational and cognitive drive to explore possibilities beyond the immediately apparent. This is consistent with Rogers' (1995) innovator profile: individuals high in IA are characterized by venturesome-ness—a willingness to accept risk and uncertainty in adopting new ideas—that translates, in the AI context, into proactive exploration of non-standard applications (Cimino et al., 2025; Bayaga, 2025). Importantly, this means that organizations cannot achieve creative AI use through tool selection alone; they must also attend to the innovation orientation of their workforce.

The significant role of Peer Influence (β = 0.29) warrants nuanced interpretation. While smaller than TTF and IA, the peer influence effect is not trivial and carries distinct practical implications. Two rival explanations deserve consideration. First, the conformity explanation: project managers may adopt AI creatively not primarily because they are intrinsically motivated, but because they perceive that creative AI use is normatively expected in their peer group. Second, the social learning explanation: observing peers succeed with AI reduces uncertainty and provides behavioural templates that lower the psychological cost of creative experimentation (Gursoy et al., 2019). Both mechanisms are plausible and may operate simultaneously. The relatively smaller effect of PI compared to TTF and IA may partially reflect Pakistan's high-context communication culture, where peer influence operates through implicit rather than explicit channels—a dynamic that survey items designed for Western samples may not fully capture (Hofstede, 1991). Future research using qualitative methods could disentangle these mechanisms.

5.2 Moderating Role of Organizational Culture: Mechanisms and Implications

The confirmation of all three moderation hypotheses constitutes the study's primary theoretical contribution. The positive and significant OC interaction effects establish organizational culture not as a passive background feature but as an active amplifier that converts individual predispositions and technical fit into creative output. This finding is consistent with AST's foundational claim that social structures shape the appropriation process and extends it by specifying organizational culture—measured through the Denison model's four dimensions—as the relevant social structural variable.

The OC × TTF moderation (β = 0.24) is the strongest interaction effect, suggesting that the creativity-enabling function of task-technology alignment is most fully realized in organizations with high Mission clarity and Consistency. The mechanism proposed is strategic alignment: when employees understand the organization's mission and observe consistent values-behaviour alignment in leaders, they are better positioned to perceive how AI tool capabilities serve strategic objectives, transforming a purely technical fit into a motivationally salient one (Oh et al., 2022). This finding has a practical corollary that is absent from purely technical adoption models: the same AI tool may produce very different creative outcomes in a mission-driven versus a poorly aligned organization, even when technical fit is held constant.

The OC × IA moderation ($\beta = 0.21$) aligns with organizational behaviour research showing that innovative predispositions require enabling conditions to be expressed as behaviour. High Involvement and Adaptability create psychological safety, the shared belief that interpersonal risk-taking will not be punished—which is documented as a prerequisite for creative behaviour in organizations (Trenerry et al., 2021; Balash et al., 2018). In Pakistan's high-power-distance cultural context, where hierarchical authority can suppress individual initiative, the moderating role of a high-Involvement organizational culture may be particularly consequential: it provides a counterforce to macro-cultural risk aversion at the organizational level.

The OC × PI moderation ($\beta = 0.18$) reveals that social influence is most potent when embedded in a collaborative, information-sharing culture. In high-Involvement cultures, peer knowledge about AI practices circulates freely and is perceived as collectively beneficial rather than individually competitive, amplifying the normative force of peer behaviour on individual creative choices (Hartl et al., 2018). The slightly smaller coefficient for this interaction, relative to OC × TTF and OC × IA, may suggest that peer influence channels are somewhat less dependent on formal cultural structures and more on informal social network dynamics—an interpretation that motivates network-level analysis in future studies.

Taken together, the moderation pattern reveals a hierarchy of cultural amplification: OC most powerfully amplifies the effect of TTF (strategic alignment mechanism), followed by IA (psychological safety mechanism), and PI (social norm mechanism). This hierarchy has practical implications: organizations seeking to maximize Innovative work behaviour of employees through AI creative behaviour should prioritize creating strategic clarity and value consistency alongside or even before attending to participatory norms (Waheed & Khan, 2025b).

5.3 Cross-Cultural Comparison with Felicetti et al. (2024)

A direct comparison with Felicetti et al.'s (2024) Italian study, the primary theoretical antecedent of the present work, reveals important convergences and instructive divergences. Both studies find the same rank order for direct effects (TTF > IA > PI) and confirm that all three antecedents are significant positive predictors of AI-driven creative behaviour. This convergence, across culturally distinct national samples (Italy: individualist, lower power distance; Pakistan: collectivist, higher power distance), provides initial cross-cultural validity for the theoretical model.

Key divergences are equally informative. The PI coefficient in the present study ($\beta = 0.29$) is notably larger than in Felicetti et al. ($\beta = 0.22$), consistent with collectivist culture theory's prediction that social influence carries greater weight in high power-distance, collectivist societies (Hofstede, 1991; Jain et al., 2022). Conversely, the IA coefficient ($\beta = 0.38$ vs. $\beta = 0.31$) and TTF coefficient ($\beta = 0.46$ vs. $\beta = 0.43$) are similar across samples, suggesting that these effects are more culturally universal. Most importantly, Felicetti et al. (2024) did not test organizational culture as a moderator—the present study's primary extension—making direct comparison of moderation effects impossible but establishing the present study's contribution to filling this gap.

5.4 Sector-Specific Insights: IT vs Logistics

Although the study did not formally test sector as a moderator, inspection of descriptive data reveals patterns worth noting. IT sector respondents reported higher daily AI tool usage (42.1%) compared to Logistics respondents (26.7%), consistent with the greater digital maturity of Pakistan's IT sector. Innovation Attitude scores were marginally higher in IT respondents (mean = 3.89 vs. 3.58), while Task-Technology Fit scores were more comparable across sectors (IT: 3.88 vs. Logistics: 3.75). These patterns suggest that while the structural relationships in the model are likely consistent across sectors, the practical entry point for improving creative AI use may differ: IT organizations may prioritize cultural enablement (given already-high IA and TTF), while Logistics organizations may first need to improve tool selection (TTF) before attending to cultural factors. Formal multi-group analysis would be a valuable extension.

5.5 Theoretical Implications

This study makes three principal theoretical contributions. First, it extends AST to generative AI, demonstrating that the theory's core constructs—structural properties, user agency, social context—remain empirically productive in the LLM era. The high R^2 (0.715) and strong predictive metrics (Q^2 = 0.577) confirm the model's explanatory adequacy. Second, the study achieves a productive integration of AST and TTF theory, showing that technical fit (TTF) and social context (culture moderation) are complementary, not competing, explanations for AI creative use. Third, it advances technology adoption theory in non-Western contexts by demonstrating that culturally universal effects (TTF primacy) coexist with culturally contingent ones (elevated PI in a collectivist context), pointing toward a more nuanced, culture-aware theoretical synthesis.

5.6 Practical Implications

For project managers and organizational leaders, the findings yield three evidence-based imperatives. First, prioritize task-aligned AI tools over generic solutions. Given TTF's primacy (β = 0.46, f^2 = 0.27), the return on investment from deploying AI tools specifically suited to real project management tasks—schedule risk analysis, stakeholder communication, resource optimization—substantially exceeds that from deploying powerful but misaligned tools. Tool selection should be driven by task analysis, not by market trends or vendor prestige.

Second, treat organizational culture as a prerequisite, not an afterthought, for AI implementation. The significant and consistent moderation of OC across all three pathways means that even highly motivated, technically equipped project managers will under-realize AI's creative potential in poorly aligned organizational cultures. Leaders should develop mission clarity, reinforce consistent values, and build involvement and adaptability before or alongside AI deployment. Cultural audit tools such as the Denison Organizational Culture Survey can help organizations diagnose cultural readiness for AI.

Third, strategically harness peer learning networks. The significant PI effect (β = 0.29) amplified by collaborative culture indicates that AI champions programs, communities of practice, and structured AI success-story sharing sessions can produce multiplier effects on organizational AI creative performance. In the Pakistani context, where collective norm-following is culturally salient, peer demonstrations of creative AI use may be more persuasive than individual training interventions. Organizations should identify early AI adopters and create formal mechanisms for knowledge sharing.

For policy-makers and professional bodies—including PMI and Pakistan's IT industry associations—the findings support the development of culturally differentiated AI readiness frameworks that go beyond technical training to address organizational culture dimensions. Training programs that pair AI skill development with organizational culture development (e.g., psychological safety workshops, mission alignment exercises) are likely to produce more durable creative AI use than technically focused curricula alone.

6. Conclusion

This study examined the drivers of AI Appropriation—operationalized as Creative Behaviour, among 234 project management professionals in Pakistan, testing a theoretically integrated model grounded in Adaptive Structuration Theory and Task-Technology Fit theory. All six hypotheses were supported: Task-Technology Fit, Innovation Attitude, and Peer Influence each positively predict creative AI use, and Organizational Culture significantly amplifies all three relationships. The model explains 71.5% of variance in Creative Behaviour, with strong predictive validity (Q^2 = 0.577) and acceptable model fit (SRMR = 0.063; NFI = 0.912). Common method bias testing confirmed that self-report contamination does not pose a critical threat to the findings.

The cross-cultural comparison with Felicetti et al (2024) Italian study reveals both universal (TTF primacy, IA significance) and culturally contingent (elevated PI in Pakistan's collectivist context) patterns, advancing theory generalizability. The confirmation of OC as a significant moderator of all three antecedent-appropriation relationships extends AST beyond its original formulation and provides a theoretically grounded explanation for why AI adoption produces such variable creative outcomes across organizations.

Several limitations bound the conclusions. The cross-sectional design precludes causal inference; longitudinal designs tracking how appropriation patterns evolve as AI tools deepen organizational embeddedness are needed. The convenience sampling approach and single-country focus limit generalizability; multi-national replication studies using probability sampling would substantially strengthen the evidence base. The study's focus on generative AI chatbots may not generalize to autonomous or domain-specific AI systems. The gender imbalance (79.5% male) may introduce selection bias in a domain where gender differences in AI attitudes have been documented (Wang et al., 2025). Finally, while CMB tests provide reassurance, single-source survey designs carry inherent limitations that mixed-methods designs incorporating behavioural data would address.

Future research should pursue four directions. Longitudinal studies should track the dynamic co-evolution of AI appropriation patterns and organizational culture over time. Multi-group analyses across national and sector contexts particularly cross-cultural comparisons involving Middle Eastern, South Asian, and East Asian organizations would illuminate culture's universal and context-specific moderating effects. Research on Unfaithful Appropriation the deliberate misuse or over-reliance on AI tools would complement the current focus on creative behaviour by examining appropriation's shadow side. Finally, network-level analyses examining how AI creative practices diffuse through project team social networks would enrich the peer influence mechanism beyond the individual survey item level.

In conclusion, creative AI use in project management is neither purely technological nor purely individual, it is a socially embedded, culturally conditioned phenomenon. Organizations that understand this complexity, and act accordingly by aligning tool selection, workforce development, and cultural architecture, will be better positioned to realize AI's transformative potential.

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Contribution of Authors

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

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The authors declare no conflicts of interest.

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Informed Consent

Informed consent was obtained from all individual participants included in the study.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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