The Role of Generative AI in P2P Rental Platforms: Investigating the Effects of Timing and Interactivity on User Reliance in Content (Co-)Creation Processes

Completed Research Paper

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Abstract. Peer-to-peer rental platforms like Airbnb increasingly rely on textual marketer-generated content to differentiate listings and inform consumer decisions. Recent advances in generative AI (genAI) have created new opportunities to enhance content creation by, for example, providing users with writing suggestions when composing textual listing descriptions. Despite growing interest in human–genAI collaboration, little is known about how the timing of genAI suggestions (before, during, or after in the content (co-)writing process) and the interactivity of genAI assistance (system-initiated versus user-prompted suggestions), affect user reliance on genAI. To address this gap, we conducted a 3×2 between-subjects experiment (n = 244) analyzing how these factors influence reliance through cognitive load. Results show that earlier genAI suggestions significantly increase reliance, with user-prompted assistance providing a marginal additional effect, while higher cognitive load reduces reliance. These findings thus advance research on human–genAI collaboration and offer guidance for effective content co-creation with genAI.
Keywords: Human-genAI collaboration, Co-writing, P2P rental platforms, Reliance

1 Introduction

Peer-to-peer (P2P) platforms play a pivotal role in the contemporary digital economy, fundamentally transforming how individuals exchange goods, services, and information (Einav et al. 2016). By facilitating direct interactions and transactions between peers, these platforms enhance user autonomy by providing greater personalization and choice. Moreover, they underscore the pivotal role of content creation, effectively decentralizing significant aspects of the content generation process and transferring them directly to individual users (Sousa et al. 2019, Einav et al. 2016). In the context of P2P property rental platforms such as Airbnb, marketer-generated content (MGC), that is "content produced by marketers and sellers to introduce and promote their goods and to engage consumer activity on official websites or third-party platforms", plays a particularly significant role (Liang et al. 2020, 2). Created by property owners or hosts, MGC serves as a key tool for showcasing listings and conveying essential information to prospective

20th International Conference on Wirtschaftsinformatik
September 2025, Münster, Germany

guests, making it on Airbnb especially pronounced for two primary reasons (Liang et al. 2020, Goh et al. 2013). First, unlike standardized hotels, Airbnb listings differ greatly in location, amenities, and rules, requiring guests to rely on detailed host descriptions rather than prior booking experiences to find suitable options (Einav et al. 2016). Additionally, given the comparatively low frequency of user-generated reviews on P2P rental platforms relative to hotels, the diminished availability of such content amplifies the importance of MGC as a key source of information influencing consumers' booking decisions(Liang et al. 2020, Fradkin et al. 2015).

Recent advancements in genAI offer transformative opportunities for enhancing the efficiency of MGC creation in P2P rental platforms. The traditionally labor-intensive process of creating MGC, particularly detailed listing descriptions (Chen et al. 2019), can now be enhanced by genAI which can analyze the uploaded property images and generate tailored, high-quality listing descriptions, thereby significantly reducing the time required to write effective MGC (Li et al. 2024). While in theory, genAI can automate MGC production on P2P rental platforms completely, such unsupervised automation poses significant risks for both platform operators and hosts. Research indicates that unchecked genAI often generates homogenized content (Schaschek 2025, Castro et al. 2023, Agarwal et al. 2024), reducing the distinctiveness of listings and undermining a key advantage of P2P platforms: variety (Doshi & Hauser 2024, Agarwal et al. 2024, Castro et al. 2023). This convergence diminishes competitive differentiation for platforms and may erode consumer trust, as guests perceive generic descriptions as inauthentic, potentially lowering booking rates (Liang et al. 2020, Einav et al. 2016). Instead of full automation, we argue that an optimal approach to integrating genAI in P2P platforms is a human-genAI collaboration, where genAI assists hosts in co-writing listing descriptions. As an intelligent assistant, genAI can provide suggestions that hosts selectively integrate into their writing process, thereby enhancing efficiency while preserving the uniqueness and personalization of listing descriptions through human oversight.

While P2P platforms are widely adopted and scholarly interest in MGC continues to expand (Liang et al. 2020, Zhao et al. 2022, Goh et al. 2013, Yang et al. 2022), empirical research into the mechanisms and transformative potential through which genAI innovates in such (co-)creation processes remains in its nascent stages, heralding the onset of a vast and promising research frontier. A critical gap exists especially in understanding *when* and *how* genAI effectively interacts with human users in co-creation processes, as the success of human-genAI collaboration hinges on key design factors. This study addresses this gap by examining two fundamental aspects of genAI-assisted writing: (1) the timing of genAI suggestions - whether users receive them *before*, *during*, or *after* drafting and writing their listing descriptions - and (2) the level of interactivity, comparing *automated* suggestions to *user-prompted* suggestions. Against this backdrop, we intend to analyze the impact of both design factors on users' reliance on genAI-generated content, in order to provide insights into how platform operators can optimize these design elements to enhance user adoption and integration of genAI suggestions. To this end, we explore the following research question: *How do variations in the timing and interactivity of genAI assistance affect user reliance on AI-generated content suggestions in P2P rental platforms?*

To investigate our research questions, we develop a theoretical model and empirically test our hypotheses through an incentivized 3×2 between-subjects vignette-based experiment (n = 244). In doing so, our study investigates how two critical genAI design factors (the timing of genAI assistance and the level of interactivity) influence users' reliance on genAI writing suggestions in the co-creation process of writing P2P listing descriptions. By shedding light on these dynamics, we contribute a foundational framework for designing genAI writing assistants in P2P rental platforms that enhance user experience, foster meaningful human-genAI collaboration, and optimize content creation on P2P rental platforms. Moreover, we offer practical guidance for optimizing genAI-assisted content creation to balance automation with human agency.

2 Theoretical Background and Hypothesis Development

To theorize how the timing of genAI writing suggestions (whether they are presented before, during, or after users write listing descriptions), and the level of interactivity (whether suggestions are presented automatically or require user prompting) affect users' reliance on AI-generated writing suggestions, we propose the conceptual research model shown in Figure 1. To illuminate the underlying cognitive mechanisms driving reliance behaviors, we draw upon Cognitive Load Theory (CLT) (Sweller et al. 1998, Paas & Van Merriënboer 1994).

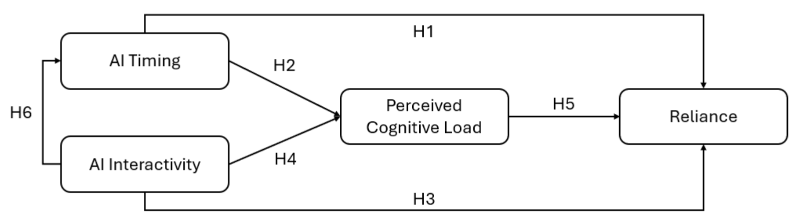

Figure 1. Theoretical research model and hypotheses

CLT posits that individuals' cognitive resources are inherently limited, and that optimal task performance depends on the effective management of cognitive load to facilitate efficient information processing and decision-making (Sweller et al. 1998). Excessive cognitive load can have deleterious consequences, such as inducing decision fatigue (Jia et al. 2022) and diminishing user satisfaction (Hu et al. 2017). Consequently, minimizing unnecessary cognitive burden has become a central objective in the design of collaborative AI systems. However, although CLT has been increasingly applied within information systems research, and a growing body of evidence demonstrates that AI design choices play a pivotal role in shaping users' cognitive load (You et al. 2022, Spatscheck et al. 2024), little is known about its role in generative AI-mediated content co-writing processes. Within this theoretical context, the timing and interactivity of genAI suggestions must be conceptualized not merely as technical configurations, but as fundamental design features that determine how cognitive load is distributed throughout the user's co-writing process. Thus, in technology-mediated co-writing environments, cognitive load is not an incidental byproduct but a direct outcome of genAI system design decisions. Specifically on P2P platforms, where content (co-)creation is inherently cognitively demanding, it is essential to understand how the timing and interactivity of genAI interventions affect users' perceived cognitive load. Only by understanding how to reduce excessive cognitive load, platforms can foster optimal reliance on AI-generated suggestions, thereby enhancing user satisfaction, improving the overall user experience, and securing competitive advantages. Accordingly, perceived cognitive load emerges as both the proximal and actionable mechanism through which genAI design features shape user reliance in genAI-assisted content co-creation. Drawing on these insights, we formulate six hypotheses in the following, with cognitive load positioned as a mediator.

2.1 The Effect of Timing on AI Reliance

The endowment effect suggests that individuals attribute higher value to resources they already possess, making them resistant to external modifications or replacements (Thaler 1980, Reb & Connolly 2007). Applied to genAI-assisted co-writing, this bias suggests users resist AI suggestions more as they progress in drafting. Early AI assistance faces less resistance since users haven't formed strong ownership over their content. However, as drafting advances, psychological ownership strengthens, making them less receptive to AI-generated text (Pierce et al. 2003), making later AI interventions feel more intrusive and less desirable. Moreover, research in decision-making highlights that people prefer to minimize cognitive demand and thus post-hoc revisions (Kool et al. 2010, Fiske & Taylor 1991). AI assistance introduced at a later stage may therefore be perceived as disrupting an already internally validated thought process, increasing resistance to adoption. As a result, reliance on AI-generated suggestions is expected to decrease progressively as users receive them later in their writing process. Thus, we hypothesize:

H1: *The later users receive genAI writing suggestions in their (co-)writing process, the less they rely on them.*

2.2 The Effect of Timing on Perceived Cognitive Load

Cognitive Load Theory posits that individuals have limited cognitive resources, and task performance depends on managing these resources effectively (Sweller et al. 1998, Paas & Van Merriënboer 1994). When genAI suggestions are introduced early in the writing process, users might integrate them seamlessly into their mental framework without needing to revise or reprocess existing content. However, when AI-generated suggestions appear later in the drafting process, we argue that users must reconcile them with their already developed structure, increasing the cognitive effort required for integration. Late-stage AI interventions require users to re-evaluate, edit, or even restructure their text, creating additional cognitive load through cognitive conflict (Yang 2010). Furthermore, as the writing process progresses, users develop a mental commitment to their self-generated content, making external inputs feel less intuitive and more cognitively taxing to incorporate. Thus, we hypothesize:

H2: *The later users receive genAI writing suggestions in their (co-)writing process, the higher their perceived cognitive load.*

2.3 The Effect of Interactivity on AI Reliance

Agency and perceived control play a crucial role in technology acceptance and human-AI collaboration (Burton et al. 2020). When users can actively prompt AI suggestions rather than receiving them passively, they experience greater autonomy in the decision-making process, fostering a sense of ownership over the AI-generated content (Burton et al. 2020, Colarelli & Thompson 2008). This aligns with self-determination theory, which suggests that individuals are more likely to adopt external inputs when they feel in control of their integration (Deci & Ryan 1985). In the context of AI-assisted writing, user-prompted suggestions allow for a more intentional and selective integration, making individuals more receptive to relying on AI outputs. Thus, we hypothesize:

H3: *Users rely more on genAI-generated writing suggestions when they actively prompt them compared to when they receive them automatically.*

2.4 The Effect of Interactivity on Perceived Cognitive Load

Drawing from IS research on human-computer interaction and cognitive load theory, we hypothesize that user-prompted writing suggestions results in lower perceived cognitive load compared to automatically provided suggestions. As proposed by cognitive load theory, users may experience cognitive overload when an excessive amount of information exceeds their working memory capacity (Sweller et al. 1998, Paas & Van Merriënboer 1994). Automatically provided suggestions may introduce additional cognitive load by interrupting users' cognitive processes, forcing them to integrate unexpected inputs. In contrast, self-initiated prompting aligns with goal-directed behavior, allowing users to control information flow and reduce cognitive strain. Thus, we hypothesize:

H4: *Users experience lower perceived cognitive load when they actively prompt AI-generated writing suggestions compared to when they receive them automatically.*

2.5 The Effect of Cognitive Load on Reliance

Research suggests that when individuals are under higher cognitive load, they struggle to process and evaluate external information effectively, leading to lower trust in the system providing advice (Ahmad et al. 2019, Zhou et al. 2017, You et al. 2022). Prior research in information systems highlights that trust is a critical determinant of reliance on AI systems systems (Spatscheck et al. 2024, Hoff & Bashir 2015, Lee & See 2004, Vasconcelos et al. 2023). Thus, when higher cognitive load decreases individuals trust, users are less likely to accept and act upon external AI suggestions, preferring instead to rely on their own judgment, even if doing so may not be optimal. Furthermore, similar to You et al. (2022), we expect that a higher cognitive load will impair users' ability to integrate external AI suggestions into their own thought and writing process, ultimately reducing their reliance on AI suggestions (Chun & Kruglanski 2006). Thus, we hypothesize:

H5: *Higher perceived cognitive load leads to lower reliance on AI-generated writing suggestions.*

2.6 The Interaction Effect between Timing and Interactivity

The extent to which timing influences reliance on AI-generated content is likely to depend on the level of interactivity in AI assistance. As suggested by the endowment effect (Thaler 1980, Reb & Connolly 2007) and Cognitive Load Theory (Sweller et al. 1998), later AI interventions disrupt the user's established mental framework, leading to lower reliance. We argue. that this disruption is particularly pronounced in the automated condition, where users have no perceived control over the AI systems (Burton et al. 2020), amplifying the negative impact of late-stage AI assistance. In contrast, when users can actively prompt AI suggestions, they exert greater control over AI writing assistance, mitigating the disruptive effects of late-stage AI intervention. Consequently, we argue that the negative effect of late timing on reliance is less pronounced in the user-prompted condition compared to the automated condition. Thus, we hypothesize:

H6: *Timing and interactivity interact with one another such that automated (vs. prompted) AI suggestions enhance the effect of timing on AI reliance.*

3 Research Method

The primary objective of this study is to examine the intricate relationships between the design parameters of genAI, specifically, the timing and interactivity of its assistance, and users' reliance on AI-generated content in the context of content (co-)writing on P2P rental platforms. To investigate these dynamics, we employed a 3 (timing: before vs. during vs. after) × 2 (interactivity: automated vs. user-prompted) between-subjects experimental design in an online study. This methodological approach was chosen because experimental designs allow for the isolation of causal effects (Palan & Schitter 2018), thereby providing robust empirical evidence on how variations in genAI assistance mechanisms impact users' reliance on AI-generated content and their cognitive load during the (co-)writing process.

3.1 Experimental Design, Task and Platform Context

To investigate the effects of AI-generated writing assistance on property listing creation, we employed a self-developed fictional beta version of Airbnb, one of the largest and most widely recognized P2P rental platforms. This platform was chosen to ensure participants' familiarity with the interface and the nature of the task, thus enhancing ecological validity and aligning with prevailing research on human-AI collaboration and incentive compatibility principles (Burton et al. 2020).

At the outset, participants were introduced to the context and objective of the experiment through a vignette-style explanation (Atzmüller & Steiner 2010). Specifically, they were asked to imagine themselves as hosts on Airbnb who want to upload a new rental property and must go through several steps on the platform, such as generating a listing description. Participants received no additional information on how to write the listing description, except to keep the 500-character limit in mind. Subsequently, they were informed about the compensation and incentive structure before being randomly assigned to one of six treatment conditions. Participants then engaged with the experimental task within our simulated Airbnb-like interface, where they viewed images of a rental property from various angles alongside additional textual information detailing the location and amenities. The interface featured a live character count to display the current length and remaining characters, allowing participants to iteratively edit their descriptions until satisfied. They could finalize their submission at any time, regardless of character count.

The timing and interactivity of AI-generated writing assistance were systematically manipulated according to each participant's assigned condition. Upon completion of their listing, participants' perceived cognitive load was measured to assess the cognitive effort involved in the (co-)writing process.

To ensure engagement and treatment compliance, participants subsequently completed attention and manipulation checks. Engagement with the study context was verified through a multiple-choice question regarding the task's objective, while a manipulation check assessed accurate recall of the timing and nature of AI-generated suggestions. Finally, control variables were collected, and participants were debriefed and provided with a completion code.

3.2 Manipulations

To test our hypotheses, we employed a 3 (timing: before vs. during vs. after) × 2 (interactivity: automated vs. user-prompted) between-subjects experimental design. Participants were randomly assigned to one of the six experimental conditions, where we systematically manipulated when they received genAI writing suggestions (timing) and how they could interact with these suggestions (interactivity).

Timing was manipulated by controlling when participants received AI-generated assistance within the writing process. In the *before* condition, AI-generated suggestions were presented at the outset, before participants had started writing their listing description. At this point, depending on their interactivity condition, they either automatically received a fully pre-generated AI suggestion (*automated*) or were given an input field to enter a prompt before receiving the AI output (*user-prompted*). In the *during* condition, AI suggestions were provided once participants had written 250/500 characters of their listing description. At this stage, they had already engaged in the writing process and begun structuring their content. The AI assistance, whether *automated* or *user-prompted*, appeared at this fixed point, allowing us to investigate how mid-process interventions impact reliance on AI-generated content. Finally, in the *after* condition, AI assistance was introduced only after participants had completed their self-written listing description. Importantly, they retained full control over their original writing, with the ability to revise or replace their text in response to the AI-generated content.

Interactivity was manipulated by varying the way participants received AI-generated suggestions based on their assigned timing condition. In the *automated* condition, participants were directly presented with a predefined AI-generated listing description at the designated timing stage. In contrast, in the *user-prompted* condition, participants were presented with an input field at the same timing stage, where they could enter their own prompt before receiving the AI-generated suggestion. To ensure that differences in reliance behavior could be attributed solely to the perceived autonomy and control in the *user-prompted* condition, rather than to variations in AI-generated text quality, the AI-generated output was identical across both interactivity conditions. Regardless of user input, participants in the *user-prompted* condition received the same AI-generated text as those in the *automated* condition. This approach allowed us to isolate the effects of user agency and freedom of choice on reliance, without introducing confounds related to content variability.

3.3 Fine-Tuning GPT-4o for Generating Airbnb Listing Descriptions

To generate AI-assisted Airbnb listing descriptions, we fine-tuned the *gpt-4o-2024-08-06* (OpenAI 2024) model using real-world Airbnb data from InsideAirbnb. Given our experiment's English-language setting, we selected only English-language listings. Our data selection process involved four key steps: (1) filtering for relevant property types (e.g., "Entire Apartment"), (2) estimating occupancy rates as a proxy for booking success, (3) sorting and cleaning the dataset by removing duplicates and HTML artifacts, and (4) selecting top listings with the highest occupancy rates as representative samples of successful Airbnb descriptions.

For model fine-tuning, we curated a dataset of 60 high-performing Airbnb listings, ensuring a minimum description length of 400 characters. The dataset was split into 50 entries for training and 10 for validation. Fine-tuning was conducted via the OpenAI-API using a batch size of 5, a learning rate multiplier of 1, and three training epochs to optimize performance.

During inference, the model was guided by a system instruction emphasizing clarity, professionalism, and a 500-character limit for descriptions. The model received property images and a standardized prompt: "Generate the corresponding listing description." This setup ensured that our fine-tuned model produced high-quality, property-specific descriptions aligned with the experiment's objectives.

3.4 Variables and Measurements

To measure our dependent variable, AI reliance, we draw on Yaniv (2004) and the concept of advice weighting, by using a formula-based measure to quantify behavioral reliance in writing tasks within the judge-advisor paradigm (Bonaccio & Dalal 2006).

Given two n-dimensional vector embeddings, $\mathbf{a}$ and $\mathbf{b}$, the cosine distance D_C quantifies their dissimilarity by measuring the angular distance between them in a high-dimensional space and is mathematically expressed as:

$$D_C := 1 - \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|} = 1 - \frac{\sum_{i=1}^{n} \mathbf{a}_i \mathbf{b}_i}{\sqrt{\sum_{i=1}^{n} (\mathbf{a}_i)^2} \sqrt{\sum_{i=1}^{n} (\mathbf{b}_i)^2}} \tag{1}$$

To measure genAI reliance on written texts, we compute embeddings of the individual's initial text ($\mathbf{i}$), the genAI suggestion ($\mathbf{s}$), and the final text ($\mathbf{f}$). Consequently, the ratio of cosine distances quantifies the weight of advice (WOA) as a behavioral reliance operationalization in writing tasks:

$$\text{WOA} = \frac{D_c(\mathbf{f}, \mathbf{i})}{D_c(\mathbf{s}, \mathbf{i})} \tag{2}$$

In simple terms, the cosine distance measures how similar two texts are by looking at the direction of their meaning, rather than their exact words. As such, the WOA ratio compares how much the user's final text moves away from their original draft relative to how much the AI's suggestion differs from their original. If the final text becomes much closer to the AI's suggestion (and thus farther from the initial draft), the ratio increases, indicating a higher reliance on the genAI writing suggestions. Conversely, if the final text stays close to the participant's initial draft, the ratio decreases, indicating lower reliance.

Another key variable in our study is participants' perceived cognitive load, which we measured using a validated subjective rating scale, recognized for its reliability (Morrison et al. 2014). Participants assessed their cognitive load while interacting with the genAI system on a 7-point Likert scale (1 = "extremely low" to 7 = "extremely high"). We also gathered data on participants' age, gender, prior experience with AI-assisted writing tools, and their familiarity with P2P rental platform tasks as control variables.

3.5 Sample Description and Balance Tests

We recruited 317 participants through Prolific, offering a base payment of £1.15. Additionally, participants had the opportunity to earn a performance-based bonus, with total compensation reaching up to £11 per hour, ensuring incentive-aligned remuneration. To ensure participants fully comprehended the tasks without language-related barriers, we allowed worldwide participation but restricted the sample to fluent English speakers. As a result, the dataset primarily consists of participants from the United States, United Kingdom, and Australia, with a smaller proportion from Africa and Europe. Additionally, we required participants to have a minimum approval rate of 95% on Prolific. To ensure data quality, we excluded 73 participants due to failure in our attention and manipulation checks or excessively short completion times (< 3.5 minutes; median completion time = 11.45 minutes). Thus, our final sample for analysis comprised 244 participants (M_{age} = 34.76; 54.5% women).

To validate our sample size, we conducted an a priori power analysis using G*Power, assuming a fixed effects model with an effect size (f) of 0.25, an α-level of 0.05, a power of 0.90, and six groups in the experimental design (Faul et al. 2007). The results indicated a minimum required sample size of 206, confirming that our final sample size was sufficient for detecting meaningful effects.

4 Results

To evaluate the adequacy of our randomization procedure, we performed balance checks on key control variables across treatment groups. Chi-square tests (for categorical variables) and Kruskal–Wallis tests (for continuous or ordinal variables) indicated no statistically significant differences in age, gender, prior experience, or task familiarity among the groups (all p > .05). These results suggest that random assignment was successful in producing equivalently distributed groups concerning these characteristics. Consequently, we did not include these control variables as covariates in our main analyses, as their inclusion did not substantively alter the observed treatment effects.

To test H1, H2, and H5, we conducted a mediation analysis using PROCESS v4.2 (Model 4; Hayes (2017)). Specifically, we estimated both the direct and indirect effects of the mediation model through bootstrapping with 5,000 samples and 95% confidence intervals, without applying heteroskedasticity-consistent standard errors. The results revealed a significant direct effect of timing on reliance (95% Confidence Interval (CI:) [-0.2176, -0.1568], b = -0.1872, SE = 0.0154), supporting H1 ($p < 0.001$) However, the relationship between timing and cognitive load was not significant (95% CI: [-0.0429, 0.3209], leading to the rejection of H2. Conversely, we observed a significant effect of cognitive load on reliance (95% CI: [-0.0507, -0.0090], b = -0.0299, SE = 0.0106), thereby supporting H5 ($p < 0.01$).

To test Hypotheses 3 and 4, we conducted an additional mediation analysis using PROCESS v4.2 (Model 4; Hayes (2017)), employing the same bootstrapping procedure with 5,000 samples, without heteroskedasticity-consistent standard errors and, again, excluding covariates, as their inclusion did not influence the results. The findings indicated a marginally significant direct effect of interactivity on reliance (90% CI: [-0.1075, -0.0021], b = -0.0548, SE = 0.0319), providing marginal support for H3 (p = 0.0873. However, the path between interactivity and cognitive load was not significant (95% CI: [-0.4067, 0.0947], leading to the rejection of H4.

To test Hypothesis 6 and examine whether an interaction effect exists between timing and interactivity, we conducted a two-way analysis of variance (ANOVA) on reliance. The results revealed a significant interaction effect between timing and interactivity on reliance (F(2, 228) = 8.521, $p < 0.001$, partial η^2 = 0.067). Post hoc pairwise comparisons with Bonferroni correction indicated that the difference between the automated and user-prompted conditions was significant and interacted with timing, supporting H6.
Table 1 presents the summary statistics and results, including an overview of significance levels.

Table 1. Summary Statistics and Results

Hypothesis		**B**	**SE**	**Confidence Interval**	**Significance**
H1	Timing → Reliance	-0.1872	0.0154	[-0.2176, -0.1568]	Supported***
H2	Timing → Cognitive Load			[-0.0429, 0.3209]	Rejected
H3	Interactivity → Reliance	-0.0548	0.0319	[-0.1075, -0.0021]	Marginal Supported (p = 0.0873)
H4	Interactivity → Cognitive Load			[-0.4067, 0.0947]	Rejected
H5	Cognive Load → Reliance	-0.0299	0.0106	[-0.0507, -0.0090]	Supported**
H6	Interactivity → Timing(1)				Supported***

*Notes: ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5%-level.*
(1) We do not report B, SE, or CI for H6 as it was analyzed using a two-way ANOVA

5 Discussion and Conclusion

The proliferation of genAI presents significant opportunities for P2P rental platforms by streamlining the creation of MGC. Integrating genAI as a co-writing assistant can enhance the efficiency of content creation while preserving the distinctiveness of individual listings. However, the effectiveness of such integration hinges on key design parameters, such as the timing of genAI suggestions and the degree of user interactivity in the content creation process. Our study empirically investigates how both of these factors influence user reliance in genAI-supported co-writing processes, with cognitive load serving as a mediator. The results, summarized in Table 1, advance the literature on genAI in digital platforms (e.g., Mayer et al. 2025, Katsamakas & Sanchez-Cartas 2024, Mayer et al. 2024) and enrich the broader discourse on human-AI augmentation (e.g., Jussupow et al. 2021, Abdel-Karim et al. 2023, Spatscheck et al. 2024) by providing novel empirical and theoretical insights into genAI-supported co-writing - an emerging and underexplored area within information systems research.

Our findings empirically affirm the importance of timing, extending previous work on time-related decision support (Langer et al. 2021) to the context of genAI for (co-)writing tasks. The observed decline in reliance on genAI writing suggestions that are introduced later in the writing process demonstrates that not only *how* but also *when* genAI suggestions are presented influences their effectiveness. By emphasizing the temporal embeddedness of genAI writing assistance, our study offers a more nuanced perspective to the IS literature: effective (gen)AI design must account not only for static interface features, but also for the evolving dynamics of user agency, psychological ownership, and cognitive integration throughout the (co-)writing process. This highlights the imperative for future research to systematically investigate and discuss a "chronology of reliance" in human-AI collaboration, where genAI suggestion timing becomes a critical design lever influencing user receptivity and behavioral outcomes.

With respect to interactivity, our results reveal greater nuance that warrants further consideration. While there is a tendency for user-initiated prompting to foster increased reliance relative to automated writing suggestions, this difference achieves only marginal statistical significance. These findings suggest that in collaborative human–genAI writing contexts, such as P2P content co-creation, users may not necessarily desire maximal control. Rather, they may favor an optimal balance between personal autonomy and supportive scaffolding provided by the genAI system. This preference might be shaped by habitual workflows on digital platforms (Oktaviana et al. 2019), which prioritize efficiency and familiarity and can render additional interactive steps cumbersome or disruptive. However, the marginal significance of interactivity may also stem from our experimental design: in the user-prompted condition, participants entered prompts, but the AI-generated output was pre-determined and identical across conditions. This may have inadvertently fostered an illusion of control, where users perceive agency despite having little or no actual influence (Langer 1975), and might have induced cognitive dissonance, as the mismatch between user input and genAI response could cause psychological discomfort, potentially reducing engagement, trust, and satisfaction (Festinger 1962, Morvan & O'Connor 2017). While this experimental design choice maximized internal validity by eliminating content quality confounds, it may have constrained ecological validity compared to real-world genAI systems, where user prompts more directly shape genAI responses. Thus, in practical applications, combining genuine user agency with meaningful system responsiveness may yield a more pronounced effect on reliance than observed in our controlled setting.

From a practitioner's perspective, our findings yield several actionable recommendations for P2P platform operators aiming to effectively implement genAI-assisted writing tools. First, the timing of AI-generated suggestions is critical: our results indicate that providing such assistance early in the writing process, specifically during the drafting stage, significantly increases user reliance on genAI. In contrast, introducing AI suggestions after substantial content has already been produced diminishes their impact, likely due to heightened psychological ownership over the existing text. Accordingly, platforms should design genAI interventions that engage users before they become too invested in their initial drafts. Second, the degree of interactivity embedded within genAI tools marginally influences user reliance. While automated genAI suggestions can streamline the writing process, they may also reduce user agency, particularly when combined with late-stage interventions. Encouraging users to actively prompt genAI assistance, rather than passively receiving suggestions, not only enhances perceived control but also strengthens reliance on AI-generated content. However, looking ahead, our findings point towards important cross-cultural implications, as high user reliance on Western-centric genAI models can inadvertently homogenize user-generated content and diminish region-specific writing styles (Agarwal et al. 2025). Therefore, platforms should design interactive features that allow users to customize prompts, thereby enhancing both personalization and efficiency in MGC (co-)creation.

Finally, our findings indicate that neither the timing nor the degree of interactivity in genAI-assisted writing significantly affected users' cognitive load - a result that diverges from previous studies where AI design choices were shown to meaningfully influence cognitive load (Spatscheck et al. 2024, You et al. 2022). For platform operators, however, this finding is encouraging, as it suggests that optimizing genAI tools with respect to timing and interactivity may not necessitate extensive consideration of cognitive load implications. Instead, efforts should be directed toward developing user-friendly genAI interfaces that offer clear guidance, intuitive options for content refinement, and real-time feedback, thereby reducing cognitive burden more broadly. Consistent with our findings, minimizing cognitive load remains crucial for fostering greater reliance on AI-assisted writing.

Despite its contributions, our study has several limitations. First, reliance on a cross-sectional online experiment restricts our ability to observe long-term behavioral changes. Future research could employ longitudinal studies to examine user adaptation to genAI-assisted writing over time. Second, our controlled, lab-like setting improves internal validity but may not capture the complexities of real-world P2P rental platforms. Field experiments could better assess the impact of genAI writing assistance on listing performance and user engagement. Third, both the automated and user-prompted conditions used identical AI-generated writing suggestions, potentially limiting variation in user responses. Future studies could explore how different genAI prompts influence reliance and creativity.

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