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Generating creativity through ChatGPT: an empirical investigation in open innovation platforms

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Abstract

Since the release of ChatGPT, the remarkable content comprehension and generation abilities of large language models (LLMs) have spurred knowledge democratization, however, on the one hand, they can lower the barriers to individual innovation, potentially facilitating the enhancement of personal innovative capabilities. On the other hand, their exceptional capabilities and popularity may lead to resistance and speculation, hindering demand for innovation. This work aims to examine whether they can assist people in creative tasks. This study utilizes an extensive dataset from an Open Innovation Platform (OIP), known for fostering creativity through external ideas. Leveraging ChatGPT's release as a natural experiment, it employs the Difference-in-Difference (DID) technique to examine how LLMs impact people's creative participation. The results indicate that the launching enhances peoples' willingness to engage in creative tasks, reflected in increased works. And this enhancement is not necessarily a threat to the quality of innovation, as the works have increased in length by 44%, complexity by 35%, and votes by 1.5% on average. Additionally, heterogeneity analysis shows these effects are more pronounced in higher-tier innovation works and among less experienced users. Further mechanism analysis suggests that the improvement in innovation performance in OIPs stems from the lowering of the innovation threshold enabled by ChatGPT. Moreover, LLMs can increase interaction feedback to stimulate external creativity, thereby improving innovation performance. This study's conclusions contribute to understanding the impact of the new technology, LLMs, on innovation activities across diverse populations.

Keywords Large language models · Creativity · Open innovation platforms · Innovation performance

1 Introduction

The Open Innovation Platforms (OIPs) known as Google Cloud, distinguish themselves by offering a holistic range of tools, including project management, collaborative spaces, and blockchain integration, thereby fostering enhanced security and transparency. Startups and established companies alike can leverage OIPs to access a vast pool of talent and ideas, accelerating the pace of product development. In this vein, scholars such as Fleming and Waguespack [23], affirm the pivotal role of OIPs in facilitating enterprises to acquire resources efficiently and achieve technological breakthroughs. Besides, Kitsios and Kamariotou [39] find that the organization of open innovation competitions is a significant opportunity for nascent entrepreneurs to collaborate with external partners, accelerate their creativity, and launch their prototypes on the market. Furthermore, research by Esposito De Falco et al. [18] underscores the capacity of OIPs to enhance innovation efficiency and concurrently reduce innovation costs.

The emergence of Large Language Models (LLMs) signifies a transformative milestone in artificial intelligence, offering unprecedented capabilities for understanding and generating multimodal information. These advancements have profound implications for enterprise innovation and the optimization of industrial structures, as innovations at the enterprise level dynamically influence and interact with

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broader changes in industrial structures [14, 19]. LLMs overlap in functionality with some of the most creative and highly educated professionals [19], introducing both opportunities and fundamental challenges within knowledge-intensive domains.

From one perspective, LLMs enhance productivity by automating repetitive tasks and providing support in creative endeavors such as coding and story generation [67]. Tools like ChatGPT have demonstrated the ability to stimulate brainstorming, generate ideas, and solidify thoughts, thereby enabling individuals and enterprises to accelerate idea generation and implementation while reducing human resource costs. This efficiency gain allows creators to focus more on enhancing interaction performance and acquiring external creativity, potentially increasing their innovative intent and improving the quality of their work.

Conversely, the capabilities of LLMs may also lead to the displacement of creators [21], as their functions overlap with those of highly skilled workers. According to the Protection Motivation Theory (PMT) [56], individuals' motivation to protect themselves and their subsequent behaviors depend on their perception of a threat and their ability to cope with it. Creators who perceive LLMs as a threat but lack coping mechanisms may adopt passive strategies, such as reducing productivity or withdrawing from competitive activities [50], which could diminish their drive to innovate. Additionally, over-reliance on LLMs may introduce anchoring effects in decision-making processes [36], potentially limiting the creativity of final outputs [7] and introducing information biases that could degrade innovation quality.

Given these dualistic impacts, the influence of LLMs on both the quantity and quality of innovation activities within OIPs remains uncertain. While LLMs have the potential to expedite knowledge flow, increase user engagement, and enhance platform value, they may also foster speculative behavior and discourage genuine innovation, posing risks to the development of these platforms.

Despite the significance of these developments, limited empirical research has been conducted to examine how LLMs affect individual innovation performance within OIPs. Understanding this impact is crucial for enterprises, creators, and platform stakeholders to navigate the challenges and harness the opportunities presented by LLMs.

To fill this gap, our study investigates an OIP for IT entrepreneurs, obtaining a large-scale granular dataset of user-generated works before and after the release of ChatGPT. This dataset provides an opportunity to analyze the heterogeneous responses of IT entrepreneurs to this exogenous change. In this study, we aim to explore the following research questions:

(1) How does the introduction of LLMs influence user innovation performance within OIPs?
(2) To what extent is this influence moderated by user heterogeneity and the various types of innovation?
(3) What are the underlying mechanisms driving LLMs' impact: lowering the innovation threshold, or increasing interaction feedback?

To execute our research agenda, we utilize an API to acquire data related to user-generated works and discussions from the "show" module of the Hacker News. This platform, established by the renowned entrepreneurial incubator YC (Y Combinator), allows IT entrepreneurs to freely publish and engage in discussions regarding original IT creations. Employing a quasi-experimental research design, we use NLP methods to examine the textual content of works and comments, quantifying the impact of ChatGPT's release on user behavior, including innovation quantity (i.e., number of works published), innovation quality (i.e., length and readability of the work description, points and novelty measured by readers). Subsequently, we apply the LDA and Difference-in-differences-in-differences (DDD) model to explore heterogeneous effects under different types of innovation works and user experience and examine various potential mechanisms of user behavioral changes.

Our analysis reveals several noteworthy findings. Firstly, the release of ChatGPT increases the quantity and enhances the quality of user-generated works on the platform. Moreover, the impact of the release of ChatGPT is more pronounced on high-tier innovative works. Additionally, after the release of the ChatGPT, experienced users show a modest improvement in their innovation performance. Mechanism analysis quantitatively indicates that LLMs can lower the innovation threshold and enhance user innovation ability, as more new users have been attracted and more users tend to innovate across tiers, especially moving from lower-tier works to higher-tier works. Additionally, LLMs can accelerate the occurrence and enhancement of innovation by facilitating user interaction performance, promoting the acquisition of external creativity, and expanding the market.

The findings of this study hold significant theoretical contributions. Firstly, our research provides critical insights into the role of LLMs like ChatGPT in innovation activities. Secondly, our study supplements and even challenges existing literature on the impact of AI on innovation performance, particularly concerning the heterogeneity of task types and user experience. Thirdly, our research offers new perspectives on the pathways and mechanisms through which AI and LLMs enhance innovation performance by identifying how ChatGPT lowers the innovation threshold and improves interaction.

Furthermore, our research provides empirical evidence that LLMs can enhance individual innovation performance, offering crucial insights for OIPs and individuals. For platform managers, leveraging ChatGPT's capabilities can attract a diverse user base and foster a dynamic innovation ecosystem, accelerating innovation and improving resource efficiency. Incorporating metrics like innovation level and cross-tier innovation into ranking algorithms can provide greater exposure for high-tier works and less experienced users, while moderately relaxing restrictions can foster new talent. Additionally, emphasizing both the quantity and quality of interactions in ranking criteria can further stimulate engagement and innovation. For individuals, ChatGPT can boost both the quantity and quality of user-generated works, particularly aiding higher-tier contributions and less experienced users. To maximize benefits, individuals should utilize ChatGPT for idea generation, focus on higher-tier innovations, and actively embrace new technologies. Collaboration and feedback within the community are crucial for refining ideas and integrating diverse perspectives. However, users should balance ChatGPT's use as an assistant rather than a crutch, ensuring continuous personal skill development and validating information to avoid biases. Engaging in cross-tier innovation and staying updated with LLM advancements will further enhance innovation capabilities, allowing individuals to effectively utilize ChatGPT while maintaining quality and originality in their work.

The subsequent structure of this paper is as follows. In Sect. 2, we review related literature and hypotheses. Section 3 outlines the empirical content and dataset of our study. Section 4 presents the empirical models and results. Section 5 provides the mechanism analysis. We conduct additional robustness checks in Sect. 6. Finally, in Sect. 7, we discuss the theoretical and practical contributions of our study, its limitations, and potential future research directions.

2 Literature review and hypotheses development

2.1 The societal impact of LLMs

With the rapid and widespread adoption of ChatGPT, scholars have shown a great interest in LLMs. Current research on LLMs primarily focuses on fields such as education [16, 51, 54, 60], healthcare [57–58, 59], marketing [41], and the labor market [14, 19, 52], emphasizing their overall societal impact.

In education, frequent use of ChatGPT has been associated with a potential decrease in research creativity and an increased likelihood of plagiarism [54]. However, generative AI also offers opportunities to enhance specific areas of research namely problem formulation, data analysis, and writing assistance [60]. In addition, assistance from GPT-4 can augment human legal reasoning and equalize the legal profession, mitigating inequalities between elite and nonelite lawyers [16]. In the medical field, although ChatGPT provides limited personalized recommendations and may sometimes generate a few medically inaccurate claims [57], it offers good results in terms of clarity, precision, and respondent satisfaction as well as medical accuracy and comprehensiveness [59]. In the labor market, some scholars have found that applying LLMs can enhance user productivity [14, 19, 52]. Generative AI creates commercial solutions with better overall value but less novelty than human crowdsourcing [8]. Therefore, even though the advent of ChatGPT could conceivably substitute existing occupations, it also unfolds immense opportunities and carries the potential to reconfigure the future of work [47].

While some scholars have delved into the utilization of LLMs for idea generation [29], a noticeable research gap persists in understanding the role of LLMs in tasks centered around creativity. Therefore, this paper innovatively shifts the focus towards investigating whether and how LLMs affect individual innovation performance in creative tasks.

2.2 AI and innovation

Previous work has offered valuable insights into the relationship between AI and innovation. Empirical studies show that AI promotes pharmaceutical innovation by reducing the complexity and cost of drug discovery [48], enhancing flexibility and innovation in healthcare services [43], reducing information transmission and sharing costs between enterprises, fostering technological innovation in manufacturing, and increasing profits [46]. And Wang et al. suggest that the innovative use of chatbots can create agility and develop business sustainability [62]. AI is also expected to improve professionals' judgment and engagement in knowledge work [44]. With AI systems in creative tasks, humans can either withdraw or compete with AI using their creativity [22, 33, 35, 49]. Lysyakov and Viswanathan [50] find that AI on innovation crowdsourcing platforms leads skilled designers to more complex competitions, improving design quality. Bell et al. [6] believe AI helps experts screen ideas in innovation crowdsourcing, enhancing open innovation quality. Overall, AI plays a crucial role in driving innovation and generating economic value.

However, it is essential to reevaluate AI's impact on innovation due to differences between generative AI and conventional AI models. Traditional AI technologies are designed for specific tasks [5, 26], while LLMs can rapidly evolve as model size and quality improve [19]. Some scholars argue LLMs exhibit creativity and could replace humans in creative fields [25], with LLM-generated content reflecting combined creativity from diverse data [10]. Generative AI aids artists and designers by accelerating the ideation and creation phases [24]. Conversely, other scholars argue that LLMs' autoregressive nature confines them to generating expected outputs based on existing data [2]. Notably, Noam Chomsky describes ChatGPT as "high-tech plagiarism," potentially leading to a decline in learning and creativity.

The application of LLMs in solving innovation-related problems and guiding management decisions is still in its early stages and has not been extensively explored [15]. Particularly, the role of LLMs in creative activities is a topic of considerable debate. Our study extends the research to OIPs, providing important insights into the impact of LLMs on individual innovation performance within OIPs in the new generation AI era.

In addition, existing literature extensively discusses the varying impacts of AI across different experience levels and task types. Firstly, Liu et al. [46] reported that AI had a more pronounced effect in departments focusing on low-tech tasks, while Grashof et al. [30] suggested that the impact of AI on large and small-to-medium enterprises (SMEs) varied based on the type of AI knowledge utilized—AI technology knowledge spurred innovation in SMEs, while AI application knowledge benefited larger firms. Additionally, Zhang et al. [69] argued that the nature of AI influences its effectiveness across different tasks, with perceived intelligence being more effective for employees-AI instrumental ties and perceived anthropomorphism aiding expressive ties. Regarding user experience, Jia et al. [37] found that AI's assistance in sales jobs provided limited benefits to low-experience employees, whereas Peng et al. [53] observed that AI significantly enhanced the performance of low-experience programmers.

Although existing literature extensively discusses the varying impacts of AI across different experience levels and task types, a unified conclusion has yet to be reached. With the emergence of LLMs, the discourse on the heterogeneity of AI's impact has become even more uncertain.

Some scholars have begun to investigate the heterogeneity of LLMs' impacts. For instance, certain studies suggest that LLMs offer more significant assistance to low-experience groups [16, 52]. In terms of task types, AI demonstrates substantial potential in generating semantically diverse ideas but performs relatively weaker in tasks that require human-like creative perception [31].

Overall, the advent of LLMs adds further complexity and uncertainty to these discussions, indicating the need for more nuanced investigations into their differential effects. Our research indicates that in our specific context, LLMs provide greater assistance to low-experience users and play a more significant role in the development of high-tier works. This finding may supplement or even challenge existing conclusions regarding the heterogeneous impact of AI and LLMs on innovation performance.

Finally, we reviewed the literature related to the pathways and mechanisms through which AI enhances innovation performance. Roberts [55] posits that AI can be used to analyze vast amounts of data, such as market trends and competitor analysis in the development stage of the innovation process, helping firms focus on ideas with higher market potential to promote innovation. On the other hand, some scholars [46] argue that AI influences technological innovation by accelerating knowledge creation and technological spillover, improving learning and absorptive capacity, and increasing investment in R&D and talent, thereby promoting technological innovation.

In summary, the pathways and mechanisms by which AI, especially LLMs, affect innovation performance remain uncertain. Our findings suggest that LLMs can enhance innovation performance through two main avenues: lowering the innovation threshold and increasing interaction feedback. This provides new insights for the related literature.

2.3 Theoretical analysis and hypotheses development

LLMs emerge as a promising tool that can, in certain scenarios, complement or even replace human crowdsourcing. They serve as assistants in human creative tasks, aiding in the generation and realization of ideas, ultimately enhancing innovation performance. ChatGPT is believed to enhance developers' productivity, particularly in solving complex problems and fostering creativity [45, 61]. However, the popularity of LLMs also raises the possibility that humans may face challenges in competing with these technologies and could potentially be replaced [1, 4, 9].

To understand the potential impact of LLMs on user performance within OIPs, we adopt the PMT perspective [50], developed from communication and persuasion theories in psychology [34]. It has found extensive application in information systems research to understand the response to IT threats [38]. PMT states that a person first goes through two responses to a threat: threat assessment and coping evaluation. An individual weighs the seriousness of the threat and the degree to which they are impacted when going through the threat assessment process. In the process of coping evaluation, a person considers how well they can handle the threat and the associated costs of responding. In sum, PMT focuses on how individuals' motivation to protect themselves from perceived threats can drive behavior.

In the perceived threat stage, users may perceive a threat of creative stagnation or falling behind in a fast-paced, competitive creative industry. The fear of being outpaced by peers, the rise of AI-generated content, or the need for innovation can drive the desire to use new tools like LLMs [27, 66]. Additionally, users might feel vulnerable to this threat, recognizing that staying creative and innovative is challenging, especially in industries where new ideas, originality, and productivity are crucial. The rapid pace of technological advancements and the increasing use of AI by peers could heighten this sense of vulnerability, pushing them to adopt LLMs to enhance innovation performance.

In the appraisal stage, users believe that LLMs can effectively enhance creativity by generating diverse ideas, helping overcome creative blocks, and expanding the range of possible outputs, thereby lowering the innovation threshold. The model's ability to produce unexpected combinations of ideas and phrases gives users a sense that using LLMs will improve their creative process. In addition, reducing the cognitive load associated with switching between innovation and programming [13] can also lower the innovation threshold and improve innovation performance. Furthermore, users believe that ChatGPT can free up users' time by automating routine tasks and providing immediate information, allowing them to engage more deeply in meaningful discussions and collaborative activities, and stimulating more interaction among users. By providing interesting and valuable prompts, ChatGPT encourages greater participation, bringing diverse perspectives and ideas into the conversation. Through these multifaceted approaches, ChatGPT significantly enhances the quality and effectiveness of user interactions on OIPs, leading to tighter collaboration, more efficient knowledge sharing, and ultimately, higher innovation performance.

These beliefs in LLMs' potential increases the perceived response efficacy, where users think the tool can genuinely enhance their creative output, driving adoption. Furthermore, as users successfully leverage LLMs and see positive results, their confidence in their ability to use these tools effectively grows. Additionally, they begin to perceive the adoption costs as minimal compared to the benefits, further encouraging widespread use. This positive evaluation contributes to the broader adoption of LLMs as a means of enhancing innovation performance.

In sum, by applying PMT to explain why users use LLMs, we see that users adopt these tools to lower the innovation threshold and increase interaction feedback as a coping mechanism to protect themselves from the perceived threat, combined with the belief in the efficacy of LLMs (effectiveness in enhancing creativity), collectively drive the adoption of LLMs to enhance innovation performance.

H1 *The release of ChatGPT stimulates innovation performance among users within OIPs.*

Users perceive different levels of threat depending on the tier of the work involved. We believe that users engaged in lower-level tasks face a significant threat from ChatGPT. First, in cross-tier innovation, higher-tier works can benefit from mature technologies and knowledge from other fields. This cross-pollination of ideas and technologies reduces the cost of research, development, and application because the foundational elements are already established. Thus, when faced with threats, users can adopt these higher-tier innovations at a lower cost since they are leveraging existing, well-developed solutions rather than starting from scratch.

Second, moving from lower-tier to higher-tier innovations generally necessitates significant knowledge accumulation and experience, which can be costly. However, once this knowledge threshold is crossed and the user is engaged in higher-tier innovation, subsequent improvements, and threat responses become more efficient and cost-effective. This is because users have already acquired the necessary expertise and skills, thereby lowering the marginal cost of addressing new threats.

Third, higher-tier innovations often address more complex problems and have higher technical barriers, leading to fewer competitors in this space [42]. Reduced competition allows innovators to focus more on improving their solutions rather than expending resources to outcompete others. Additionally, higher-tier innovations typically have more resources and advanced tools available, making the process of innovating and responding to threats more economical and straightforward.

In summary, higher-tier innovations can involve lower costs in countering threats because they capitalize on cross-domain knowledge, previously acquired expertise, reduced market competition, and more efficient tools and methodologies. These factors collectively contribute to a more economically efficient and effective process for innovation and threat mitigation at higher tiers.

As a result, we expect that ChatGPT poses a significant threat to lower-tier works. Therefore, users often opt for cross-tier innovation to move away from the locus of the threat by switching to higher-tier innovative works where users can counter the threat at a relatively lower cost [50].

H2 *Users tend to switch to higher-tier innovation works and show a more significant improvement after the release of ChatGPT.*

According to PMT, in the perceived threat stage, experienced users may perceive lower levels of threat to their creative process. Because they have already established effective workflows with LLMs, they might feel less vulnerable to creative stagnation. They rely on past successes and familiarity with the tool, reducing the perceived severity of any creative challenges they might face. However, new users, on the other hand, feel more vulnerable to creative risks and are motivated to explore the tool more fully, as they perceive a higher threat of failing to generate fresh or innovative ideas.

In the appraisal stage, experienced users often have a fixed sense of how LLMs can enhance creativity based on their previous experiences. They might believe that what has worked before will continue to work, which reduces their willingness to explore new prompts, approaches, or ways to use the tool. This limits their response efficacy in creative contexts, leading to less divergent thinking and reduced creativity. However, new users, with fewer preconceived ideas, tend to experiment more broadly with LLMs. They believe that by trying different inputs or approaches, they can discover new ways of using the tool, resulting in greater creativity. Their higher exploratory response efficacy leads to more varied and creative outputs.

Therefore, we believe that experienced users do not exhibit greater innovation performance enhancement following the release of ChatGPT.

H3 *After the release of ChatGPT, experienced users exhibit a lower increase of innovation performance compared to new users.*

3 Data

In this section, we present the empirical context of our study and discuss the descriptions of our data and variables of interest.

3.1 Background

Hacker News is an OIP for IT entrepreneurs, established by YC, a renowned startup incubator that has successfully invested in companies like Airbnb. This platform allows IT entrepreneurs and founders to freely share their creations, such as websites, apps, plugins, and receive feedback and opinions from other users. Some startups choose to showcase their works on this platform, benefiting from valuable feedback for further refinement, as well as gaining initial traction and potential investment opportunities. YC leverages this platform to scout for more high-tech talents and potential projects. Therefore, Hacker News can be regarded as an OIP tailored for IT entrepreneurs. This platform has over ten million visits per month, and the number of new users, new works, and comments is growing daily. Therefore, it has a sufficiently large user base. Secondly, the platform does not impose restrictions on the publication of works, attracting both newcomers to the industry and experienced developers. And this platform encourages the release of new technologies and innovative works, as well as objective and effective interactions. Moreover, the platform strictly limits vote solicitation behaviors, ensuring that the competition for exposure on the homepage is equal for everyone. Overall, it is a highly recognized professional OIP, which can reduce innovation costs, enhance innovation efficiency [18, 63], and assist enterprises in more efficiently acquiring resources and achieving technological breakthroughs [23], with a particular emphasis on users' innovation performance. Therefore, the characteristics of this platform can reflect our research questions and validate our research hypothesis.

In the "show" module of Hacker News, users submit links to their creations, and all other users can vote and comment on them. Based on the voting system, works that meet certain criteria can be ranked on the front page of the website, while those that don't make the cut are quickly replaced by others.

By clicking on the title of a work, users can directly navigate to the page showcasing the creation. Clicking on the comment button allows users to comment and see the title, the detailed description, and discussions of the work, providing users with a better understanding of the work. Figure 1 provides an example of a showcased work.

We collected all works published in the "show" module of the platform during the study period, along with corresponding author information, to form our research sample. This full dataset ensures that there is no assumption of selection bias in our identification strategy and allows us to estimate the impact of ChatGPT across the platform.

ChatGPT can provide practical assistance to IT entrepreneurs on this platform by offering innovative advice and helping to implement creative ideas. Therefore, the release of ChatGPT on November 30, 2022, has an impact on the innovation performance of IT entrepreneurs on this platform. Thus, this platform is valuable for our research.

We estimate the impact of ChatGPT using the DID method. Given the lack of a suitable control group within the same time window, as the release of ChatGPT can affect all users and works on the platform, we use data from the same period in the previous year (June 1, 2021– May 30, 2022) as the control group. This choice follows established causal inference practices, ensuring comparability between pre- and post-intervention periods by accounting for seasonal patterns and baseline behaviors. The control group consists of 5,892 users who published works during this period, while the treatment group comprises 8,143 users who published works between June 1, 2022, and May 30,

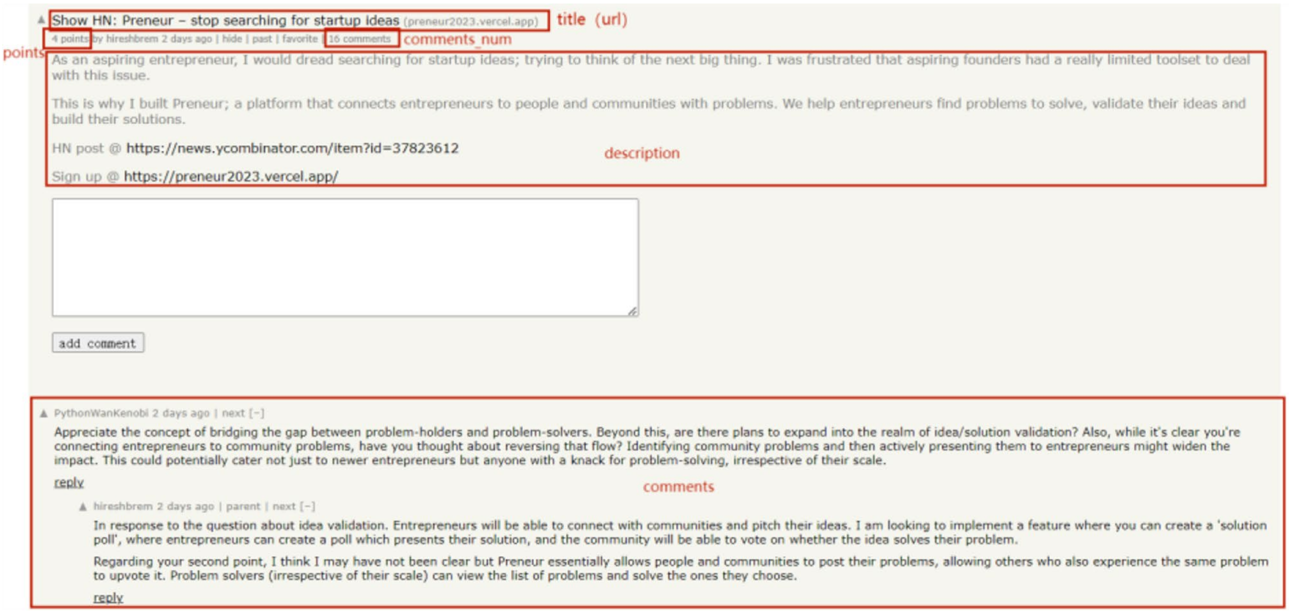

Fig. 1 Components of a work

Table 1 Variable statistics

Variable	Mean	Standard deviation	Min	Max
# Works	0.025	0.164	0	4
Smog	4.087	4.325	2.9	22.2
Length	45.059	90.732	1	1873
Points	0.535	12.406	0	1859
Novelty	1.596	0.803	-1.872	3.178

2023. Importantly, the same individual is treated as two "different" individuals in the treatment and control groups, which, while differing from traditional controlled trials, does not distort the analysis. Because this approach aligns with prior studies [12, 66] and satisfies key assumptions such as no exposure to ChatGPT during the control period and parallel trends between control and treatment groups. Fig.A1 in the appendix provides a visual explanation of our research design.

3.2 Variables

We obtain a dataset by scraping the platform's show module using the website's API from June 1, 2021, to May 30, 2023. This dataset encompasses a total of 14,625 works, associated with 11,048 distinct users (Only 3861 users registered during the observation period, indicating that the majority of users are existing members of the platform.), and includes 115,035 comments. The dataset includes specific details such as titles, detailed descriptions, users, points, creation time, and the number of comments received, among other information. We provide the complete summary statistics of all relevant variables in Table 1.

We have assessed innovation performance from two dimensions: quantity and quality.

Initially, we measure the dimension of quantity, reflecting users' willingness to innovate, by examining the number of works they publish each week. However, due to the subjective nature of innovation quality, it is challenging to measure directly. Therefore, we construct various indicators to minimize potential biases as much as possible.

We opt for metrics from both the authors' and readers' perspectives. From the authors' standpoint, we have established two indicators: (1) $Smog_{it}$, (2) $Length_{it}$. Readability refers to the ease with which a reader can comprehend a text [20]. The computation of word and syntactic complexity yields the readability score. There are many ways to measure it in NLP, and different readability standards can be used for an overall evaluation. Following earlier research, we use the SMOG method to determine the number of years of education required to completely understand descriptions [28]. We calculate the average SMOG score of all work descriptions for the user per week by taking into account the number of words with multiple syllables. A description that is harder to understand is indicated by a higher SMOG score. Additionally, in accordance with previous literature [40], longer ideas are often more innovative. Therefore, in this study, we measure innovation quality by calculating the average length of titles and descriptions.

From the readers' perspective, this study establishes two metrics: (1) Points_{it}, (2) $\mathrm{Novelty}_{it}$. The former represents the average number of upvotes received by a user each week, while the latter is a metric quantifying user comment text based on NLP methods. Specifically, we employ a dictionary search approach. By utilizing a standard English dictionary, we create two lists of English words indicating "creative" and "lack of creativity." When a comment contains more "creative" words, it is labeled as 1. Conversely, if it contains more "lack of creativity" words, it is labeled as -1. If the counts are equal, the comment is labeled as 0 [65]. These labels are then aggregated at the user-week level. The variable is computed as follows: log (#creativity + 1)– log (#lackofcreativity + 1), where #creativity (or #lackofcreativity) denotes the number of comments marked as creative (or lack of creativity) received by the user in a week.

3.3 Model-free evidence

In this section, we visualize the changes in innovation performance after the release of ChatGPT as model-free evidence, as shown in Fig. 2.

We observe that, after the release of ChatGPT, the average number, complexity, and length of works per week have increased significantly, and there are unclear changes for other characteristics. This shows that LLMs will promote the quantity and quality of innovation within the platform. Moreover, almost all the characteristics exhibit a uniform distribution, suggesting a stabilizing tendency. However, these findings can only partially reveal changes in user behavior and may be influenced by various other confounding factors. Therefore, in the following sections, we will further analyze the impact of ChatGPT using empirical results.

4 Empirical design and results

4.1 The impact of ChatGPT on user innovation performance

4.1.1 Identification strategy and main results

The availability of a control group allows us to employ the DID method to identify the impact of the release of LLMs on user innovation performance, after controlling for ongoing confounding factors and time-specific confounding factors. The DID formula utilized in this study is as follows:

$$\text{Outcome}_{it} = \alpha + \gamma \text{Treat}_i \times \text{Post}_t + \theta_i + \lambda_t + {}_{it} \tag{1}$$

Where $Outcome_{it}$ is the dependent variable (indicators related to user weekly innovation performance). Due to the right-skewed nature of the data, all variables have undergone a logarithmic transformation (it is included in the

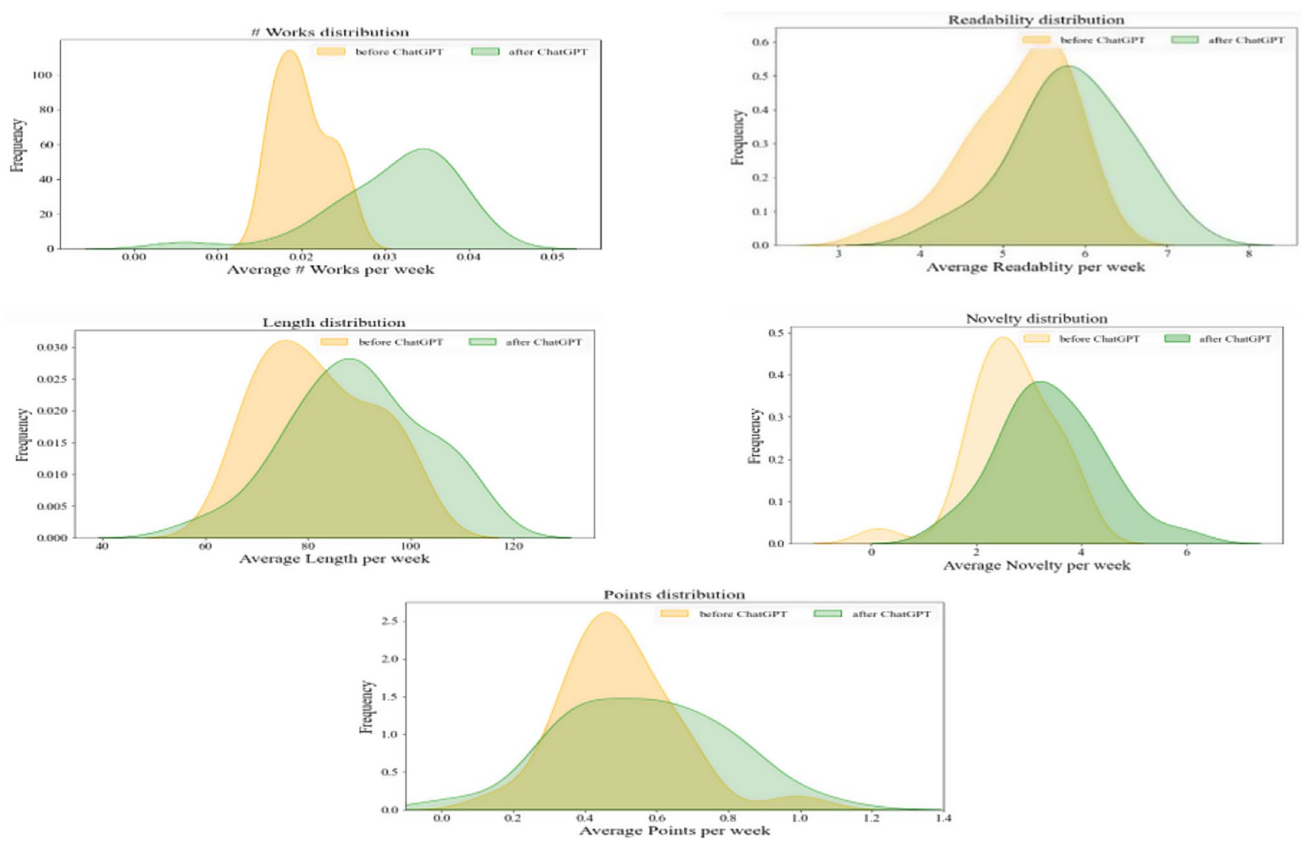

Fig. 2 Model-free evidences

calculation of $novelty_{it}$). Among the independent variables, $Post_t$ is a dummy variable, taking a value of 1 if the sample occurs after November 30, and 0 otherwise. $Treat_i$ is a dummy variable indicating whether a user is affected by the release of ChatGPT. The coefficient γ of the interaction term in the formula can be utilized to estimate the complete effect of ChatGPT on user performance. Additionally, λ_t and θ_i are individual and date level fixed effects respectively. Finally, $?_{it}$ represents the error term.

The effects of the release of ChatGPT on innovation performance are presented in Table 2. Firstly, we observe a user's weekly output of published works increases by 0.8% after the release of ChatGPT suggesting a significant increase in the number of works published by users. However, a concern might arise that such an increase in quantity could come at the expense of quality. Nonetheless, as indicated in Table 2, we do not find evidence supporting this concern.

The presence of ChatGPT leads to an increase in the innovation quality of user-generated content in the platform. From the perspective of authors, users who receive the ChatGPT intervention have titles and descriptions of their published works that are approximately 44% longer compared to those who don't receive the intervention. Additionally, the readability of the works decreases by around 35%. As outlined in Sect. 3.2 regarding the variables, this result suggests that the introduction of the LLM has enhanced the innovativeness and complexity of works. From the readers' perspective, users who are affected by ChatGPT receive more points, and the novelty measured through comments is higher. Since these metrics largely measure the perceived innovativeness by readers, readers' perception is crucial for the commercial success of such digital products. Therefore, from the readers' viewpoint, we can also argue that LLMs enhance users' innovation performance. However, an alternative interpretation of the increased perception of quality by readers is that the user's intrinsic creative ability has not changed. Instead, due to the release of more LLM-related works, users naturally gain more attention and positive reviews from other users, representing a short-term gain from opportunistic behavior. We will explore this possibility further in the subsequent robustness checks.

The findings of this study are aligned with H1. The release of ChatGPT appears to stimulate users to contribute more and higher-quality works to the platform. From this perspective, ChatGPT can be regarded as a valuable addition that can stimulate the internal innovation of OIPs.

4.1.2 Results of the relative time model

The validity of our primary identification strategy that leverages the DID model largely depends on the pretreatment parallel trends assumption (i.e., no significant differences between treatment and control groups before the intervention). To test this assumption, we utilize a relative time model with the leads and lags periods [3]. Following the extant literature [20, 32], we add a series of time dummies that indicate the relative chronological distance between observation time and November 30. Our specification for the relative time model is as follows:

$$\text{Outcome}_{it} = \sum_j \tau_j \text{Pre}_{it}(j) + \sum_l \omega_l \text{Post}_{it}(l) + \theta_i + \lambda_t + {}_{it} \tag{2}$$

Where $Outcome_{it}$refers to variables in Sect. 3.2. In addition, θ_i, λ_t denote individual fixed effects, date fixed effects, respectively. The newly added term $Pre_{it}(j)$ is an indicator function that equals one if month t is $|j|$ month(s) prior to the treatment. Similarly, the term $Post_{it}(l)$ is an indicator function that equals one if month t is l month(s) after the treatment. To estimate all of the effects, we use dummy variable $Pre_{it}(-7)$ to represent all pretreatment periods that are greater than or equal to 7 weeks prior to treatment. Similarly, we assemble all posttreatment periods that are greater than or equal to 7 weeks following treatment into another dummy $Post_{it}(7)$. To prevent collinearity, the coefficient of $Pre_{it}(-1)$ is normalized to zero.

The result of relative time model can prove that the parallel trend assumption holds in our analysis so our DID specification is valid. As shown in Table 3, we find all of the coefficients of the pretreatment dummies, to be statistically insignificant. This result confirms that there is no detectable pretreatment dissimilarity across users that affected by ChatGPT or that do not be affected; hence, the parallel trend assumption is satisfied.

Table 2 The change of innovation performance

	Ln(1+#Works)	Ln(1+Smog)	Ln(1+Length)	Novelty	Ln(1+Points)
$Treat \times Post$	0.008***	0.353***	0.439***	0.127*	0.015***
	(0.001)	(0.030)	(0.033)	(0.060)	(0.002)
Individual FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
# Observations	574,496	24,610	24,610	17,716	574,496
R^2	0.011	0.497	0.823	0.598	0.013

Clustered (Individual) standard-errors in parentheses; FE: fixed effects

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 3 Parallel trend test for innovation performance

	Ln(1+#Works)	Ln(1 + Smog)	Ln(1 + Length)	Novelty	Ln(1 + Points)
Pre (-7)	-0.003	-0.326	-0.455	-0.040	-0.006
	(0.002)	(0.179)	(0.237)	(0.137)	(0.005)
Pre (-6)	-0.001	-0.030	0.013	0.240	-0.006
	(0.002)	(0.189)	(0.202)	(0.188)	(0.008)
Pre (-5)	0.001	0.420	0.431	-0.145	0.009
	(0.003)	(0.283)	(0.233)	(0.189)	(0.008)
Pre (-4)	0.002	-0.119	-0.192	0.161	0.002
	(0.002)	(0.193)	(0.211)	(0.195)	(0.008)
Pre (-3)	-0.002	0.045	-0.105	0.016	-0.009
	(0.003)	(0.175)	(0.192)	(0.191)	(0.009)
Pre (-2)	0.003	0.105	-0.115	-0.168	0.010
	(0.003)	(0.182)	(0.203)	(0.180)	(0.008)
Pre (-1)	baseline				
Individual FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
#observations	574,496	24,610	24,610	17,716	574,496
R^2	0.011	0.499	0.824	0.598	0.013

Clustered (Individual) standard−errors in parentheses; FE: fixed effects

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 4 Heterogeneous effects of ChatGPT across innovation types

	Basic	Entertainment	Professional
Ln(1+# Works)	0.004***	0.008***	0.010***
	(0.001)	(0.001)	(0.001)
Ln(1 + Smog)	0.284***	0.398***	0.402***
	(0.044)	(0.050)	(0.066)
Ln(1 + Length)	0.357***	0.480***	0.492***
	(0.048)	(0.057)	(0.073)
Novelty	0.092	0.093	0.223*
	(0.096)	(0.107)	(0.101)
Ln(1 + Points)	0.007*	0.018***	0.017***
	(0.003)	(0.003)	(0.003)
# Observations	211,796	282,256	134,888

Clustered (Individual) standard−errors in parentheses; FE: fixed effects

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

4.2 Heterogeneity analysis

In this section, we further explore the impact of ChatGPT on user performance within OIPs by examining the heterogeneity across different types of works and user experience.

4.2.1 Heterogeneous effect across innovation types

Due to varying demands in idea generation and execution for different types of works, the assistance of ChatGPT also differs across different tiers of works. This section will explore the impact of ChatGPT on different types of innovative works. We categorize works into three themes—Basic, Entertainment, and Professional. The specific classification methods and results can be found in the appendix B.

The innovation performance for different types of works is presented in Table 4. It indicates that after the release of ChatGPT, there is a significant increase in the quantity of works across all three tiers, with a more substantial increase observed in higher-tier works. Similarly, the improvement in innovation quality is more pronounced for Entertainment and Professional. This suggests that LLM has an impact on works at various tiers, exhibiting a more pronounced improvement in the innovation performance of higher-tier works. This outcome indicates that LLMs contribute to automation and efficiency, saving time on routine tasks and enabling more users to focus on high-tier innovative works.

In summary, H2 can be convinced. On the one hand, the release of ChatGPT urges users to switch to higher-tier works to avoid the threat; on the other hand, a potential underlying mechanism is that the release of ChatGPT leads to the decline of innovation threshold, enhancing user innovation capability. Moreover, routine tasks such as programming and performance optimization, can be delegated to the LLM. Consequently, ChatGPT's release can streamline the user's workload and enable more users to shift to higher-tier innovation works and produce more and higher-quality works.

4.2.2 Heterogeneity in user experience

Next, we seek to understand how prior experience moderates the impact of ChatGPT. Specifically, we categorize users into two groups, high experience and low experience, based on their total number of published works in one year before the latest date of the treatment group and the control group. We then employ the DDD model to investigate the moderating effect of user experience.

$$\begin{aligned} \text{Outcome}_{it} &= \alpha + \beta_1 \text{treat}_i \times \text{Post}_t + \beta_2 \text{treat}_i \\ &\times \text{Post}_t \times \text{group}_i + \beta_3 \text{treat}_i \times \text{group}_i \\ &+ \beta_4 \text{Post}_t \times \text{group}_i + \theta_i + \lambda_t + {}_{it} \end{aligned} \tag{3}$$

Table 5 Heterogeneous effects of ChatGPT on user experience

	Ln(1+#Works)	Ln(1+Smog)	Ln(1+Length)	Novelty	Ln(1+Points)
Treat×post×group	-0.722***	-0.248***	-0.353***	-0.569***	-1.976***
	(0.007)	(0.074)	(0.084)	(0.086)	(0.062)
Individual FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
# Observations	574,496	24,610	24,610	17,716	574,496
R^2	0.318	0.499	0.824	0.600	0.191

Clustered (Individual) standard−errors in parentheses; FE: fixed effects

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Where $group_i$ represents user experience, where 1 indicates experienced users and 0 indicates inexperienced users.

In consistence with H3, Table 5 supports our concern that past successes and familiarity with the tool reduce perceived severity, leading to less divergent thinking and reduced creativity. The innovation performance of experienced users shows a less significant improvement after the release of ChatGPT.

This finding is consistent with previous studies by Noy and Zhang [52], Choi and Schwarcz [16], and Dell'Acqua et al. [19], underscoring how LLM reduces the inequality in innovation performance among knowledge workers by providing more advantages to users with less experience.

Based on the aforementioned research findings, LLM has an overall positive impact on innovation within OIP. This effect is particularly notable for works at higher tier. Moreover, it provides more significant assistance to less experienced users.

5 Mechanism analysis

In this section, we present additional analyses to further understand the underlying mechanisms behind the changes in innovation performance induced by ChatGPT. Because OIP involves using purposeful knowledge inflows to accelerate internal innovation and leverages external innovation to expand the market [64]. Therefore, the innovation performance within OIPs mainly depends on the lowering of the innovation threshold and the increase in interaction feedback.

. In this regard, we will explore how and why user performance changes from these two perspectives.

5.1 Lowering the innovation threshold

LLMs help users overcome creative blocks, reducing the cognitive load required in the innovation process. This enables users to focus more on higher-level creative tasks. Second, LLMs provide unexpected combinations of ideas and phrases, fostering cross-disciplinary innovation and broadening users' creative thinking. Therefore, the introduction of LLMs helps to reduce the technical and cognitive barriers to innovation.

Table 6 Mechanism analysis of innovation threshold

	Diversity	Increase	FirstTimer
$Treat \times Post$	0.011***	0.008***	0.001***
	(0.001)	(0.001)	(0.000)
Individual FE	YES	YES	YES
Date FE	YES	YES	YES
# Observations	574,496	574,496	574,496
R^2	0.011	0.002	0.015

Clustered (Individual) standard−errors in parentheses; FE: fixed effects

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

It's worth noting that some of the observations in both our main analysis and heterogeneity analysis have already hinted at potential mechanisms. Taking into account the result of heterogeneity analysis, which shows a more significant improvement in innovation performance for users of high-tier works, one potential reason is that LLM brings about long-term changes in the platform by decreasing the innovation threshold, resulting in an enhancement in user innovation capabilities.

For this analysis, we introduce three new dependent variables, $Diversity_{it}, Increase_{it}$ and $FirstTimer_{it}$. The former two variables are used to measure the number of types to which users' weekly created works belong and whether users shift from developing low-tier works to high-tier works in a given week. If a user's published work in a certain week belongs to a tier higher than the most frequently published tier in the past, $increase_{it}$ is recorded as 1. Additionally, the latter one is a binary indicator signifying whether the user is new and posting on the platform for the first time. A user is considered new if registered within one year before the latest date of the treatment group and the control group. We employ these variables as the dependent variables in our DID model to ascertain if ChatGPT's introduction has lowered the innovation threshold and encouraged more users to shift to higher-tier innovation works and new users to join the platform and focus on creation.

We observe an increase in the number of users engaging in cross-tier innovation after the release of ChatGPT from Table 6. Additionally, there is a notable increase in the number of users moving from not developing or primarily developing low-tier works to developing high-tier works. Therefore, ChatGPT has partially dismantled the technical barriers and has enhanced users' innovation abilities, encouraging and enabling them to promote diversity in innovation and turn to the development of works that were previously challenging or even impossible to realize.

Furthermore, as evidenced in Table 6, the introduction of ChatGPT has led to a substantial surge in the volume of new users on the platform who are now sharing their work for the very first time. This clearly demonstrates that LLMs are instrumental in encouraging a considerable number of new users to participate in innovative tasks on the platform.

In summary, an increasing number of new users are joining the platform to engage in creative activities, and users begin developing more challenging works, and the innovation performance of their works see significant improvement. Our findings provide strong evidence indicating that after the release of ChatGPT, the innovation threshold has declined and users experience an enhancement in their innovation capabilities.

5.2 Increasing interaction feedback

ChatGPT also facilitates enhanced user interaction on the platform. By automating routine tasks and providing immediate information, LLMs free up users' time, allowing them to focus more on engaging with other users. Additionally, the presence of ChatGPT encourages more frequent and constructive exchanges between users, as the model's capabilities help guide discussions, suggest improvements, and support idea refinement, thereby enhancing the quality of interactions. As a result, users are more likely to refine their ideas based on this feedback loop, leading to more innovative and high-quality outcomes.

In order to verify this mechanism, we introduce the following metrics from both the readers' and the authors' perspectives to measure interaction performance: (1) $\# \, Comments_{it}$. From the readers' viewpoint, the average number of comments received per week on works can to some extent reveal the quantity of feedback collected by the user.

Furthermore, by constructing the following metrics from the authors' perspective, we can assess how users accept and adopt feedback to enhance their own innovation performance: (1) $\# \, AuthComm_{it}$(2) $AuthCommLen_{it}$. These two variables indicate the average number of comments users make on their own works and the average length of these comments respectively.

From both the authors' and readers' perspectives, the release of ChatGPT has a facilitating effect on user interaction performance within OIPs, as shown in Table 7. From the readers' standpoint, works influenced by ChatGPT receive significantly higher numbers of comments from other users, which suggests that users can receive more feedback from other users. Furthermore, there is a significant increase in the number and length of comments posted by users under the works. This is sufficient to illustrate that as users receive more feedback, they are also more willing to interact with other users for discussions, thereby leveraging external knowledge and creativity to enhance their own innovation performance.

Table 7 The change of interaction performance

	Ln(1+#Comments)	Ln(1+#AuthComm)	Ln(1+Auth-CommLen)
Treat×post	0.005***	0.004***	0.468**
	(0.001)	(0.001)	(0.153)
Individual FE	YES	YES	YES
Date FE	YES	YES	YES
#Observations	574,496	574,496	16,899
R^2	0.022	0.019	0.595

Clustered (Individual) standard−errors in parentheses; FE: fixed effects

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

The changes in interaction performance are consistent with the changes in innovation performance within OIP, that's to say, users who engage in interaction more actively will create more works and improve innovation performance, which are validated by parallel trend assumption, as shown in Table C1 in the online appendix. Therefore, we have reasons to believe that the release of ChatGPT can promote innovation performance within OIP by facilitating interaction performance and speeding innovation.

In addition, the presence of LLMs has a more pronounced positive impact on the interactive enthusiasm and quality of users producing works at higher tiers, as shown in Table C2 in the online appendix. A plausible explanation is that the lowering of the platform's innovation threshold frees up more time and energy for users to engage with other users. As a result, higher-quality interaction outcomes lead to higher-quality works.

Furthermore, as table C3 in the online appendix, inexperienced users show a more pronounced improvement in interaction performance compared to experienced users, which is similar to innovation performance. It can further confirm that the changes in user innovation performance can be brought about by changes in interaction.

In summary, after the release of ChatGPT, user interaction performance within OIPs has been significantly improved, and the performance is more obvious among high-tier innovation works and less experienced users. These findings are consistent with the conclusion of innovation performance, that is to say, the increase in interaction helps stimulate external creativity and knowledge acquisition, accelerates the innovation process, and improves innovation performance.

6 Robustness check

To further validate our results, we conducted several robustness checks. The specific details and results of these checks can be found in the online appendix D.

First, we use a DDD model to investigate whether speculative behavior influences innovation performance. Results indicate that speculative works show significantly smaller improvements in innovation performance compared to non-speculative works, suggesting that speculative behavior is not the primary driver of changes in innovation performance. Second, to more accurately measure the novelty of works, we introduce a new metric $Similarity_{it}$ based on the content itself [11] and quantified the similarity between works. The results are consistent with the main analysis: following the release of ChatGPT, the similarity of user-generated content decreases, indicating an improvement in innovation quality. Third, to control for potential confounding factors that might influence innovation performance, we introduce several control variables, llm_{it}, $created\_days_{it}$, and $comment\_sum_{it}$, $points\_sum_{it}$ [17]. The results show that, even after accounting for these factors, the release of ChatGPT still significantly enhance innovation performance. Lastly, we perform an endogeneity test using Google search trends as an instrumental variable. The results show that the estimated changes in innovation performance are consistent with the main model, further validating the robustness of our findings.

Through these checks, we confirm that ChatGPT indeed improves innovation performance on the platform.

7 Discussions

7.1 Conclusions

Through quasi-experimental design, we have uncovered empirical evidence of a significant impact from LLMs on user innovation performance within OIPs. This result indicates that LLMs encourage more frequent and profound user engagement and creativity, thereby enriching the innovation ecosystem. This effect is particularly pronounced for users engaged in higher-tier works. In addition, less experienced users exhibit greater improvement compared to their experienced counterparts. Thus, LLMs help reduce inequalities in innovation performance, providing cognitive support that enables users to tackle more complex projects. ChatGPT's release boosts innovation performance by reducing barriers and enhancing capabilities. Improved interactions also lead to better external knowledge acquisition, further enhancing innovation outcomes.

Our work makes significant contributions to both academic literature and practical applications. Academically, this research provides vital insights into how LLMs, like ChatGPT, facilitate innovation. It both complements and challenges existing literature on AI's impact on innovation performance, with an emphasis on the diversity of task types and user experiences. We also elucidate the pathways and mechanisms through which AI and LLMs enhance innovation, demonstrating how ChatGPT supports idea generation and interaction quality.

7.2 Implications

From a practical perspective, this study offers valuable guidance for platform managers and individuals. Firstly, for administrators of the platform, our findings suggest that ChatGPT can significantly enhance users' innovation performance. Therefore, it is recommended that platform managers leverage LLM's capabilities to attract a broader and more diverse user base, fostering a dynamic innovation ecosystem. This approach not only accelerates the pace of innovation but also improves resource efficiency by automating repetitive tasks and facilitating efficient knowledge transfer. Given ChatGPT's more substantial impact on higher-tier innovative works and less experienced users, managers should consider incorporating metrics such as the level of innovation and cross-tier innovation into their ranking algorithms, thereby providing greater exposure for these works. While ensuring the quality of new users' contributions, managers could also moderately relax restrictions to foster new talent. Additionally, considering the mechanisms through which ChatGPT boosts innovation, it would be beneficial for managers to incorporate both the quantity and quality of interactions in their ranking criteria to further stimulate engagement and innovation [68].

And for individuals, based on our research findings, individuals can take specific steps to maximize the benefits of using ChatGPT within OIPs and enhance their innovation performance. Our analysis revealed that ChatGPT significantly boosts both the quantity and quality of user-generated works, particularly benefiting higher-tier innovative contributions and less experienced users. Therefore, individuals should leverage ChatGPT for idea generation and brainstorming, enabling them to explore a wide range of suggestions and perspectives that enhance creativity. First, to fully leverage this advantage, users should harness ChatGPT's powerful capabilities to push beyond their limitations and focus on higher-tier innovative contributions. Second, experienced users, in particular, should actively embrace new technologies to enhance their innovation efficiency. Additionally, engaging with the community through collaboration and feedback is crucial, as it refines ideas and integrates diverse viewpoints, thereby improving the quality of work. However, it is important to balance the use of ChatGPT as an assistant rather than a crutch, ensuring continuous personal skill and creativity development to maintain the originality and quality of contributions. Validating information generated by ChatGPT is essential to avoid biases and inaccuracies, ensuring reliable and high-quality output. Engaging in cross-tier innovation by using ChatGPT to tackle more complex projects can push users' boundaries and enhance their innovation capabilities. Staying updated with the latest best practices and advancements in LLM technology will further help users utilize ChatGPT effectively and remain competitive.

7.3 Limitations and future research

As one of the early studies examining the impact of LLMs on user innovation performance in the new AI era, our work has its limitations. Firstly, this research takes the release of ChatGPT as an intervention, but it cannot microscopically measure whether users utilize LLMs to aid in product development. This could involve tracking user interactions with LLMs, analyzing the content created with LLM assistance, and assessing the direct contributions of LLMs to innovation processes. Secondly, this study focuses on the OIP for IT entrepreneurs, and whether LLMs have a consistent impact on human creativity in other contexts such as education, design, or academy requires further investigation. Comparative studies across different fields can reveal the versatility and limitations of LLMs in fostering creativity and innovation. In addition, we also can conduct longitudinal studies to examine the long-term effects of LLM integration on innovation dynamics within OIPs or explore how LLMs influence collaborative innovation efforts, particularly in team-based projects.

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