AI and Creative Process: the Time-Quality Relationship and its Implications*

Yvonne Jie Chen† Jie Gong‡ Jin Li‡ Zibo Zhao‡

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Abstract

This paper investigates how AI affects creative work by examining changes to the time-quality relationship. In an experiment comparing professionals working with and without AI assistance, we measured the quality of their creative outputs at 15-minute intervals. Our results reveal that AI not only raises the overall time-quality curve but also transforms its shape. Specifically, AI significantly accelerates quality improvements during the initial production stage; however, it subsequently reduces the rate of quality improvement, flattening the curve after the first 15 minutes. In response to this flattened curve, 30% of creators choose to produce lower-quality work that requires substantially less time. These findings suggest that the current GenAI-induced technological change is biased towards time-saving rather than quality-enhancing.

Keywords: Generative AI; Time-quality trade off; Production process; Creative work

JEL classifications: O33, J2, D2, D8, M15

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†School of Entrepreneurship and Management, ShanghaiTech University, China.

‡Faculty of Business and Economics, The University of Hong Kong.

1 Introduction

The rapid rise of generative artificial intelligence (GenAI) has dramatically transformed the way intellectual and artistic works are created, impacting diverse fields such as writing, music composition, and visual art. Recent studies have begun to uncover how GenAI influences creators' productivity: highlighting how this technology can change both the amount of time required for production and the quality of outputs (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023b; Noy and Zhang, 2023; Doshi and Hauser, 2024; Jia et al., 2024; Zhou and Lee, 2024; Toner-Rodgers, 2024; Dell'Acqua et al., 2025).

Yet, an important and unexplored question is how GenAI changes the relationship between time spent and quality achieved. Understanding this "time-quality" relationship is crucial for creative and knowledge workers because they enjoy considerable discretion over the quality of their work. Some creators dedicate years to perfecting a single masterpiece, while others generate floods of works of mediocre quality. These decisions on qualities are undoubtedly dependent on personal characteristics and many other factors, but the relationship between time and quality will also play a role. When the time-quality curve is flat, that is, an incremental increase in quality with regard to time is small, creators will stop early because the return to time spent is low. When the slope of the time-quality curve is high, creators will have stronger incentives to continue their work.

How will GenAI change the relationship between time spent and quality achieved? How will the change in time-quality relationship influence creators' decisions regarding the time spent on the work? How will these two forces combine to affect the quality of work? And ultimately, will the current technological change, induced by GenAI, be biased toward time saving or quality enhancement?

To explore these questions, we conducted an experiment with 219 professionals in the creative industry. Each participant created two illustrations: the first without AI assistance, and the second with unrestricted access to a text-to-image AI system.[1] A distinctive feature of our experiment was the video recording of participants' entire creative processes, providing a unique window into how their illustrations evolved over time. By extracting snapshots at 15-minute intervals and having experts assess the quality of these intermediate outputs, we reconstructed the time-quality rela-

[1] We use AI rather than Gen AI hereafter to shorten the exposition.

tionship both with and without AI assistance. Leveraging this within-subject design, we compared participants' choices regarding quality and time spent across the two conditions, enabling us to clearly identify their strategic responses to AI.

We find that AI transforms the time-quality relationship in two important ways. First, AI shifts the entire curve upward, enabling creators to achieve higher quality for any amount of time spent. Second, and more importantly, AI changes the shape of the time-quality curve. AI dramatically accelerates quality improvement during the initial stages of production, but subsequently reduces the rate of improvement, causing the curve to flatten after the first 15 minutes.

At the 15-minute mark, the creators using AI achieved an average quality score of 49 points, substantially higher than the 34 points obtained without AI. After this initial boost, however, the advantage starts to diminish: the quality improvement for AI-assisted creators slows considerably, becoming statistically indistinguishable from zero by minute 60. Ultimately, by the end of the 150 minutes, the initial quality gains from using AI disappear entirely: using AI has no statistically significant impact on the creator's final quality.

We also find that the change in the time-quality curve has a significant impact on the behaviors of the creators. Although AI raises the time-quality curve, approximately one-third of creators have lower output quality than before. Importantly, for these creators, the vast majority (30% out of 35%) have simultaneously reduced the time they spent on the work. This suggests that the creators may have deliberately reduced the time they spent in response to the changes in the time-quality curve.

To further understand how changes in the time-quality curve influence creators' time choice, we examine the distribution of time spent on tasks, comparing scenarios with and without AI assistance. Without AI, the distribution is unimodal, peaking around 150 minutes, indicating that creators typically work until the allotted time limit. In contrast, with AI assistance, the time distribution becomes bimodal, with a new peak at approximately 60 minutes. Notably, this new peak corresponds to the point at which the slope of the time-quality curve with AI becomes statistically indistinguishable from zero.

As an additional check, we estimate the relationship between the slope of the curve and the creator's likelihood of stopping work. We confirm that creators are more likely to terminate their efforts when the marginal return to additional time becomes smaller. This underscores a deliberate strategic adjustment by creators in response to diminishing returns in the time-quality relationship. Moreover, because the time-quality curve under AI becomes flatter, the effect from human responses implies that the technological change is biased towards time saving.

Finally, we analyze how these changes in time allocation, combined with the changed time-quality relationship, influence the overall distribution of output quality. Despite the observed reduction in time spent, the overall quality distribution shifts positively (to the right) with AI assistance. Interestingly, the emergence of a new peak in the time-use distribution at the 60-minute mark does not correspond to a new peak in output quality; instead, the quality distribution remains unimodal both with and without AI. The explanation lies in the flatter portion of the time-quality curve beyond the 60-minute threshold: past this point, additional time spent yields little quality improvements. In other words, the quality dispersion under AI arises more from the earlier, idea-generation stage rather than the time and skill in implementing the ideas.

This study contributes to the extensive literature that examines how technology influences worker productivity, particularly the rapidly growing research on the impacts of AI (Kanazawa et al., 2022; Dell'Acqua et al., 2023a; Mollick, 2024; Peng et al., 2023; Bick et al., 2024; Bono and Xu, 2024; Boussioux et al., 2024; Haslberger et al., 2024; Kreitmeir and Raschky, 2024; Wang et al., 2024; Dell'Acqua et al., 2025). Most prior studies find that AI assistance reduces task-completion time and enhances output quality. For instance, Noy and Zhang (2023) conduct an experiment with online participants engaged in writing tasks, demonstrating that ChatGPT assistance reduces time spent and improves output quality. Similarly, in a field experiment at Boston Consulting Group, Dell'Acqua et al. (2023b) show that, within the limits of AI capability, consultants using GPT-4 completed tasks more quickly and produced higher-quality results. Brynjolfsson et al. (2025) study the adoption of a generative AI-based conversational assistant in customer support, finding shorter chat handling times and modest improvements in customer satisfaction.

A related strand of research specifically examines AI's impact on creative professions, highlighting benefits to individual productivity alongside concerns about decreased diversity. Lee and Chung (2024) demonstrate that ChatGPT assistance increases average creativity in idea generation tasks. Zhou and Lee (2024) analyze artworks created with AI assistance, revealing an overall increase in output quantity but a reduction in novelty over time, even as maximum content novelty increases. Similarly, Doshi and Hauser (2024) conduct an online experiment in which participants complete a story writing task, finding that exposure to AI-generated ideas enhances individual creativity, but reduces collective novelty.

Our paper complements this literature by providing micro-level evidence on how AI reshapes the fundamental relationship between time spent and output quality in creative tasks. Our research is closely related to recent studies that examine how AI transforms workflows in contexts where workers have significant autonomy over their time allocation and output quality. For example, Toner-Rodgers (2024) study scientists in an R&D lab and show that AI automated much of the idea generation process. As a result, researchers shifted their effort towards evaluating AI-generated suggestions, improving productivity primarily among top researchers who could effectively leverage their domain-specific knowledge. Similarly, Hoffmann et al. (2024) find that GitHub Copilot helps software developers shift their attention towards core coding tasks and away from non-core activities. Our study contributes by directly tracing how AI changes the time-quality relationship itself and by explicitly identifying strategic human responses to these technological shifts.

Finally, by emphasizing human strategic responses to generative AI, our study contributes to the broader literature advocating a system-based view of organizations (Milgrom and Roberts, 1990; Ichniowski et al., 1997; Brynjolfsson and Milgrom, 2013). Specifically, as generative AI flattens the relationship between time spent and output quality, organizations may need to reconsider traditional approaches to motivating and incentivizing workers—–approaches that typically assume sustained positive returns to additional time input. Our findings suggest that fully realizing productivity gains from technological advances such as AI likely requires complementary organizational adjustments.

2 Experimental Setting and Background

2.1 Methods

Our experiment involved 219 professional and student visual artists. Artists represent creative workers who typically have autonomy over their production processes, tools, time spent and output quality[2] Participants are employed full-time in the visual art and design industries or college

[2]These features are common to many knowledge workers, including researchers, writer, and etc, who have flexibility in their input choices and output quality decisions.

students majoring in related fields. They were tasked with creating illustrations based on textual excerpts from well-known novels—a moderately constrained creative task familiar to these participants through prior professional or academic experience.[3]

We employed a within-subject design in which each participant completed two illustrations, the first without AI assistance and the second one with free access to AI. We imposed a time limit of 2.5 hours per illustration to ensure comparability.[4] To control for potential spillover effects between tasks —-such as learning or fatigue—we randomly assigned 51 participants to a control group that completed both illustrations without AI access. The main analysis examining how AI impacts the time-quality relationship and individual time spent is based on within-subject comparisons. For average treatment effects, we utilize the control group to implement a difference-in-difference estimation.

The experiment took place remotely from August 7 to September 12, 2024. During the AI-assisted task (second illustration for the treatment group), participants had free access to Tiamat, a text-to-image AI comparable to Midjourney and DALL-E, specifically optimized for Chinese inputs. Participants completed tasks from their usual workplaces or homes and were required to video-record the entire illustration process. Our experimental design aimed to closely replicate the real-world conditions and incentives faced by professional illustrators.[5]

Participant motivation included both intrinsic and extrinsic components. First, we advertised the experiment as a research study aimed at understanding the creative production process. Participants voluntarily signed up to help researchers study the creative process, indicating intrinsic motivation to produce high-quality outputs. Second, each participant received a show-up fee of 100 RMB, with an additional bonus based on illustration quality. Specifically, for each task, outputs from the control and treatment groups were pooled together, and we awarded one top prize (10,000 RMB), two second-tier prizes (5,000 RMB each), and five third-tier prizes (2000 RMB each). The winning illustrations would be displayed in an online gallery on the event website. This incentive

[3] We predefined illustration topics based on paragraphs extracted from four well-known novels. Each participant was randomly assigned two different topics from this set, one for each illustration task.

[4] Some participants exceeded the time limit due to overlooking the end notification, technical difficulties accessing instructions, or extra time spent uploading files. We retained this extra time, as it was not systematically related to the treatment assignment.

[5] Participants primarily used digital applications such as Photoshop or Procreate and screen-recorded their drawing process. Participants who drew on physical paper recorded their process via camera. In both cases, the recording captured only the artwork itself, without faces or identifying features.

structure closely resembles the prize-based rewards common in creative industries. Importantly, participants were not informed about the total number of contestants or had access to the identities or outputs of other participants, ensuring similar competition levels and incentive structure across groups.[6]

Output quality is a key outcome variable in our experiment, measured by expert ratings of overall quality on a scale of 0-100. Expert raters are professors from art and design schools or industry professionals with extensive experience. In addition to rating the final illustrations, experts evaluated intermediate snapshots taken from participants' video recordings—specifically at 15-minute intervals throughout the illustration process. These intermediate ratings allow us to track how output quality evolves with the time spent by the participants. Expert raters were blinded to the experimental conditions and the use of AI. Each image was evaluated by at least five independent raters. For analysis, we normalize quality scores by rater and topic, then calculate the average normalized rating for each illustration.

We collected demographic characteristics, professional backgrounds, and AI experience through a baseline survey administered prior to the first illustration task. Table 1 reports summary statistics for the treatment and control groups, as well as results of t-tests comparing the means of the groups. The sample consists of over 70% female participants, reflecting the gender composition commonly observed in the fields of art and visual design. Approximately 70% of the participants are college students majoring in art and design, while the remaining participants are employed full-time. On average, the participants have 16 years of education and are 23 years old. The treatment and control groups are comparable for most baseline characteristics, with the exception of years of education. However, the magnitude of the difference (0.35 years) is small relative to the mean of the control group (16.02 years).

Notably, 80% of the participants reported previous experience with AI tools such as large language models and text-to-image systems. To ensure familiarity with the specific AI interface used in our experiment, we provided treated participants with instructions 30 minutes prior to their second illustration task. Given their baseline AI experience and the brief instruction provided, most

[6] Prior experimental literature supports tournament-style incentives in creative tasks. Bradler et al. (2019) finds that a tournament-style performance-based bonus effectively increases the participants' output. Charness and Grieco (2018) shows that tournament-style financial incentives positively impact creativity in constrained tasks. Gross (2020) demonstrates that intensified competition, particularly when participants observe each other's outputs, motivates creative effort, but heavy competition discourages investment altogether.

of the participants possessed the necessary skills to use AI technology for illustration tasks.

Table 1: Summary Statistics

VARIABLES	**Treatment (N=168)**	**Control (N=51)**	**Difference**	**p-value**
Female	0.76	0.76	0.00	0.95
Age	23.38	22.78	-0.60	0.51
Education (yrs)	16.37	16.02	-0.35	0.02**
Employed	0.26	0.33	-0.37	0.31
Majored in Art	0.68	0.73	0.05	0.54
Took art exam	0.62	0.61	-0.01	0.92
Working experience (yrs)	2.25	2.35	-0.20	0.87
Ever full-time in Art/Design	0.27	0.25	-0.10	0.59
Used Graphic AI	0.82	0.78	-0.61	0.91
Used LLM	0.84	0.84	0.00	0.96

Notes. This table reports the raw means for the treatment and control groups, along with the differences in means and corresponding p-values. "Employed" equals 1 if a participant has ever worked either full-time or part-time, and 0 otherwise. "Took art exam for college" equals 1 if the participant took the art track entrance exam for college, and 0 otherwise. "Ever full-time in Art/Design" indicates whether the respondent has ever held a full-time job in an art or design-related field. "Used Graphic AI" and "Used LLM" refer to self-reported use of generative AI tools for visual and language-based tasks, respectively.

We provided treated participants with free access to the AI system, allowing them full autonomy to decide whether and how to integrate AI into their illustration production. In our experiment, 79% of the treated participants chose to adopt AI for their second task. We analyzed the relationship between AI adoption and participant characteristics, finding that older participants and those from nonart majors (e.g. engineering, design, architecture, etc.) were more likely to adopt AI. In terms of other demographic characteristics, AI adopters closely resemble the overall sample of participants.

2.2 Illustration Workflow and AI Tool

Our experimental setting is the production of illustrations, where artists visually interpret and represent excerpts from novels through drawings. Unlike fine art, which primarily pursues pure self-expression, illustration balances creative interpretation with the depiction of specific narrative content. Because the quality of an illustration can be assessed relatively clearly in terms of narrative accuracy and visual effectiveness, this setting is particularly suitable for our experiment.

Traditionally, artists create illustrations following a two-phase workflow: ideation and implementation. During ideation, artists typically gather background information related to the text, sketch initial compositions, and experiment with multiple visual concepts before selecting a final direction. The implementation phase involves refining the selected concept into a detailed drawing, complete with precise lines, coloring, shading, and other finishing touches. Without AI assistance, participants in our study generally adhered to this flow, spending on average 21.8% of their total production time on ideation and 78.2% on implementation.[7]

Text-to-image AI tools, such as Midjourney and DALL-E, disrupt this traditional two-phase linear workflow, transforming it into iterative cycles of "searching and judging." These AI tools quickly generate complete visual output based on user-provided text prompts. However, AI-generated images rarely match exactly what creators have in mind. This discrepancy arises from both the inherent challenge of clearly communicating complex visual ideas through language inputs and from the stochastic nature of AI-generated outputs, which introduces randomness into each attempt.

Consequently, creators engage in a cycle of evaluating AI outputs and deciding whether to stop or continue working on them. In the latter case, creators modify their prompts or explore new concepts to guide AI toward alternative solutions. Each iteration carries uncertainty, potentially diverging significantly from the desired outcome. Thus, creators must strategically balance the quality achieved through iterative refinement against the cost of multiple attempts. Unlike the traditional linear process, AI-assisted illustration involves the continuous exploration of possible visual ideas.

3 Results

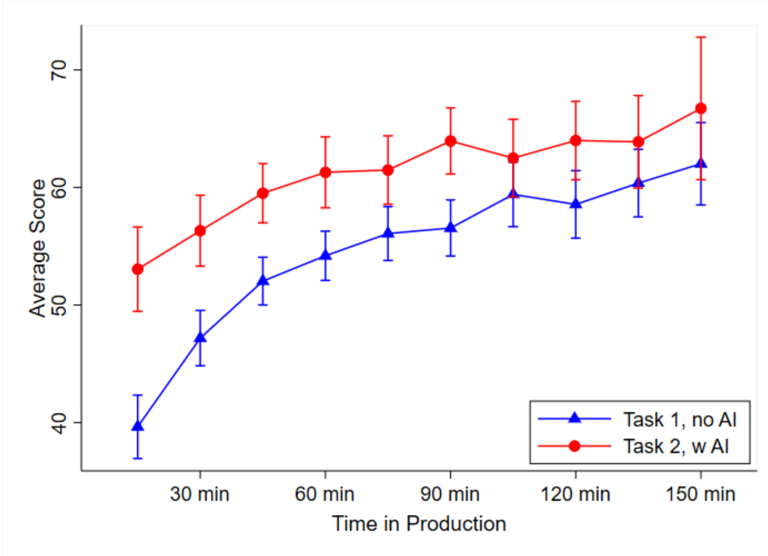
3.1 Technological Change: Time-Quality Relationship

We first examine how AI affects the relationship between time spent and quality of the output. To measure the quality achieved at different times, we extracted image snapshots every 15 minutes from video recordings that capture the creators' production process. Expert evaluators then rated the quality of these snapshots.[8] Our analysis focuses on AI adopters within the treatment group,

[7] We reviewed all process videos and identified the completion of ideation as the point when the creator finished sketching the composition and started drawing precise linings.

[8] Of the original 219 participants, 146 provided complete video data. The remaining participants were excluded from the time-quality analysis due to file errors. Those included in the analysis are slightly older and have, on average, 0.3 more years of education, but otherwise exhibit similar characteristics.

Figure 1: Time-quality relationship



Notes: This figure plots the average quality of illustrations over time, along with 95 percent confidence intervals, for participants in the treatment group who chose to use AI in the second task. The red curve represents their scores in Task 2 (with AI), while the blue curve shows their scores in Task 1 (without AI). Average scores are plotted at 15-minute intervals. AI adoption is defined as either self-reported use in the exit survey or observed use in the video recording.

that is, the 79% of participants who utilized AI in their second illustration task. We directly compare the quality of their outputs produced with AI to their outputs without AI, conditional on AI adoption in the second illustration.

Figure 1 plots the average quality of images captured at successive intervals (15, 30, 45 minutes, etc.) among AI adopters. It is important to note that the average quality at each point is conditional on creators continuing to work, and therefore reflects both quality improvements and composition changes in the pool of active creators over time. Robustness checks confirm that the observed patterns persist even after accounting for these composition effects. The blue curve illustrates the time-quality relationship when creators work without AI (their first illustration task). It demonstrates an upward trend in quality with time spent. However, the quality gain appears to slow down over time, suggesting diminishing returns to time spent on the task.

The red curve illustrates the time-quality relationship when creators employ AI. Compared to the blue curve (no AI), a prominent feature is that AI shifts the entire time-quality curve upward, enabling creators to consistently achieve higher quality at any given point in time. However, the quality differences between AI-assisted and non-AI methods diminish and become statistically insignificant after approximately 90 minutes, a feature we examine in detail below. The elevated time-quality curve indicates that creators using AI can either attain higher quality within a fixed amount of time or achieve the same quality level in substantially less time. For instance, the quality reached at the 75-minute mark with AI matches the quality produced at approximately 150 minutes without AI.

In addition to shifting the overall time-quality curve upward, AI also changes its shape in two ways. First, AI substantially accelerates quality improvement in the early stages of the creative process. Specifically, at the 15-minute mark, the creators using AI achieved an average quality score of 53 points, significantly higher than the average score of 39 points obtained without AI.

Second, after the initial rapid improvement, AI reduces the subsequent rate of quality gain considerably. Consequently, the quality gap between AI-assisted and non-AI-assisted illustrations narrows over time. As mentioned previously, conditional on working the full 150 minutes, the quality differences between AI-assisted and traditional methods are no longer statistically significant.

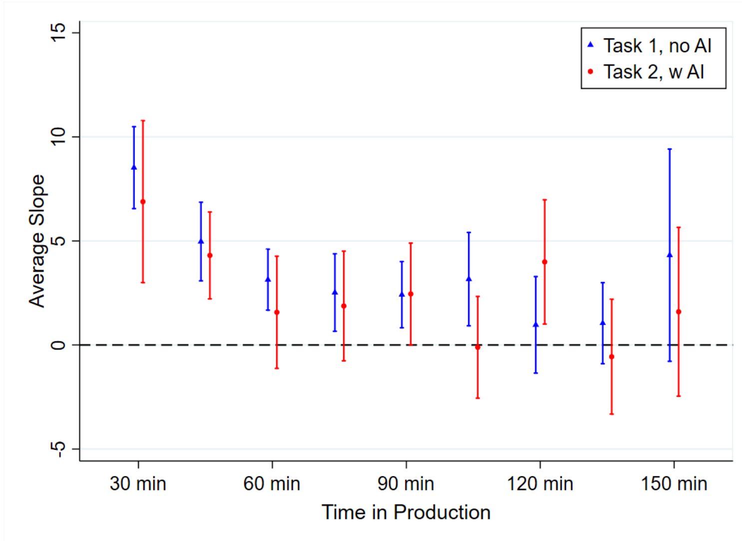
To further illustrate how AI changes the slope of the time quality curve, Figure 2 plots the average incremental quality improvement between adjacent time intervals (e.g., from 15 to 30 min, 30 to 45 min, etc.).[9] Without AI, incremental quality gains remain strictly positive until the 120-minute mark, indicating consistent and sustained improvement throughout most of the production process. In contrast, quality improvements with AI are consistently lower than those achieved through traditional methods, indicating that quality gains plateau more quickly when creators use AI.

Notably, by the 60-minute mark, the quality improvement with AI becomes statistically indistinguishable from 0, suggesting that subsequent time spent yields little additional benefit. This change in the shape of the time-quality curve highlights a key aspect of AI usage: creators reach a quality plateau earlier, whereas traditional methods continue to yield steady, albeit diminishing, quality improvements over a longer duration.

These observed changes in the time-quality curve—particularly its changed shape—reflect AI's role in assisting the creative process. Specifically, AI enables creators to quickly generate detailed illustrations from initial input (prompts), resulting in a rapid initial increase in quality. However,

[9] We exclude the 0-15 minute interval, as its incremental change is identical to the initial quality measure shown previously in the time-quality curves.

Figure 2: Slope: Quality Change over 15 Minute Interval



Notes: This figure plots the average change in illustration quality over each 15-minute interval, along with 95 percent confidence intervals, for participants in the treatment group who chose to use AI in the second task. The red curve represents quality improvements in Task 2 (with AI), while the blue curve shows quality improvements in Task 1 (without AI). AI adoption is defined as either self-reported use in the exit survey or observed use in the video recording.

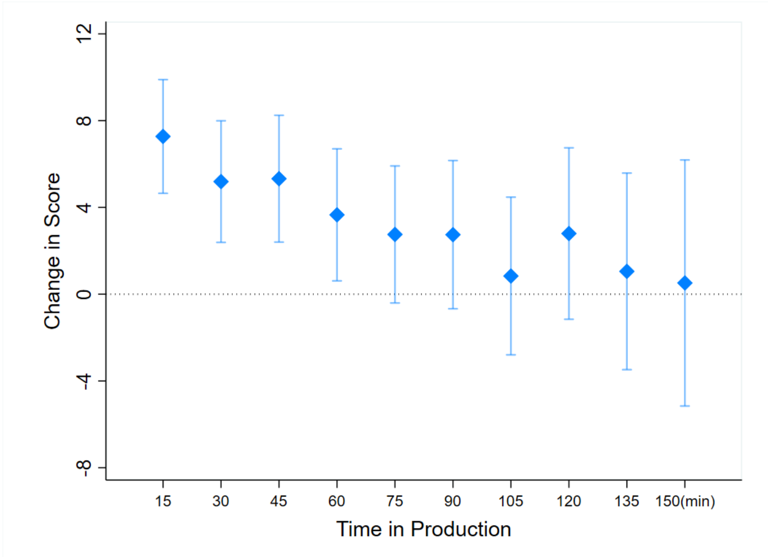
precisely because AI-assisted outputs achieve higher quality levels early on, further improvements become increasingly difficult over time: subsequent quality gains require fine-tuning of details and exploration of ideas, tasks that do not necessarily improve quality. In contrast, quality improvements without AI arise primarily from manual implementation of details, leading to a steady and sustained increase in quality throughout most of the production process.

Discussion. Our analysis above is carried out on creators who stop their work at different times. As creators exit the task at varying intervals, the observed quality difference between AI-assisted and non-AI-assisted outputs could partly reflect changing participant compositions rather than AI-driven quality changes. In other words, our findings above may capture the composition effect.

To account for this, we estimate the quality difference between AI-assisted and traditional outputs using a difference-in-differences (DID) framework that includes creator fixed effects.[10] The coefficients capture within-creator changes in quality attributable to AI adoption. Figure 3 shows that AI significantly increases quality during the first 60 minutes; thereafter, the magnitude of the

[10]The DID estimates utilize all participants and thus represent a lower bound for AI's impact, as the presence of non-adopters in the treatment group may dilute the estimated treatment effects.

Figure 3: Within-person Quality Gain by AI



Notes: This figure plots point estimates and 95 percent confidence intervals for the estimated impact of being assigned to the treatment group (with AI) on illustration quality at each time interval. The analysis uses process data from all 219 participants. Each diamond represents the estimated effect at given time interval. The specification includes individual fixed effects and time-interval fixed effects.

improvement decreases and becomes statistically insignificant after 90 minutes. These results align with our findings that AI primarily enhances early-stage quality, with diminishing returns during the subsequent refinement phase.

As an additional robustness check, we investigate whether the observed changes in the time-quality relationship differ by creators' stopping times. Appendix Figure A.4 plots time-quality curves separately for creators finishing earlier versus later, divided at the median duration in their first illustration task (120 minutes). The figures indicate that AI consistently accelerates initial productivity in both groups. Quality plateaus earlier for fast-paced creators, reflecting their decision to finish the task sooner.[11] Taken together, these findings confirm that AI's impact on the time-quality relationship is robust across different creator groups, suggesting that differential attrition is not driving our primary results.

Lastly, we conduct a placebo test by examining the time-quality relationships among participants in the control group and non-adopters within the treatment group. Figure A.3 reveals that their time-quality trajectories remain consistent across both illustrations. This consistency confirms

[11] Among fast-paced creators, some increased time in the second (AI-assisted) illustration task compared to their first. As a result, the corresponding time-quality curve for their second illustration thus extends beyond 120 minutes.

that the observed curve indeed captures inherent workflow patterns. Moreover, the consistency observed among non-adopters, who received AI-related instructions but chose not to adopt the tool, suggests that the experimental instructions alone did not affect their creative process.

3.2 Human Responses

We now analyze how the changes in the relationship between time and quality influence the creators' decisions on time spent and the resulting quality obtained. Section 3.2.1 first describes the joint changes in time use and quality achieved following AI adoption. We then examine in detail, in Subsection 3.2.2, how creators adjust their time inputs in response to this changed time-quality relationship. Finally, Subsection 3.2.3 presents the change in the overall distribution of the quality of the output, which reflects the combined effects of technological changes and human responses.

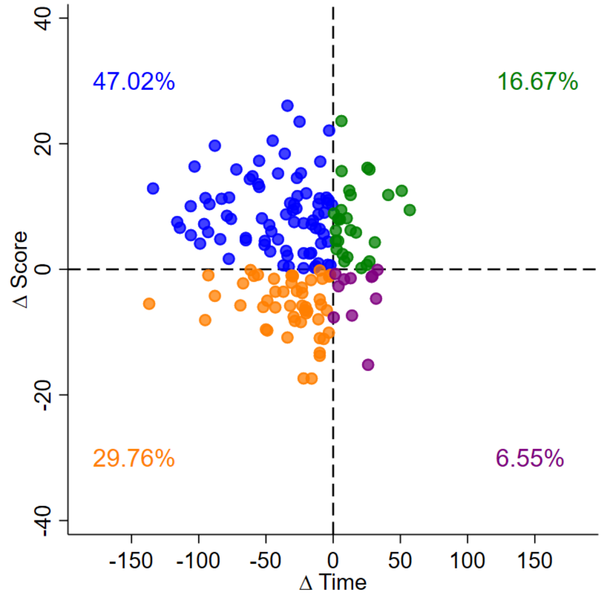
3.2.1 Joint Changes in Time and Quality

Figure 4 illustrates the joint changes in time spent and output quality achieved by creators after adopting AI. Figure 4 shows that around 64% of the creators achieve higher output quality compared to their earlier work without AI. In terms of time use, 77% of the creators reduce the time they spend on their work.

However, it is important to note that time spent and quality obtained are not independent outcomes: they are inherently connected through the underlying time-quality relationship. This link implies that the distributions of the changes in time and quality are not independent. For instance, the bottom right quadrant is notably sparse, reflecting that very few creators simultaneously spend more time, yet achieve lower quality. More notably, Figure 4 reveals that among creators who experienced lower quality, the vast majority (30% out of the 36%) also reduced their time spent on the task.

This pattern suggests that creators deliberately adjust their time choices in response to technological change. If they were randomly deciding how long to spend on the task, around 50% of the creators would reduce their time inputs, and the other 50% would increase. In this case, there would probably be more than 64% of creators who would obtain a higher quality: after all, the time-quality curve with AI lies entirely above the curve without AI. In addition, if creators were solely targeting a specific quality level independent of time considerations, one would expect

Figure 4: Joint Change in Time-Quality after using AI



Notes: This figure shows the joint change in time spent and output quality between Task 1 (without AI) and Task 2 (with AI available) for all participants in the treatment group. Each dot represents one participant. The figure plots the change in time on the x-axis and the change in quality score on the y-axis. The percentages indicate the share of participants falling into each quadrant.

that half of the creators would experience a quality decline after adopting AI. This is not what is observed.

To the extent that the creators deliberately adjust their time choices, the distribution of time and quality change should then react to the shape of the time-quality curve, which is affected by the AI use. We compare the observed joint distribution of time and quality changes with and without AI, and reject the null hypothesis that the treatment and control groups have the same distribution of time-quality changes ($p = 0.005$).

To account for the strategic actions in response to the technological changes, we note that the behaviors of the creators can be understood via the neoclassical model of labor supply, where individuals allocate limited time between work and leisure. In this framework, the upward shift in the time-quality curve introduced by AI functions similarly to an income effect—enabling creators to achieve higher quality with the same time inputs, thus potentially reducing their incentives to allocate more time to work. Meanwhile, the changed slope of the time-quality curve affects the relative returns to additional work time: the initial acceleration of productivity incentivizes greater time input, but the subsequent plateau in productivity growth encourages creators to stop sooner. In summary, the income and substitution effects both push toward reduced time spent on the task, though their effects on qualities are more complicated because the income and substitution effects go in opposite directions.

However, unlike the standard labor supply model, the returns to additional time spent in creative output are not constant. Specifically, the time-quality relationship is non-linear, and the degrees of non-linearity (the shape of the curve) differ before and after AI use. We explore this implication in detail in the following subsection.

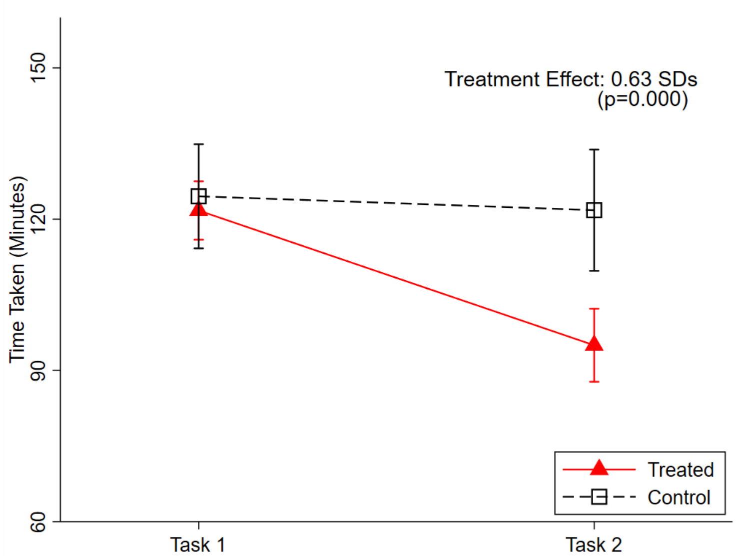
3.2.2 Strategic response in time spent

We now examine in detail how creators adapt their time use in response to the changed time-quality relationship introduced by AI. Figure 5 presents the average effect of AI assistance on creators' time spent, estimated using a standard difference-in-differences (DID) regression framework. In the first task without AI, the creators spent an average of 122 minutes. In the subsequent AI-assisted task, the creators in the treatment group significantly reduced the time they spent by 24 minutes, equivalent to a 0.63 SD decrease, compared to the control group. Figure A.7a further compares the time reductions across creators with high and low baseline skills, measured based on their performance in the first task without AI. The results indicate similar magnitudes of time reduction across skill groups, suggesting that strategic adjustments in time spent were widespread among creators rather than concentrated within particular skill segments.

The reduction in the average time spent by the creators, however, masks important underlying changes in the full distribution of time used. Figure 6 highlights these distributional changes. Without AI, most creators work up to the maximum allowed duration, resulting in a single peak near the 150-minute time limit. With AI, the distribution of time use becomes bimodal, with a new peak emerging around 60 minutes.

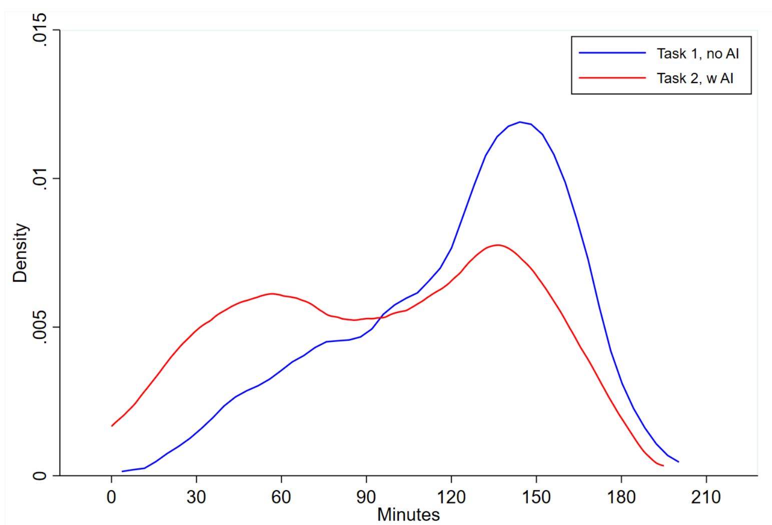
This bimodal pattern again suggests that the creators actively adjust their time spent in response to changes in the time-quality relationship. Recall that with AI assistance, quality improvements beyond 60 minutes become statistically indistinguishable from zero. When additional time no longer produces quality gains, creators are more likely to stop earlier. Note that the new peak around 60 minutes emerges only among AI-adopters. Non-adopters and creators in the control

Figure 5: Average Effects on Time Spent



Notes: This figure reports the average time taken to complete each task, along with 95 percent confidence intervals, separately for the treatment and control groups. The treatment effect is estimated using a regression where the outcome is the within-individual change in time taken (Task 2 minus Task 1), and the explanatory variable is a treatment group indicator. Robust standard errors are used.

Figure 6: Distribution of Time Spent



Notes: This figure shows the distribution of time taken to complete the first task (without AI) and the second task (with AI available) for all participants in the treatment group. The blue curve represents Task 1, and the red curve represents Task 2.

group maintain a single-peaked time distribution, further supporting that this bimodal pattern arises from the changed time-quality relationship rather than random (Appendix Figure A.6).

While it is natural to think that the creators are more likely to stop working when the returns to additional time spent become low, we also check it formally. Figure 7 plots the creators' average stopping probability against the quality improvement achieved in the past 15 minutes. We observe a clear negative relationship: a lower recent quality improvement corresponds to a higher chance of stopping. Most stopping occurs when the quality gain within the preceding 15-minute interval is below 10 points.

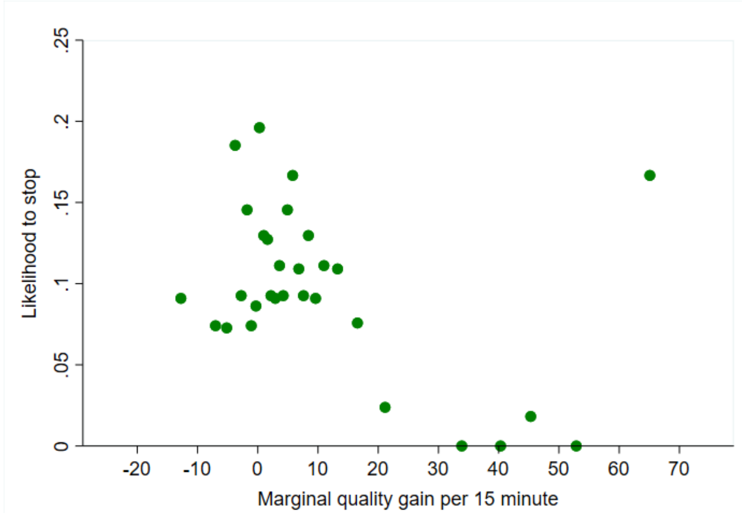
Although, on average, the creators are more likely to stop when the return is lower, we also note that there is heterogeneity in responses. The rightmost bin consists of a small number of creators who stopped around 15 minutes after achieving substantial quality gains. This group suggests that some creators also behave like "target earners": they stop the work once a desired quality threshold is reached. But such creators constitute only a small fraction of our sample (about 6%), and most instances of this behavior occur within the treatment group, when the creators were equipped with AI assistance.

Finally, we regress an indicator variable for stopping (equal to 1 if the creator stops, 0 otherwise) on the recent 15-minute quality improvement. The estimated coefficient is negative and statistically significant, indicating that an increase of 10 points in quality gain per 15 minutes is associated with a three-percentage-point decrease in the probability of stopping working. Conducting the same regression separately for the control group yields a nearly identical coefficient.

The striking similarity in these estimates reveals a fundamental stability in creators' decision-making processes: despite significant technological shifts, creators maintain a consistent balance between time spent and quality gained. Specifically, their marginal rate of substitution between time spent and quality gained, which are measured by these coefficients, remains unaffected by the adoption of AI technologies.[12]

[12] The similarity of estimates across treatment and control groups also suggests that the marginal cost of time may not drastically change with AI adoption. If it did, we would expect AI adopters to rebalance their choice between time spent and quality gained.

Figure 7: Probability of Stopping by Quality Improvement



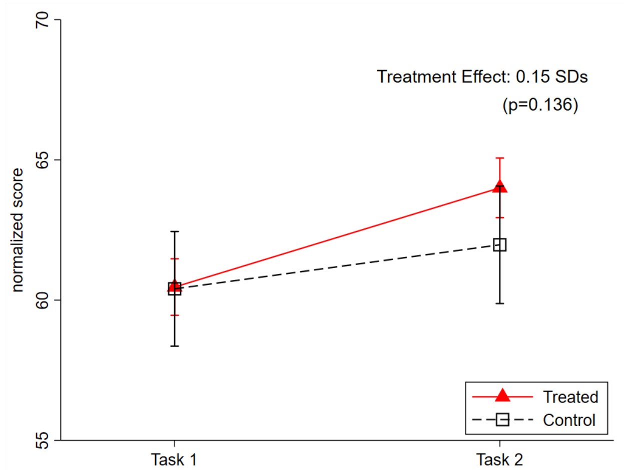
Notes: This figure shows the relationship between marginal quality gained over the past 15 minutes and the likelihood of stopping. Creator-time observations are binned together according to the marginal quality over the past 15-minute interval. The sample includes all participants.

3.2.3 Combined Effects on Quality and Implications on Inequality

Lastly, we examine how the altered time-quality relationship and the resulting adjustment in creators' time spent jointly shape the distribution of output quality and discuss the implications for inequality. Figure 8 shows that the average quality slightly increases by 0.15 standard deviations, although this number is not precisely estimated. As mentioned earlier, the change in quality reflects two opposing effects: better quality for any given time spent (the income effect) and lower return in time because of the flattened time-quality curve (the substitution effect). This modest net improvement in quality suggests that the income effect appears to slightly outweigh the substitution effect.

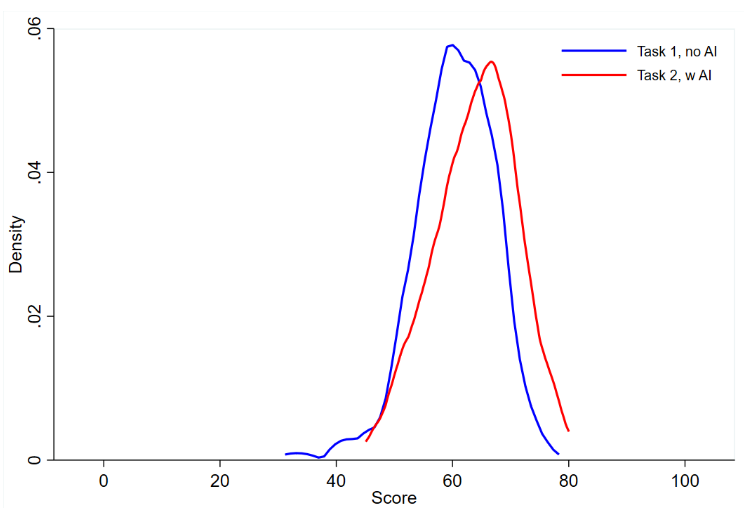
In addition to the changes in average quality, we also examine changes in the entire quality distribution. Figure 9 shows that AI assistance reduces the share of low-quality outputs while simultaneously increasing the proportion of high-quality work. The cumulative distribution similarly indicates that AI-assisted outputs achieve higher quality levels at every percentile compared to outputs created without AI. Additionally, output similarly does not decline with AI adoption (Appendix Figure A.8), suggesting that collective diversity is preserved despite reductions in time spent.

Figure 8: Average Effects on Final Output Quality



Notes: This figure reports the average quality of final output for each task, along with 95 percent confidence intervals, separately for the treatment and control groups. The treatment effect is estimated using a regression where the outcome is the within-individual change in quality of final output (Task 2 minus Task 1), and the explanatory variable is a treatment group indicator. Robust standard errors are used.

Figure 9: Distribution of Output Quality



Notes: This figure shows the distribution of final output quality for the first task (without AI) and the second task (with AI available), separately for all participants in the treatment group. The blue curve represents Task 1, and the red curve represents Task 2.

Figure 9 also shows that the distribution of the final output quality remains single-peaked. This may appear surprising because the distribution of time spent is bi-modal. One explanation for this is that the AI has weakened the relationship between time spent and quality spent, particularly after minute 60. As a result, the distribution in time spent is no longer strongly linked to the distribution in quality.

Specifically, the average output quality at minute 60 is 64.45 points, whereas by minute 150 it only slightly increases to 65.40 points—a negligible improvement given the substantial additional time investment. In fact, the correlation between the total time spent and the final output quality is close to zero and statistically insignificant (Appendix Figure A.11). The near-zero correlation between time and quality suggests that final output quality mainly depends on creators' initial idea generation and conceptualization. In other words, creative input during the first 60 minutes drives quality differences.

This pattern contrasts with the scenario without AI, where the correlation between time spent and output quality remains positive. In the absence of AI, every additional 10 minutes increases output quality by approximately 0.3 points, a statistically significant improvement ($p=0.03$). The consistent incremental quality gain indicates that creators' implementation skills and the marginal cost of their time investment play substantial roles in determining final output quality when AI assistance is unavailable.

Implications on Inequality. The change in the skills necessary for quality naturally leads to the discussion of how AI adoption affects inequality among creators. Whether AI equalizes human performance or exacerbates existing gaps remains an open empirical question with mixed findings in the literature. For instance, Noy and Zhang (2023) and Brynjolfsson et al. (2025) find that less-experienced and lower-skilled workers benefit more, whereas Toner-Rodgers (2024) and Otis et al. (2024) document greater gain for top-performing individuals.

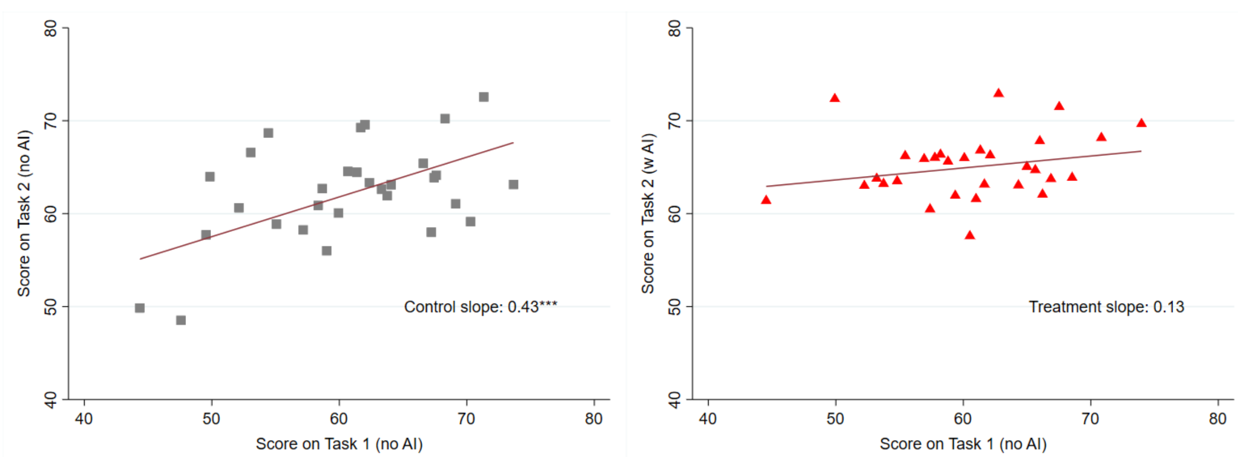
We provide two pieces of evidence suggesting that AI adoption may reduce inequality between high- and low-ability creators, defined by their baseline illustration performance without AI assistance. First, Appendix Figure A.7b examines heterogeneous quality effects by baseline performance quartiles, revealing greater quality gains among lower-skilled creators. Although the differences across quartiles are statistically insignificant, the observed patterns are consistent with

AI compressing the productivity distribution.

Second, Figure 10 shows that AI adoption weakens the correlation in individual performance between tasks. In the control group (without AI), productivity inequality persists strongly: creators who perform better on the first illustration task also tend to perform better on the second, with a positive and statistically significant correlation of approximately 0.43. In contrast, among AI adopters, this correlation falls substantially to just 0.13 and is statistically insignificant.

One explanation for this finding is that AI reduces the role of manual implementation skills, mitigating skill-based inequality. Without AI, creators differ significantly in implementation abilities, such as drawing technique, and these individual differences strongly correlate with performance across tasks. With AI assuming responsibility for much of the implementation process, these specialized technical skills become less relevant, weakening the performance correlation between tasks. Our findings point toward an increased importance of creative skills, along with a reduction in inequality in technical implementation skills.

Figure 10: Quality Correlation between Two Illustrations



(a) Control Group (b) AI Adopters

Notes: Output observations are binned together according to the first illustration score. Within each bin, the figures plot the average second illustration task for the observations in the bin separately by control (a) and AI-adopters (b). The slopes are estimated from a creator-level linear regression of second illustration score on first illustration score.

4 Conclusion

This paper examines how AI affects the creative process by analyzing changes in time-quality relationships and creators' strategic responses. Our analysis reveals three key findings. First, AI not only boosts the time-quality curve, but also changes its shape. AI accelerates quality gains in the initial phase of production, but this improvement plateaus over time. The return in quality to time spent is not statistically different from zero after minute 60. In summary, AI makes the time-quality curve higher, but also flatter.

Second, in response to this flattened time quality curve, 77% of creators reduce their time spent. More importantly, 30% produced lower-quality work despite the time-quality curve being lifted up. But the vast majority of these creators have reduced the time spent. We also find that the time distribution shifts from single-peaked to bi-modal when AI is used, with a new peak emerging around 60 minutes, when the return in quality to time becomes not statistically different from zero. These findings suggest that creators make deliberate trade-offs between time spent and quality gained. The technological change from AI, as a result, appears to induce human responses that are biased toward time savings rather than quality enhancement.

Third, despite these strategic responses of the creators, we observe an overall improvement in the quality distribution, although the average increase in quality is not statistically significant. The distribution remains single-peaked, but now contains fewer low-quality outputs. These findings suggest that AI has the potential to reduce inequality by narrowing disparities in technical implementation skills, which traditionally require substantial time and effort to develop and apply effectively. As a result, the determinants of final output quality shift increasingly toward creators' capacities for generating novel and imaginative designs—abilities that tend to become evident earlier in the production process. These changes suggest that AI can elevate creativity and innovation as key differentiators while diminishing the advantage previously held by creators with extensive technical proficiency.

While our findings suggest that AI primarily drives technological change toward time-saving rather than quality-enhancement, it is important to note that our analysis does not account for potential general equilibrium effects. Specifically, as more products are created quickly but with moderate quality, market competition will naturally drive down their prices, paradoxically incentivizing producers to differentiate through the ability to generate higher-quality products.[13]

The pursuit of higher-quality work will pose significant challenges for organizations that produce knowledge work. When technological advancements flatten the quality-time curve and diminish the returns on time spent, motivating creative workers becomes more challenging. Traditional pay-for-performance incentives, for example, will become less effective. Organizations then need to figure out how to redesign their motivation systems. More research on this topic is needed.

[13]This observation extends to scenarios beyond the art market. For instance, in educational settings, AI enables students to complete assignments and projects more quickly and at acceptable quality levels. However, if most students produce similarly moderate-quality work, instructors must reconsider how they evaluate and assign grades to such outputs.

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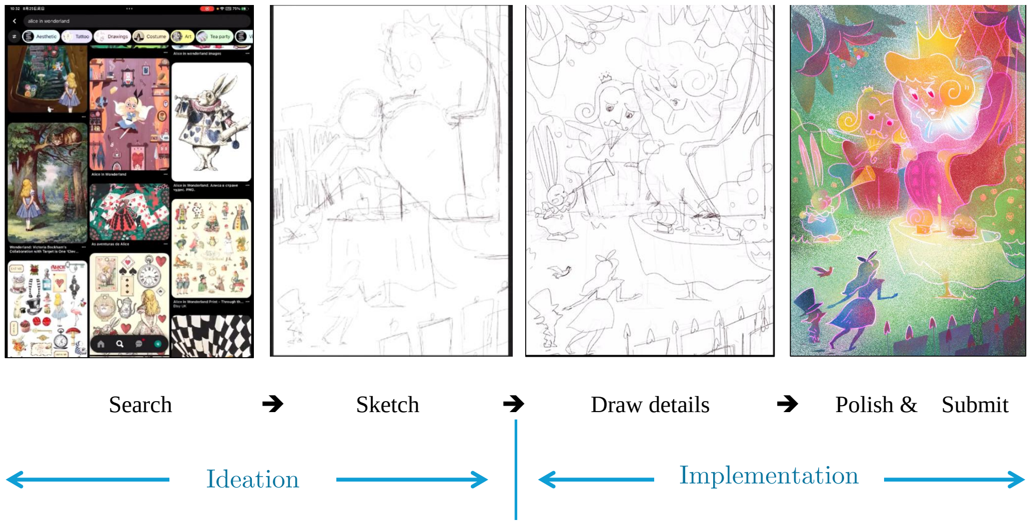
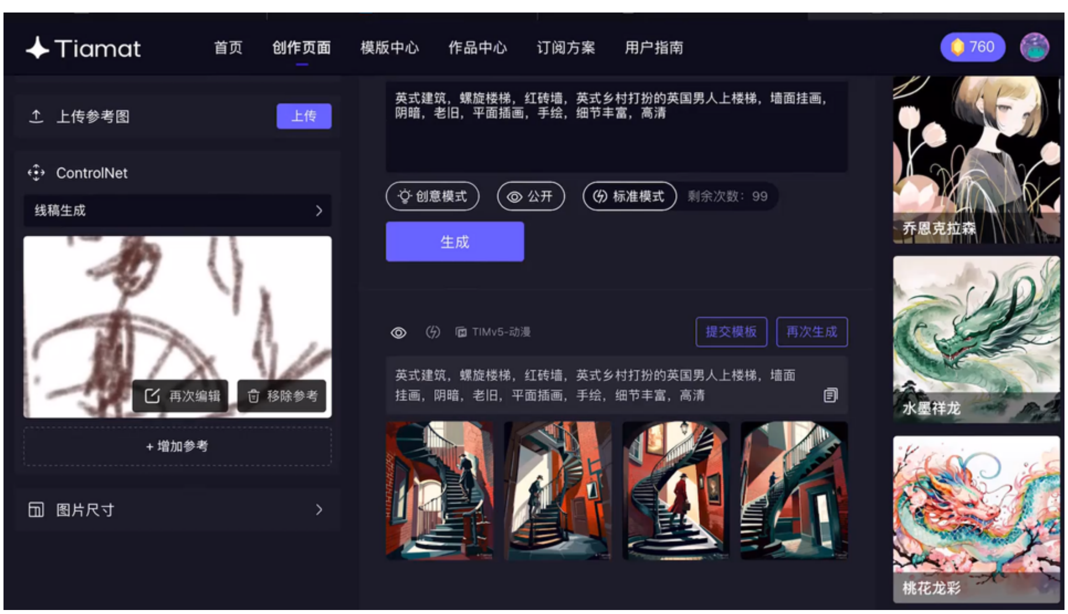
A Appendix Tables and Figures

Figure A.1: Sample flow of drawing illustration without AI



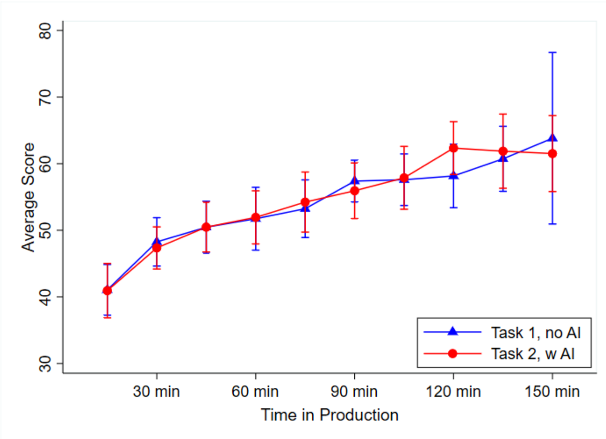
Notes: This figure shows a sample workflow of drawing an illustration without AI.

Figure A.2: Sample AI user interface

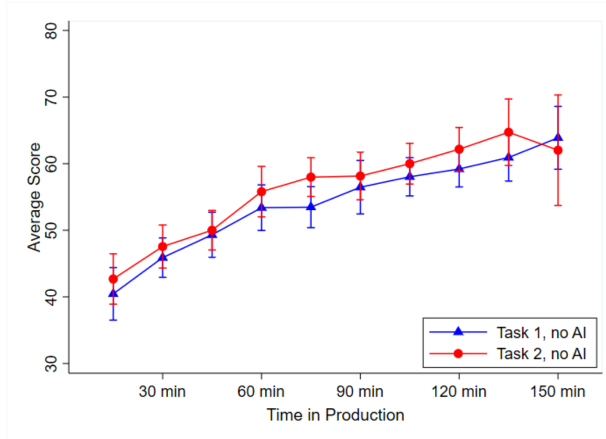


Notes: This figure shows a sample of creator using AI to generate images via text prompts.

Figure A.3: Time-quality relationship for control group and non-adopters in treatment group



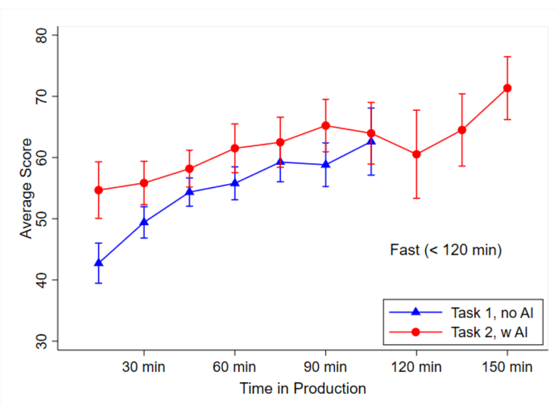
(a) Non-adopters



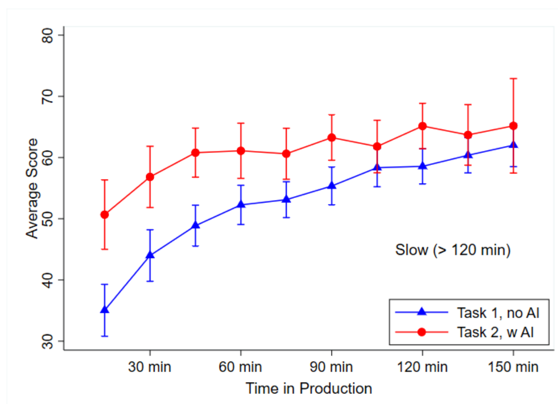
(b) Control Group

Notes: This figure shows the time-quality relationship for non-adopters in the treatment group (a) and control group (b). Each point is the average quality of images captured at the corresponding time interval, along with 95% confidence interval.

Figure A.4: Time-quality Relationship by Time Spent in Task 1



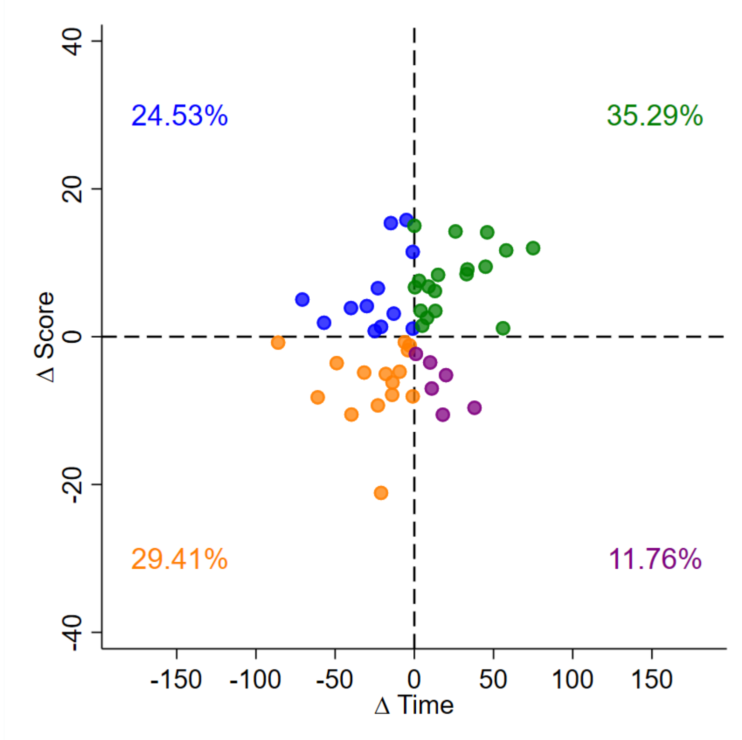
(a) Stop early in Task 1



(b) Stop late in Task 1

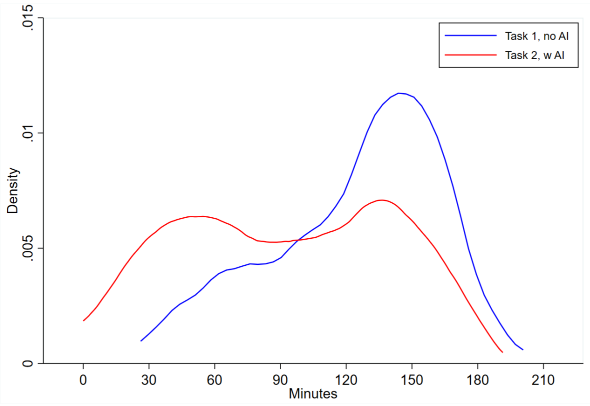
Notes: This figure shows the time-quality relationship for creators finishing early or late, split by the median time use in the first illustration. Each point is the average quality of images captured at the corresponding time interval, along with 95% confidence interval.

Figure A.5: Change in Quality and Time (Control Group)

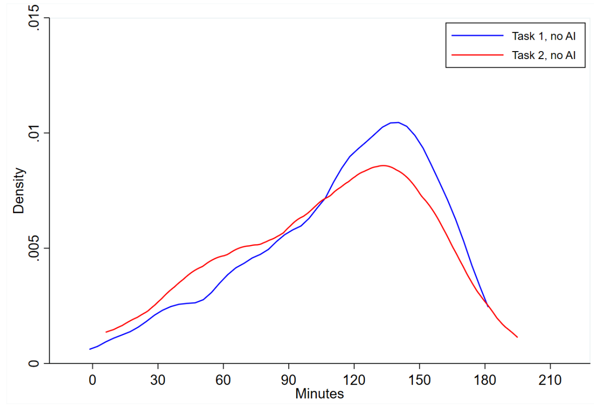


Notes: This figure shows the joint change in time spent and output quality between Task 1 (without AI) and Task 2 (with AI available) for participants in the control group. Each dot represents one participant. The figure plots the change in time on the x-axis and the change in quality score on the y-axis. The percentages indicate the share of participants falling into each quadrant.

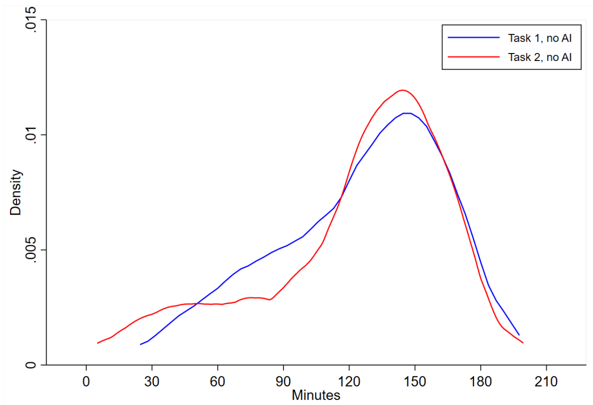
Figure A.6: Distribution of Time Taken by AI usage



(a) AI adopters



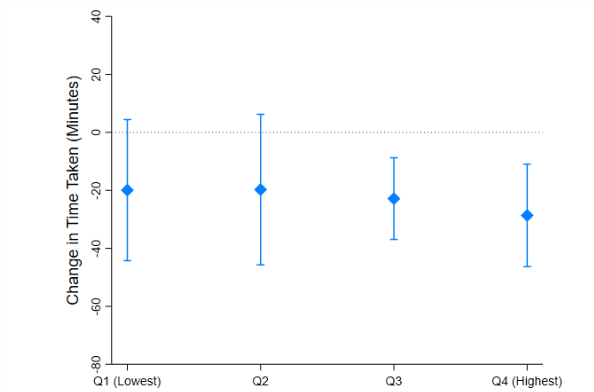
(b) Non-adopters



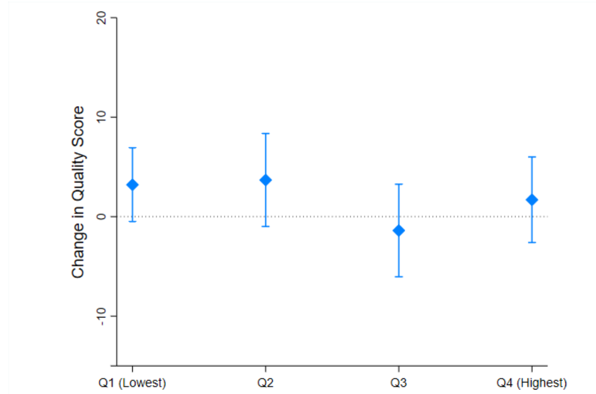
(c) Control group

Notes: This figure shows the distribution of time taken to complete the first and second illustration task for AI-adopters in the treatment group (a), non-adopters in the treatment group (b), and the control group. The blue curve represents Task 1 (without AI), and the red curve represents Task 2 (with AI available for the treatment group only).

Figure A.7: Heterogeneous Effects on Time Spent and Quality by Baseline Skills



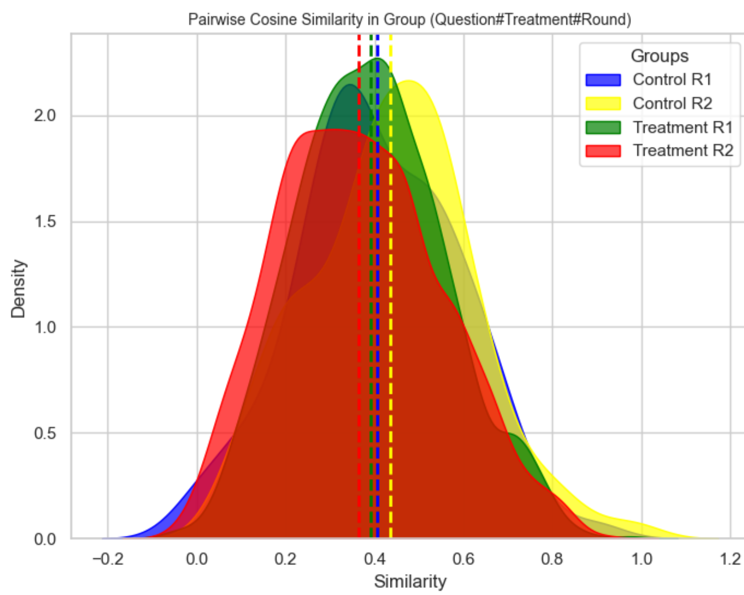
(a) Time use



(b) Output Quality

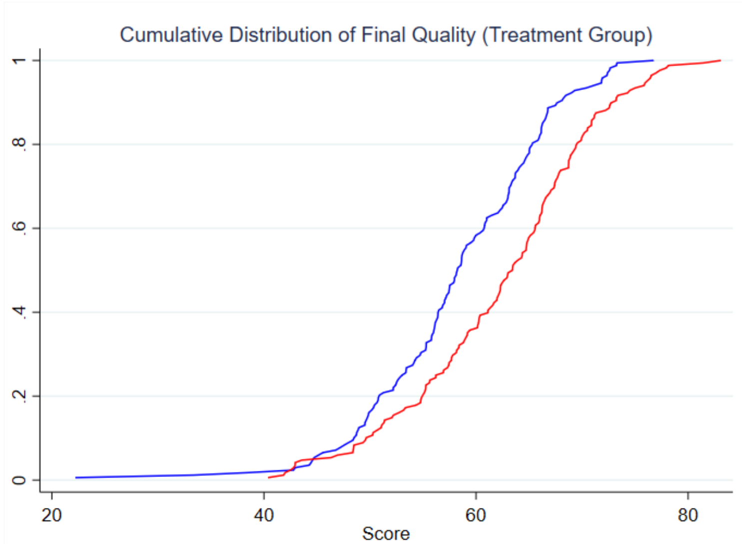
Notes: The figures plots the heterogeneous effects on time use (a) and output quality (b) by workers' baseline skills, measured by quality ratings in the first illustration task (without AI).

Figure A.8: Similarity among output



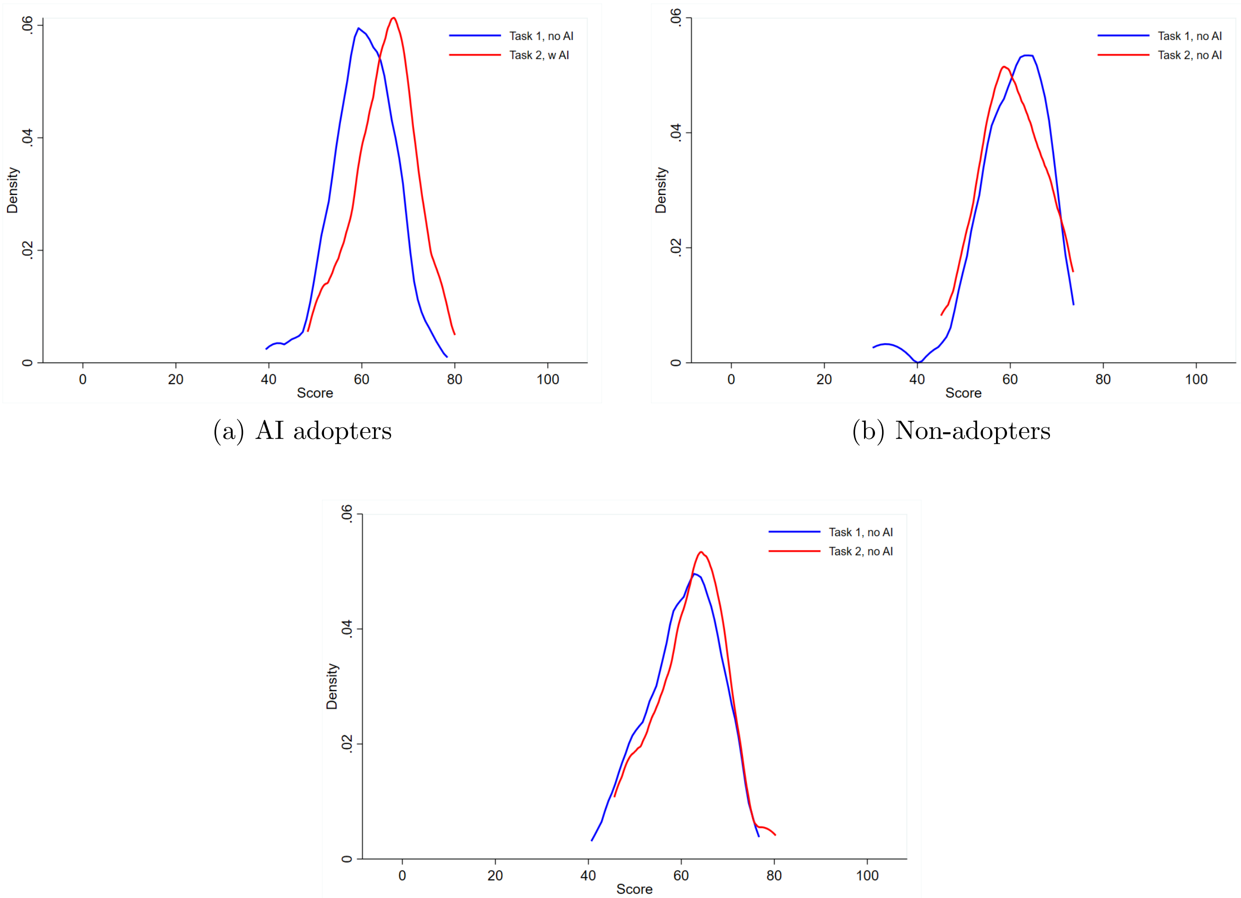
Notes: This figure show the distribution of pairwise cosine similarity among the outputs for each group. Specifically, we first extract key elements in the illustrations and map them into vectors. Similarity is measured by the distance of the corresponding embedding vectors using prompt generated by BLIP-2 (Li et al., 2023) and latest version of sentence bert (Reimers and Gurevych, 2019) ('paraphrase-multilingual-MiniLM-L12-v2').

Figure A.9: Cumulative Distribution of Final Quality (Treatment Group)



Notes: This figure shows the cumulative distribution of final outputs for all participants in the treatment group. The blue curve corresponds to Task 1 (without AI) and the red curve corresponds to Taks 2 (with AI available).

Figure A.10: Distribution of final output quality by AI usage



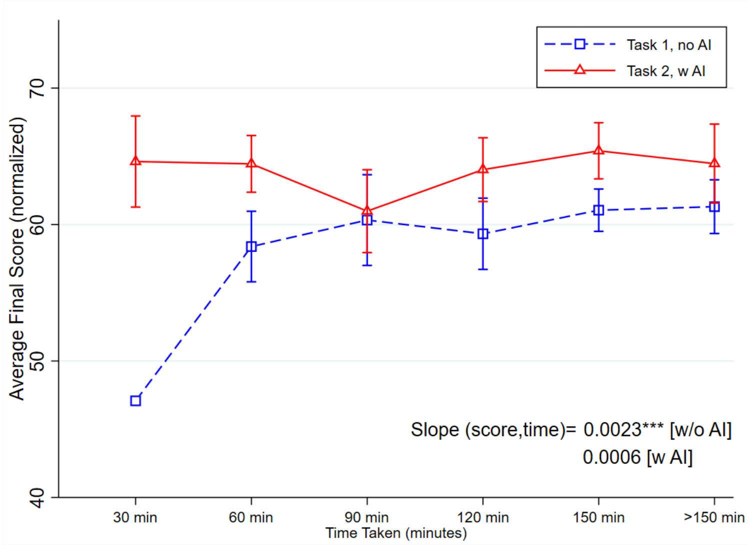
(a) AI adopters

(b) Non-adopters

(c) Control group

Notes: This figure shows the distribution of output quality for each task for AI-adopters in the treatment group (a), non-adopters in the treatment group (b), and the control group(c). The blue curve represents Task 1 (without AI), and the red curve represents Task 2 (with AI available for the treatment group only).

Figure A.11: Quality of final output by time taken



Notes: Creator-task level observations are binned together according to the time spent on the task. Within each bin, the figure plots the average score of final output for the observations in the bin separately by first and second illustration task. The correlation are estimated from a creator-task level correlation between time spent and final score achieved.

Table A.1: Regression Results for Stopping Decision

	Control Group		Treatment Group	
	Task 1	Task 2	Task 1	Task 2
Slope	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.107***	0.123***	0.101***	0.172***
	(0.024)	(0.027)	(0.017)	(0.034)
ID Fixed Effects	✓	✓	✓	✓
Observations	195	187	691	559
R-squared	0.115	0.118	0.147	0.242

Notes. This table reports estimates of the probability of stopping drawing as a function of marginal quality gain over the preceding 15-minute interval. The dependent variable is an indicator equal to 1 if the creator stopped drawing before the next 15-minute window. Marginal quality is defined as the change in output quality between two adjacent intervals. All regressions include creator fixed effects. Robust standard errors are in parentheses.