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Artificial intelligence and project management: An empirical investigation on the appropriation of generative Chatbots by project managers

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A B S T R A C T

The integration of generative AI tools, such as chatbots, into project management is revolutionizing the field. This paper explores how project managers are adopting and adapting these tools, specifically focusing on ChatGPT, for enhanced project management. Using Adaptive Structuration Theory, the study examines project managers' appropriation of generative AI. It considers factors like Innovation Attitude, Peer Influence, and Task-Technology Fit, employing a survey of Italian project managers. The approach adopted to analyze data is based on Partial Least Square - Structural Equation Modeling. The research confirms the significance of the hypothesized antecedents in AI tool appropriation. Innovation Attitude and Peer Influence are shown to positively impact the creative and 'unfaithful' use of AI in project management. Task-Technology Fit is crucial for effective AI integration, impacting both creative behaviour and unfaithful appropriation. The study highlights the role of an innovative mindset, peer dynamics, and task compatibility in the effective use of AI tools in project management. It suggests potential areas for future research, including exploring cultural and organizational contexts and the rapid evolution of AI technologies.

Introduction

The advent of generative artificial intelligence (AI) tools is revolutionizing the current business paradigm, challenging traditional strategies and fostering a new era of digital transformation (Kanbach et al., 2023; Obreja et al., 2024). These advanced AI systems, capable of learning, adapting, and generating content, are redefining what it means to be innovative, allowing businesses to automate complex creative tasks that once required significant human intellect and time (Jia et al., 2024). In this emerging landscape, technology goes beyond the boundaries of operational tasks (Yu & Gong, 2024), extending its impact to the intellectual domain. Generative AI, characterized by its creative feature and capacity to ideate, has the potential to reshape approaches towards intellectual work (AL-Sa'di & Miller, 2023)

This transformative technology is not just an enabler of efficiency but also a driver of growth, reshaping competitive dynamics by prioritizing those who can most effectively integrate AI into their core business processes. In this rapidly evolving landscape, the capacity to leverage generative AI is becoming a critical determinant of success, marking a shift from conventional business operations to a future where innovation and AI proficiency define market leadership (Kim & Kim, 2023).

The advent of AI is ushering in a new era in various domains, with project management being no exception (Taboada et al., 2023). These chatbots' capabilities extend beyond mere task automation; they are revolutionizing how project managers interact with team members, stakeholders, and the project environment (Kaplan &Haenlein, 2019). With generative AI tools, such as ChatGPT, workers access a unique source of creativity potential (Jia et al., 2024), now executing tasks that were usually accomplished by humans (Fuller et al., 2022). Generative AI helps overcome limitations in human information processing. These tools have the ability to identify problems, opportunities, and threats outside of conventional search routines and knowledge areas (Haefner et al., 2021), paving the way for advancements in various project-related tasks, including project planning and risk management. Furthermore, generative AI enhances information processing and decision-making, potentially taking over these functions (Verganti et al., 2020). The integration of AI tools into project management represents a transformative shift in the field,

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particularly through the appropriation of generative chatbots by project managers.

The existing literature highlights the general use of AI in project management (Bento et al., 2022). Wagner and Wagner (2023) carried out a systematic review to point out the development of AI technology over the past few years and any new trends, while investigating the state of application of AI in PM. Bahi et al. (2024) placed in evidence how generative AI streamlines workflows and mitigates challenges in software projects, through tasks like code generation and predictive analytics. In project risk management, AI's predictive capabilities enable proactive risk anticipation and real-time collaboration (Li et al., 2024). Comparative studies highlight the complementary strengths of AI and human expertise in project planning, suggesting that AI can enhance human decision-making when effectively integrated (Barcaui & Monat, 2023).

The scientific literature on the impact of generative AI in project management is still in an embryonic stage, marking an emerging and highly pertinent field of study. Current research predominantly addresses technological aspects, such as the optimization of workflows, enhancement of risk management, and effective integration of human expertise in project planning through AI. However, a significant gap remains in the research concerning the managerial perspective, particularly those factors influencing the adoption of these technologies by project managers. It is posited that the evolution of technology, while traditionally focused on enhancing operational efficiency and productivity, now extend into the domain of cognitive tasks, fundamentally reshaping project management strategies.

This paper aims to overcome this gap, presenting an empirical investigation into this phenomenon; it explores what influences project managers when adopting and adapting (namely appropriate) generative AI tools like ChatGPT for enhanced project oversight. The research question we intend to address can be summarized as follows: *What factors influence the appropriation of generative AI Chatbots by project managers?* In this study, we adopt the theoretical lens of the *Adaptive Structuration Theory* (AST) (De Sanctis & Poole, 1994) to understand how generative AI technologies are structured and adapted in the context of project management, highlighting how the impact of the same technology varies across organizations due to the diverse ways people use it in line with their work needs.

At the heart of AST is the concept of appropriation, which refers to how individuals or groups adopt and adapt technologies to fit their specific requirements or integrate them into their social practices (Wang et al., 2023). Leveraging on appropriation theory, we delve into how project managers leverage generative AI tools within their unique operational contexts. We specifically focus on Innovation Attitude (IA), Peer influence (PI) and Task-Technology Fit (TTF) as independent variables impacting the appropriation of generative AI tools by project managers.

From a theoretical point of view, this work attempts to enhance the understanding of how project managers adopt and effectively utilize generative AI, underscoring the pivotal role of project manager capabilities in this process. Preliminary findings suggest that these factors play a crucial role in how project managers integrate ChatGPT into their workflow, providing new insights into the theoretical understanding of technology adoption in the field of project management.

The remainder of the paper is organized as follows: section 2 presents the study's theoretical framework, including the theoretical background and the formulation of hypotheses to guide the research. Section 3 reports the methodology employed in this research. Section 4 is dedicated to presenting the research results, while section 5 discusses the main findings of the study. Section 6 presents both the theoretical and practical implications of the study. Finally, section 7 summarizes the conclusions of the work, pointing out the limitations and potential future research challenges.

Theory

Theoretical background

The impact of Information and Communication Technologies (ICTs) on organizational performance has been extensively investigated over the last thirty years. The integration of ICTs in various business operations led to enhanced efficiency, improved communication, and innovation fostering (Brynjolfsson & Hitt, 1996; Melville et al., 2004), with a substantial impact on professional practices (Dabić et al., 2023). With specific reference to project management, ICTs have been identified as critical enablers of efficient project execution and management (Kanski & Pizon, 2023). The advent of sophisticated project management software and collaboration tools has reshaped the way projects are planned, monitored, and controlled (Henderson & Venkatraman, 1999; Peslak, 2012). It is worth noting that organizational performance depends not only on technology itself but also on how organizations adapt and align technologies to their specific needs (Orlikowski, 2000). Technologies are often utilized in both anticipated and unanticipated ways. This flexibility in technology use can lead to outcomes that are sometimes unexpectedly positive (Leonardi & Barley, 2010). The process of technology adaptation is not just about technical integration but also involves cultural, procedural, and strategic considerations to ensure that the technology aligns well with the organization's ethos and goals (Boudreau & Robey, 2005).

Adaptive Structuration Theory (AST) offers a framework for understanding how groups and organizations adapt and use advanced technologies (De Sanctis & Poole, 1994). This framework traces its roots back to sociotechnical studies, which have historically focused on analysing the ways users engage with and adapt technologies within their social contexts and how social systems and structures evolve (Giddens, 1979). AST posits that the adoption and utilization of technology in organizations are influenced by existing structures; these structures are simultaneously modified by technology use, leading to an adaptive structuration process. In the realm of ICTs, AST has been instrumental in examining how technologies are incorporated within organizations. Further research (e.g. Orlikowski & Iacono, 2001; Jones & Karsten, 2008) extended AST by emphasizing the role of human agency in technology use, suggesting that individuals actively interpret and shape technology use, which in turn impacts organizational structures and processes. Technologies are not just passive instruments but are social artefacts influenced by the cultural and social milieu in which they are deployed.

At the heart of AST lies the concept of appropriation, highlighting how technology is adopted and adapted within organizational settings. Appropriation is a multifaceted concept, encompassing not only how technology is used but also how it is adapted and reinterpreted by users in an organizational setting (De Sanctis & Poole, 1994). This dynamic interpretation of technology reflects the complex interplay between technology, organizational structures, and individual actions. The appropriation of technology, particularly ICTs, often leads to changes in organizational routines and practices (Leonardi, 2011). Orlikowski (2000) emphasizes that this change is not always linear or predictable, as appropriation can vary greatly among different users and contexts, leading to diverse and sometimes unexpected outcomes.

The core concept of technology appropriation revolves around two key processes: customization and reinterpretation. Customization involves users adapting a technology to better fit their specific requirements (Carroll & Rosson, 2007), while reinterpretation entails users uncovering novel meanings or applications for the technology (Dourish, 2003). Research has found that some technologies are more amenable to adaptation than others. A technology with high appropriability is flexible and can be shaped by users to better fit their work processes or social needs.

Some scholars use the concept of “malleable technology”, referring to technological systems or tools that are inherently flexible and adaptable. Unlike rigid technologies, which have fixed functionalities and limited scopes of application, malleable technologies can be shaped, modified, and customized by users to fit their specific needs and contexts (Schmitz et al., 2016; Shao & Li, 2022). As noted by Leonardi (2011), malleable IT allows users to modify and adapt the technology in various ways, leading to diverse patterns of use and outcomes. Generative AI chatbots, characterized by their ability to learn and evolve from user interactions, represent a quintessential form of malleable IT. Such systems are not static but continually evolve, presenting a dynamic interface for user interaction and appropriation (Kaplan & Haenlein, 2019)

Prior research extensively addressed Information Technologies and Information Systems appropriation. Schmitz et al. (2016) identified three main categories of antecedents to individual appropriation: task, technology, and user characteristics. Nguyen et al. (2021) adopted these three categories to investigate individual appropriation of accounting information systems. Ko et al. (2021) combined AST and the Technology Acceptance Model to investigate the appropriation of Smart Work technologies. Some recent studies have adopted the lens of appropriation theory to explore how individuals integrate and adapt emerging AI technologies (Dolata et al., 2023; Gkinko & Elbanna, 2023; Booyse & Scheepers, 2023). However, the literature in this specific domain is still in its infancy and is far from being consolidated.

Generative AI, with its capacity for ideation and creative problem-solving, can revolutionize project management, offering support for several activities, such as streamlining task allocation, optimizing resource usage, forecasting project timelines, and enhancing decision-making processes (Kanabar, 2023). AI acts as a multifaceted enabler, augmenting project managers’ capabilities across various dimensions of their roles in a rapidly-evolving business environment. In particular, the role of generative AI in the realm of project management profoundly impacts the knowledge and capabilities of project managers. These advanced AI tools, characterized by their ability to learn, adapt, and generate new content, are fundamentally changing the way knowledge is accumulated, processed, and applied in the project management domain. Continuous interaction with these AI systems facilitates a constant learning process, where project managers can be updated with the latest technologies and methodologies in project management. This ongoing education ensures that project managers remain at the forefront of their field, equipped with cutting-edge knowledge and skills.

In this regard, we aim to investigate factors impacting the adaptation of generative AI chatbots for efficient and effective customized use by project managers, namely Generative AI Appropriation. In the realm of project management, the appropriation of generative AI chatbots involves not only their integration into project workflows but also their adaptation by project managers to fit specific project needs. This appropriation can significantly influence project outcomes, as it alters communication, decision-making, and information management practices.

According to Nguyen et al. (2021, p. 3), ‘Appropriation reflects IT use as either “faithful” based on the designer’s intention or “unfaithful” as based on a user’s accidental experiences that eventually result in an outcome”’ As pointed out by De Sanctis and Poole (1994, p.130) ‘Unfaithful appropriations are not "bad" or "improper" but simply out of line with the spirit of the technology’. Following the approach adopted in past research, this study characterizes appropriation as occurring on a scale ranging from faithful to unfaithful (Chin et al., 1997; Barrett & Stephens, 2017). Creative behaviour draws from Amabile’s componential theory of creativity, which posits that creativity involves expertise, creative-thinking skills, and intrinsic task motivation (Amabile, 1988).

The adoption of AI generative chatbots by project managers could significantly impact their creative behaviour in multiple ways along the whole project management lifecycle. This integration of AI tools indicates a potential enhancement in the creative capacities of project managers, leading to more innovative project management approaches (Nevo et al., 2020). This dimension is aligned with the concept of computational creativity, where AI aids in extending human cognitive abilities (Boden, 2009).

In this work, we integrate the degree of faithfulness and creative behaviour to model the appropriation of AI chatbots in project management. This approach aims to underscore the dynamic nature of project management in the digital age, where the creative and adaptive use of technology plays a pivotal role in achieving project success.

Research model and hypotheses development

To address our research objective, we define and validate the research model proposed in Fig. 1. We hypothesize the presence of three antecedents, predicting project managers’ appropriation of generative AI tools. These antecedents are Innovation Attitude (IA), Peer Influence (PI) and Task-Technology Fit (TTF). In this paper, appropriation was operationalized, using two scales designed specifically to assess the Unfaithfulness of Appropriation (UFOA) and the Creative Behaviour (CB) of users adopting new technology. As posed by Barrett and Stephens (2017), the UFOA scale is coded such that higher scores indicate that more appropriation is occurring.

Innovation attitude

Innovation attitude is a multifaceted concept that encapsulates an individual’s propensity towards adopting new ideas, practices, or technologies (Ferraro & Iovanella, 2016). The psychological underpinnings of innovation attitude are rooted in theories of creativity, motivation, and cognitive flexibility (Wu & Koutstaal, 2020). Other works refer to the same or closely related concepts, using terms like actualized innovativeness (Lee et al., 2013), individual innovativeness (Aldahdouh et al., 2019), personal innovativeness (Shao & Li, 2022), innovative attitude (Zasa et al., 2022) or innovative job performance (De Jong & Den Hartog, 2007). Innovation attitude is a persistent personal trait that is closely associated with an individual’s openness to

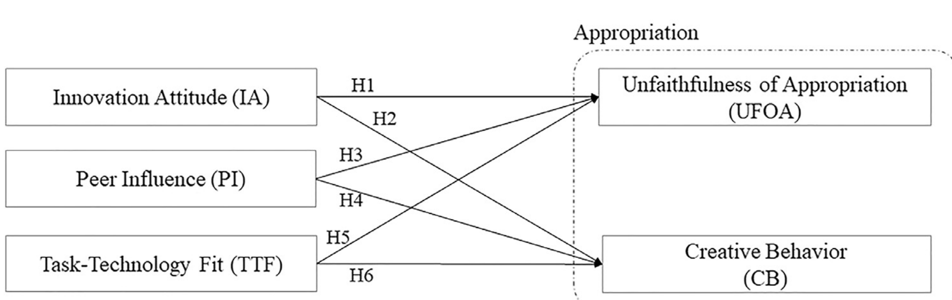

Fig. 1. The research model.

taking opportunities; it is recognized as a relevant factor for new technology adoption (Setiawan et al., 2021).

In project management, AI tool adoption is a multifaceted concept. It encapsulates a project manager's inclination towards embracing and utilizing innovative technologies, especially AI tools, in managing projects. This attitude is not merely about being open to new technologies; instead, it is closely related to one's ability to think outside the box, problem-solve creatively, and exhibit open-mindedness toward novel experiences and ideas (Vartanian, 2016).

The relationship between innovation attitude and IT appropriation has been investigated in several studies (e.g. Ciftci et al., 2021; Paganin & Simbula, 2021; Bubou & Job, 2022). People with a high degree of innovation attitude are characterized by openness, a strong intrinsic motivation, and intellectual curiosity. They are more inclined to embrace and find new uses for emerging technologies, such as generative AI chatbots, thereby discovering new opportunities and applications. A person who is innately motivated and enthusiastic in exploring new ways of using AI chatbots, persists in the face of obstacles and challenges inherent to new technologies. As a result, they will be more inclined to adapt them to work practices (Shao & Li, 2022). individuals with a high innovation attitude tend to challenge the status quo and are more open to experimenting with new ways of using technology. This mindset encourages one to think creatively and look beyond conventional uses of technology. A willingness to take risks and explore uncharted possibilities with technology often results in innovative applications that deviate from the original use, embodying the essence of "unfaithful" appropriation.

Innovation attitude is also intrinsically linked to creative behaviour in the context of project management. This attitude fosters an environment where experimenting with AI tools becomes the norm, encouraging project managers to think outside the box and innovate in their project approaches. Creative Behaviour here involves finding novel solutions to project challenges, developing unique AI application strategies, and continuously exploring the potential of AI to enhance project outcomes.

As a consequence, the following hypotheses are formulated:

H1: *Innovation Attitude has a positive impact on Unfaithfulness of Appropriation*

H2: *Innovation Attitude has a positive impact on Creative Behaviour*

Peer influence

Peer influence refers to the degree to which individual behaviours and attitudes are shaped by one's colleagues and industry peers (Venkatesh et al., 2016). This is closely related to the construct of 'subjective norm' as introduced by the Theory of Planned Behaviour (Ajzen, 1991). The theory posits that the stronger the subjective norm in favour of a behaviour, the higher the intention to engage in that behaviour. Similarly, in the UTAUT model, peer influence is embodied in the concept of 'social influence', one of four core determinants of technology acceptance and use (Venkatesh et al., 2003).

Previous research found that the adoption of AI-based tools is significantly influenced by peer pressure. According to van Esch and Black (2019), this pressure is mainly due to the fear of being left behind. In general, Pan et al. (2019) found showed that subjective norm has a positive effect on behavioural intention towards using AI-driven services. Gursoy et al. (2019) investigated the impact of social influence as an important antecedent of AI-based device acceptance. AST emphasizes the role of existing social structures and their evolution through technology use. Peer influence, within this theory, acts as a critical social structure impacting how technology is appropriated in workplace settings (Ilie & Turel, 2020).

The peer influence encourages experimenting with technology, leading to innovative and sometimes 'unfaithful' uses. This behaviour is shaped by the observation of peers who might use the technology in novel, unconventional ways, demonstrating the benefits of such applications. Moreover, observing peers using technology creatively inspires individuals to experiment and explore the full potential of the technology themselves. This leads to a culture where creative use of technology is not only accepted but encouraged, fostering a breeding ground for innovative thinking and problem-solving.

Hence, we propose the following hypotheses:

H3: *Peer Influence has a positive impact on Unfaithfulness of Appropriation*

H4: *Peer Influence has a positive impact on Creative Behaviour*

Task-technology fit

Task-Technology Fit theory posits that technology is more likely to positively impact individual and organizational performance when it is well-aligned with the tasks at hand (Zigurs & Buckland, 1998). It measures the degree to which technology assists users in performing their specific tasks (Goodhue & Thompson, 1995). This concept has been widely discussed in the information systems field of study. Previous work highlighted how the fit between technology features and task requirements positively affects technology utilization (Lin & Huang, 2008; Lu & Yang, 2014). A good fit between technology and tasks ensures that the technology supports the users' work processes effectively, leading to better appropriation of the technology.

Many works have integrated these two perspectives into the so-called fit-appropriation model (Dennis et al., 2001; Schmitz et al., 2010). As people develop perceptions of how well the technology fits the task, these perceptions may trigger changes in the way in which they subsequently appropriate the technology and define the task, to produce new structures in which the technology is used (Dennis & Garfield, 2003). When there is a high Task-Technology Fit, it is more likely that the technology will be appropriated effectively within the organizational context, as it meets the users' needs and enhances their work processes (Dennis et al., 2001).

When technology aligns well with the tasks at hand, users are more likely to engage deeply with the technology. This increased engagement can result in a greater exploration of the technology's capabilities, often leading to innovative uses or 'unfaithful' appropriations that deviate from the intended use. Deep engagement fosters a sense of ownership and comfort with the technology, encouraging experimentation Technologies that align well with users tasks often provide a solid foundation upon which they can build creative solutions. They offer the necessary functionalities and flexibilities that enable users to think innovatively about task solutions. A well-fitting technology acts as a springboard for creative ideas and novel approaches (Zhou & Shalley, 2003). If the technology is adaptable to the tasks (i.e. malleable), project managers (as domain experts) may be more likely to employ these technologies to seek creative solutions to solve problems or improve performance (Nevo et al., 2020).

H5: *Task-Technology Fit has a positive impact on Unfaithfulness of Appropriation*

H6: *Task-Technology Fit has a positive impact on Creative Behaviour*

Research methodology

Measurement instrument

The authors surveyed from June 2023 to September 2023 by using a specifically-developed questionnaire to empirically test the hypotheses proposed within this study. To ensure accurate measurement, a total of 22 items were derived from existing scientific literature and tailored to fit the research objectives of this work. Each questionnaire item was paired with a 5-point Likert scale, ranging from ‘strongly disagree’ to ‘strongly agree’. This scale was selected as it has already been scientifically validated in the literature from which the items were adapted. Appendix A reports the complete list of items as well as the scientific references used as sources. In addition, a section of the questionnaire is dedicated to gathering general and demographic information from the project managers participating in the study. This information, including gender, age, working experience, and the size of the company they work for contribute to the understanding of the respondent’s backgrounds.

Data collection

Before starting the survey, the authors conducted a testing phase to validate the questionnaire. Copies were distributed to 11 project managers working for diverse companies. Each participant received guidance from one of the authors during the answering process. The specific focus of this phase included inviting respondents to evaluate: (1) whether the number of questions per construct was sufficient for a clear and reliable assessment, (2) the coherence of the questions with the construct being assessed, and (3) the clarity and understandability of each question. These activities took place in May 2023 and the feedback gained from these pilot interviews allowed the authors to improve the effectiveness of the questionnaire.

Upon the questionnaire finalization, it was submitted to the Project Management Institute - Southern Italy Chapter (PMI-SIC), consisting of 450 members. Approximately 32 % of the survey received responses, yielding a total of 144 completed responses. The authors, prioritizing data quality, conducted a review of the responses, eliminating any entries that were repetitive or incoherent. This cleaning process resulted in 131 valid questionnaires, establishing the foundational dataset for the research analysis. The dataset dimension aligns with the minimum sample size guidelines as recommended by Barclay et al. (1995), thus confirming the consistency and reliability of the gathered data.

Data analysis

The authors employed Partial Least Squares Structural Equation Modeling (PLS-SEM) as a statistical method to empirically test the proposed research hypotheses (Bentler & Huang, 2014; Dijkstra, 2014; Dijkstra & Henseler, 2015). PLS-SEM was selected due to its suitability for small sample sizes (Willaby et al., 2015), its applicability in exploratory studies (Hair et al., 2019), and its high recommendation for datasets with a limited number of indicators per latent variable (Hair et al., 2017). For the analysis, SmartPLS4 software from SmartPLS GmbH was utilized (additional information about SmartPLS4 can be accessed at https://www.smartpls.com). The analysis started with the evaluation of the measurement model to assess the reliability of the constructs utilized in the study. Following this, the evaluation of the structural model was carried out to conclude the hypothesized relationships between the research model constructs and their statistical significance.

Results

In this section, the study results are presented. Section 4.1 outlines descriptive statistics, regarding demographic information of project managers participating in the survey. Section 4.2 presents the results of the measurement model, while Section 4.3 reports the outcomes of the structural model analysis.

Descriptive statistics

The demographic profile of the surveyed project managers can be briefly summarized. The majority of respondents are male, constituting 66 % of the interviewed project managers, while females make up the remaining 34 %. A diverse age range is observed among the project managers. Those under 25 years represent 2 % of respondents. Age groups from 25 to 60 years exhibit varying percentages, with the highest proportion in the 41 to 50 years category at 31 %. Respondents aged over 60 years account for 5 % of the total. As concerns the project managers’ work experience, those with <5 years of experience form the largest group at 27 %. The distribution then gradually decreases across the subsequent experience categories, with 7 % having over 25 years of experience. Finally, the distribution of project managers across various company sizes indicates that companies with fewer than 10 employees constitute a minority, accounting for 8 %, while the majority, consisting of 47 % of the total, belongs to companies with over 250 employees.

Measurement model results

The evaluation of the measurement model began with the assessment of the indicators’ reliability (Hair et al., 2021). In this regard, the calculation of indicator loadings was employed to assess the strength of the relationship between indicators and latent constructs (Jöreskog, 1971; Chin, 1998). The results of this analysis confirmed the model’s robustness, with all construct values exceeding the recommended threshold of 0.708 (Hair et al., 2021).

Progressing in the assessment, the authors turned their attention to the model’s internal consistency reliability, employing both the composite reliability coefficient (rhoC) and Cronbach’s alpha (Hair et al., 2017). The composite reliability rhoC represented the upper bound of internal consistency reliability, while Cronbach’s alpha served as the lower bound (Hair et al., 2021). The analysis results are presented in Table 1. It reveals that for each construct rhoC and Cronbach’s alpha values are higher than 0,7 and therefore adhere to the criteria established by Hair et al. (2021), thus further confirming the validity and reliability of the measurement model.

Moving forward, the model’s convergent validity was evaluated through the Average Variance Extracted (AVE) metric. All constructs exceeded the threshold limit of 0.5 (Hair et al., 2022), confirming the model’s validity. Specifically, the AVE values are 0.687 for CB, 0.768 for UFOA, 0.601 for IA, 0.668 for PI, and 0.739 for TTF. The evaluation of the measurement model concluded with the assessment of its discriminant validity (Hair et al., 2021). By using metrics such as Cross-loadings (Hair et al., 2017), Fornell-Larcker (Fornell & Larcker, 1981), and Heterotrait-Monotrait Ratio (HTMT) (Henseler et al., 2015), the authors assessed the relationships between the model constructs. The cross-loadings analysis (see Appendix B) confirmed that values for each item related to its construct are higher than the values for that item related to other constructs (Hair et al., 2017).

Furthermore, in alignment with the Fornell-Larcker metric, Table 2 shows that the AVE for each construct is greater than the highest correlation that particular construct has with any other construct in the model (Fornell & Larcker, 1981; Hair et al., 2021). Finally, all HTMT values (see Table 3) fall below the established threshold of 0.9 (Henseler et al., 2015; Hair et al., 2021). These findings definitely confirm the discriminant validity of the model.

Table 1
Internal consistency reliability.

	Cronbach’s alpha	Composite reliability (rhoC)
CB	0.908	0.913
UFOA	0.848	0.853
IA	0.838	0.863
PI	0.834	0.843
TTF	0.881	0.888

Table 2
Fornell-Larcker.

	CB	UFOA	IA	PI	TTF
CB	0.829				
UFOA	0.776	0.877			
IA	0.484	0.545	0.775		
PI	0.368	0.378	0.046	0.817	
TTF	0.634	0.641	0.343	0.453	0.860

Table 3
Heterotrait-Monotrait Ratio (HTMT).

	CB	UFOA	IA	PI	TTF
CB					
UFOA	0.883				
IA	0.533	0.613			
PI	0.419	0.449	0.136		
TTF	0.705	0.741	0.377	0.522	

Structural model results

The authors started the structural model assessment by examining the presence of potential collinearity issues. The Variance Inflation Factor (VIF) was used for this purpose (Hair et al., 2011). The VIF values are 1.154 for IA, 1.280 for PI, and 1.448 for TTF. As none of these values exceed the threshold limit of 5 (Hair et al., 2011), the results confirm the absence of collinearity issues in the structural model.

As next step, the study assessed the significance and relevance of the path coefficients. The PLS-SEM algorithm affirms the positive influences of the model's independent constructs (IA, PI, and TFF) on the adoption of generative chatbots by project managers (CB and UFOA), as reported in Table 4. The TTF construct exhibits the most substantial impact on both CB and UFOA, registering values of 0.458 and 0.433, respectively. Following closely, the IA construct demonstrates significant influence with values of 0.388 for UFOA and 0.320 for CB. While the PI construct also contributes positively to the appropriation of generative chatbots, its impact is comparatively lower, as indicated by values of 0.164 (UFOA) and 0.147 (CB). The statistical significance of the path model was assessed by employing bootstrapping standard errors to calculate the t-values of path coefficients. Table 4 shows that each construct yields t-values exceeding 1.96, which serves as the lower threshold to affirm the statistical significance of indicator weights (Hair et al., 2021). These findings validate all proposed hypotheses in the research model.

In addition, the authors verified the explanatory power of each independent construct (IA, PI, and TFF) on the dependent ones (CB and UFOA). To this end, the f^2 effect size of IA, PI, and TFF on CB and UFOA was assessed. For the CB construct, IA, PI, and TFF show f^2 values of 0.177, 0.034, and 0.289, respectively. For the UFOA construct, IA, PI, and TFF report f^2 values of 0.291, 0.047, and 0.289. The f^2 values for each construct are higher than 0.02, confirming a large effect size and, in turn, a satisfactory level of explanatory power for each construct (Kenny, 2018). Concluding the evaluation of the structural model, the assessment of the model's explanatory power was carried out through the coefficient of determination R^2 (Shmueli & Koppius, 2011). The R^2 values of 0.499 and 0.551 for CB and UFOA constructs respectively affirms the satisfactory level of explanatory power of the proposed model (Hair et al., 2011).

Discussion

This research study attempted to advance the theoretical understanding of the way in which project managers adopt and effectively utilize generative AI to refine project management processes and enhance decision-making within organizations. The theoretical framework employed was the Adaptive Structuration Theory (AST). Leveraging on AST, the authors propose a research model aimed at investigating the impact of three independent constructs - Innovation Attitude (IA), Peer Influence (PI), and Task-Technology Fit (TTF) - on the appropriation of generative AI tools by project managers. The concept of generative AI appropriability was operationalized through the variables of Creative Behaviour (CB) and Unfaithfulness of Appropriation (UFOA). The empirical analysis confirms all formulated hypotheses.

In the first set of findings, the study confirms a positive association between IA and both CB (H2) and UFOA (H1). Essentially, project managers characterized by a more innovative mindset, as measured by IA, are more likely not only to unfaithfully appropriate AI tools but also to engage in creative behaviours. The rationale behind this positive association can be explained by understanding that individuals with a strong inclination toward innovation tend to approach new technologies with a proactive and open-minded perspective. These project managers, characterized by an innovative mindset, are predisposed to explore and use the full potential of generative AI tools. They are more willing to experiment with these tools, finding novel ways to integrate them into their project management processes. In the context of CB, their innovative mindset likely encourages them to think creatively and apply AI tools in unconventional ways, pushing the boundaries of traditional project management practices.

On the other hand, in terms of UFOA, their openness to innovation translates into a committed and thorough adoption of AI tools, ensuring that they are used in a manner closely aligned with the purpose (goals and functionalities) for which they were initially intended. The results align well with the broader discourse on AI integration in project management. The identified role of Innovation Attitude is consistent with Setiawan et al. (2021) who emphasize the importance of openness to innovation for new technology adoption. Similarly, Ciftci et al. (2021) underscore that individuals with high innovative attitudes are more likely to explore and leverage new technological opportunities.

A positive correlation between PI and both CB (H4) and UFOA (H3) is also confirmed by the study. This suggests that the influence of colleagues or industry peers plays a significant role in how project managers adopt and utilize generative AI tools. When project managers observe their peers successfully applying generative AI tools in creative ways, it serves as a source of motivation and inspiration. This

Table 4
Path coefficients - Mean, STDEV, T values, p values.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
IA -> UFOA (H1)	0.388	0.388	0.078	4.947	0.000	Supported
IA -> CB (H2)	0.320	0.322	0.091	3.524	0.000	Supported
PI -> UFOA (H3)	0.164	0.168	0.062	2.637	0.008	Supported
PI -> CB (H4)	0.147	0.148	0.073	2.014	0.044	Supported
TTF -> UFOA (H5)	0.433	0.431	0.083	5.245	0.000	Supported
TTF -> CB (H6)	0.458	0.457	0.101	4.515	0.000	Supported

positive influence encourages them not only to adopt these tools but also to apply them in innovative and creative ways. Peer success stories create a positive social norm, motivating project managers to explore the full potential of AI tools and think creatively about their applications.

The positive correlation with UFOA indicates that the influence of peers shapes how project managers engage with AI tools in an unfaithful and committed manner. When peers make effective and unfaithful use of AI tools, it sets a standard for best practices. This highlights the social dynamics in technology adoption, emphasizing the significant impact of peer success stories in motivating project managers to creatively adopt and unfaithfully use generative AI tools. The importance of Peer Influence in technology adoption is supported by previous research, including the work of Venkatesh et al. (2003), which highlights the role of social influence in the acceptance of new technologies. Furthermore, the concept of Peer Influence resonates with the findings of Nguyen et al. (2021), who demonstrated that peer dynamics significantly impact the appropriation of new technological tools.

In particular, the significance of Peer Influence found in this study echoes the conclusions drawn by Pan et al. (2019) and Gursoy et al. (2019), who highlighted the role of social influence in the adoption of AI-driven services. This particular study extends these findings by showing that peer influence not only impacts adoption but also promotes creative and unfaithful appropriation of AI tools, which is crucial for realizing their full potential in project management.

Finally, the positive relationship between TTF and the dependent constructs CB (H6) and UFOA (H5) indicates that when project managers perceive AI tools as well-suited for their project tasks, the likelihood of effective utilization increases. When project managers perceive that generative AI tools align well with the requirements and demands of their project tasks, it creates a sense of synergy between the technology and the tasks. This alignment creates a favourable environment for creative thinking and problem-solving. Project managers, confident in the suitability of AI tools for their tasks, are more likely to engage in creative behaviours.

A positive correlation with UFOA implies that the AI tools are perceived as valuable and relevant to the specific context of project management tasks, leading to an unfaithful appropriation. Therefore, project managers are more committed to integrating the technology into their project processes. The concept of Task-Technology Fit (TTF) and its impact on the effective appropriation of AI tools supports the assertions of Goodhue and Thompson (1995) and Dennis et al. (2001). Their work on the importance of aligning technology with task requirements is validated within the context of generative AI, highlighting how perceived fit enhances both Creative Behaviour and faithful use of technology. Additionally, the role of TTF in fostering Creative Behaviour extends the work of Nevo et al. (2020), who found that appropriate task-technology alignment can stimulate innovative use of IT systems. This study contributes to the literature by applying TTF in the realm of generative AI and project management, providing empirical evidence of its critical role.

Implications

In this section, the authors explore the theoretical and practical implications arising from the research study.

The findings contribute to the development of theory in several key ways. Firstly, this research extends the application of AST into the domains of artificial intelligence and project management. It effectively demonstrates how AST can be utilized to examine the dynamic processes involved in the adoption and adaptation of advanced AI technologies, thereby enriching the theoretical foundation of AST in the context of modern technological advancements.

The study further validates the relevance of AST in contemporary settings as well as enhances its applicability to new and emerging technological frameworks. Secondly, this research also contributes to the body of knowledge related to the theories of innovation adoption, highlighting the pivotal role of a proactive and open-minded approach in exploring and maximizing the potential of emerging technologies. Thirdly, through empirical evidence, this work extends the conceptualization of the interplay between technology and the social environment in which it operates.

The research underscores how social dynamics and interactions within professional networks can significantly impact technology adoption and adaption, thus emphasizing that social influence is a critical component in the appropriation of innovations within organizations. Finally, the study contributes to technology adoption theories, emphasizing the importance of perceived fit between AI tools and project tasks, aligning with models like the Technology Acceptance Model.

In terms of the practical implications, understanding the influence of an innovative mindset on AI adoption suggests that training programs can focus on improving innovation attitudes among project managers. Emphasizing the benefits of open-mindedness and proactivity in approaching new technologies can enhance their willingness to explore and creatively utilize generative AI tools. In addition, organizations can leverage the positive influence of peers by promoting a culture that shares success stories and innovative applications of AI tools.

Peer-led initiatives and knowledge-sharing platforms can create positive social norms, motivating project managers to adopt and use AI tools creatively and unfaithfully. Finally, to enhance the effective utilization of AI tools in project management, companies can implement targeted training programs and employ clear communication strategies to emphasize the direct benefits of AI tools about the demands of project tasks. By improving the perceived fit between the technology and tasks, a favorable environment for creative usage and unfaithful adoption by project managers can be established. The synergy between UFOA and CB in the domain of project management can lead to transformative outcomes.

Project managers who engage in unfaithful appropriation are often those who exhibit high levels of Creative Behaviour. This combination can significantly enhance project efficiency, effectiveness, and innovation. It allows project managers to go beyond traditional project management constraints, leveraging AI chatbots to explore new methodologies, optimize processes, and engage stakeholders in more meaningful ways. Moreover, this synergy can foster a more adaptive and responsive project management environment. As project challenges become more complex and dynamic, the ability to creatively appropriate technology becomes a crucial skill. Project managers who effectively integrate UFOA and CB are better equipped to navigate these challenges, leading to more successful project outcomes.

Conclusions

The emergence of generative artificial intelligence (AI) tools is transforming the business landscape, introducing a new phase of digital evolution. These AI systems, which can learn, adapt, and create content, are reshaping innovation, enabling companies to handle complex creative tasks efficiently. This breakthrough is a catalyst for both enhanced efficiency and growth, altering the competitive field and highlighting the importance of integrating AI into fundamental business operations. In this dynamic context, the ability to effectively harness generative AI is becoming a key factor for success, signaling a transition from traditional business models to a future where innovation and AI expertise are central to market dominance. This paper examines the significant shift in project management due to the adoption of generative AI tools, particularly focusing on the use of generative chatbots by project managers. The authors investigate how project managers are not only adopting but also adapting generative AI tools like ChatGPT for more effective project management.

This research findings suggests that technological evolution is moving beyond merely enhancing operational efficiency to altering cognitive tasks, thereby significantly transforming project management approaches. The study attempted to advance the theoretical understanding of how project managers adopt and effectively utilize generative AI to refine project management processes and enhance decision-making within organizations. Foremost, the study contributes to the body of knowledge on the use of generative AI in project management by underscoring the essential role of adaptability in project managers for the effective application of these advanced technologies.

The results demonstrate the practical applicability and utility of integrating generative AI tools in project management. By emphasizing the importance of Innovation Attitude, Peer Influence, and Task-Technology Fit, we offer actionable insights for project managers and organizations. Specifically, organizations should invest in training programs that cultivate an innovative mindset among project managers and promote a culture of collaboration and knowledge sharing through peer-led initiatives. Ensuring that AI tools are well-suited to the specific needs and tasks of project managers can facilitate their effective appropriation, leading to enhanced project performance.

The findings of the work highlight the importance of an innovative mindset, Peer Influence and task-technology alignment in determining the way in which project managers adopt and use generative AI tools. This research remarks on the multifaceted nature of technology adoption, where psychological factors (like Innovation Attitude), social dynamics (Peer Influence), and task-related considerations (Task-Technology Fit) play a significant role in how new tools are integrated into professional practices. This exploration provides valuable insights, contributing to an overall understanding of AI adoption in the context of project management.

From a theoretical perspective, the research fills a critical gap in the existing literature on AI appropriation in project management. While previous studies have primarily focused on the general use of AI, our research delves into the specific factors that influence how project managers adopt and adapt generative AI tools in their unique contexts. This detailed examination provides new insights into the dynamic interplay between individual attitudes, social influences, and Task-Technology Fit, contributing to a deeper understanding of technology adoption in project management. Our study not only enhances the understanding of AI tool appropriation; but it also provides a robust framework for future research.

By focusing on the critical factors of Innovation Attitude, Peer Influence, and Task-Technology Fit, this research offers valuable guidance for practitioners and researchers aiming to navigate the complexities of AI integration in project management. UFOA plays a crucial role in fostering an environment where CB can thrive. This deviation is not merely a matter of non-compliance but a creative reimagining of the technology's capabilities. In the context of AI chatbots, project managers often find themselves navigating uncharted territories, necessitating a departure from traditional methods and a move towards more innovative practices.

Such a scenario confirms the work of Nguyen et al. (2021), who highlighted the creative reinterpretation of technology beyond its original scope, suggesting that such unfaithfulness can lead to unforeseen but beneficial outcomes. CB, on the other hand, is characterized by the ability of users to leverage technology for novel idea generation, problem-solving, and the implementation of innovative solutions. In AI chatbot adoption, this involves harnessing the bot's capabilities to brainstorm new project strategies, analyse complex data, and implement solutions that traditional methods might not conceive. This notion aligns with Amabile's (1988) theory of creativity, emphasizing the role of expertise, creative thinking, and intrinsic motivation in creative outcomes.

When project managers engage in CB with AI chatbots, they not only utilize the technology but also extend its boundaries, leading to innovative project management approaches. The findings offer project managers guidance on how to adapt and leverage generative AI tools, effectively ensuring that they are equipped to meet the evolving demands of modern project management. Finally, the findings guide organizations on leveraging the positive impact of Innovation Attitude, Peer Influence, and Task-Related Fit to facilitate the appropriation of AI tools within the project management context.

Limitations and future research

Acknowledging the valuable contributions of this research study, it is essential to recognize and address certain limitations. The study focused on Italian project managers, which may limit its generalizability to other cultural or organizational contexts. To enhance the validity of the study, further research should be conducted in other national contexts by either replicating the study or considering international samples. Moreover, the study's findings may not fully capture the rapid evolution of AI technologies. Continuous advancements may impact how project managers perceive and adopt newer AI tools. Ongoing research in this domain is imperative to remain updated and informed on these evolving dynamics. Furthermore, the use of a questionnaire as a single data collection method may have limitations in capturing the richness of project managers' experiences. Combining multiple methods, such as interviews or focus groups, should provide a more holistic view. Finally, the study doesn't explore a potential moderating factor that could influence the strength of the relationships identified in the study, such as organizational culture, project complexity, or individual differences.

Future research might aim to validate these findings across different cultural and organizational contexts to enhance their generalizability. Additionally, investigating the long-term impacts of AI tool adoption on project management outcomes and exploring the potential moderating effects of organizational culture and project complexity would provide further depth to this field of study. Addressing these limitations in future research would certainly contribute to further expanding knowledge in this field.

CRediT authorship contribution statement

Alberto Michele Felicetti: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Antonio Cimino:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alberto Mazzoleni:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Data curation. **Salvatore Ammirato:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Supplementary materials

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