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From Curiosity to Fatigue: How Repeated Interaction with Generative AI Changes Consumer Motivation

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ABSTRACT
The rapid diffusion of generative artificial intelligence (AI) has transformed consumer interaction with digital systems, shifting AI use from an exploratory novelty to a routine component of everyday tasks. While existing research has primarily focused on initial adoption and perceived usefulness of AI technologies, far less is known about how consumer motivation and interaction behavior evolve with repeated use. This study investigates how consumers' motivational states and effort investment change over the course of repeated interactions with generative AI. Drawing on consumer motivation and effort allocation perspectives, the research examines whether continued exposure leads to sustained engagement or systematic behavioral adjustment. Using interaction-level data that track consumers' sequential engagements with generative AI systems, the study distinguishes between early-stage and later-stage interactions within usage sessions, and examines changes in behavioral indicators of effort, including prompt length and the time interval between successive interactions. The results show that later-stage interactions are characterized by significantly shorter prompts and shorter inter-interaction intervals, indicating reduced cognitive effort and faster interaction pacing rather than disengagement. These patterns suggest that consumers adapt their interaction strategies toward more streamlined and economical use as experience accumulates. Importantly, the findings exhibit pronounced temporal heterogeneity. Interaction routinization intensifies as generative AI usage becomes more mature and normalized. This study extends consumer research on human–AI interaction by moving beyond adoption-centric models and conceptualizing motivation as an experience-dependent and temporally evolving construct. From a managerial perspective, the findings highlight the importance of adaptive AI interface design that supports efficient and routinized interaction, rather than relying solely on novelty or early-stage performance improvements to sustain long-term use
Keywords: Generative artificial intelligence; consumer motivation; repeated interaction; effort allocation; engagement fatigue....

1. INTRODUCTION:

The rapid proliferation of generative artificial intelligence (AI)—especially large language model (LLM)–based systems—has begun to reshape how consumers interact with digital interfaces. Unlike earlier automation or decision-support tools, generative AI operates through open-ended, conversational, and iterative exchanges, requiring users to actively specify goals, provide context, and refine instructions over multiple turns. This interaction mode positions consumers not merely as passive recipients of algorithmic outputs but as co-producers of outcomes through their ongoing input and feedback. More broadly, this shift reflects the long-standing insight that people often respond socially to media technologies and computational agents, applying interpersonal heuristics even when they recognize the interaction partner is nonhuman (Reeves & Nass, 1996).

Prior research on consumer–technology interaction has largely emphasized initial adoption and early-stage evaluations of new technologies (Cheng & Jiang, 2020; Wu et al., 2024). Classic acceptance frameworks highlight perceived usefulness and perceived ease of use as primary drivers of adoption intentions (Davis, 1989), and later extensions in consumer contexts incorporate hedonic motivation, price value, and habit as additional determinants of technology use (Venkatesh et al., 2012). In AI-enabled services, emerging work further emphasizes trust, perceived intelligence, and social cues as influential in shaping early engagement and compliance with AI agents(Ashfaq et al., 2020; Han et al., 2024; Hasan et al., 2021). Consumer research also documents skepticism toward algorithmic expertise in sensitive domains such as healthcare, underscoring that receptivity to AI can be contingent on context, task meaning, and perceived appropriateness(Longoni et al., 2019). Collectively, these perspectives clarify why consumers try AI systems, but they tend to treat motivation and engagement as relatively stable once usage begins.

However, a growing body of theory and evidence suggests that consumer experience with interactive technologies is dynamic, shaped by learning, familiarity, and diminishing novelty. Theories of curiosity and arousal predict that novelty effects decay as stimuli become familiar(Berlyne, 1960), while consumer research on experiential and hedonic consumption underscores that repeated exposure can shift affective responses and engagement intensity(Hirschman & Holbrook, 1982). In information systems and digital behavior research, repeated use often produces adaptation rather than a binary outcome of continuation versus abandonment: users develop routines, form habits, and streamline effort in ways that change both the form and tempo of interaction (Agarwat & Karahanna, 2000). These insights motivate a critical but underexplored question for generative AI: how does consumer motivation evolve as interaction shifts from novelty-driven exploration to routine, repeated use?

This study addresses that gap by examining the within-session trajectory of repeated consumer interactions with generative AI. Rather than focusing on adoption or discontinuance, we investigate a subtler shift: how consumers recalibrate effort and pacing as experience accumulates. Theoretically, this approach builds on cognitive economy and bounded rationality perspectives, which argue that individuals allocate limited attention and effort strategically, especially once tasks become familiar and goals can be met with lower marginal input (Kahneman, 1973; Simon, 1955). In human–AI interaction, these perspectives imply that consumers may continue using generative AI while reducing cognitive investment—simplifying prompts, relying on minimal viable instructions, and spacing interactions further apart—reflecting effort re-optimization rather than disengagement.

Accordingly, the objectives of this research are threefold. First, document the trajectory of consumer motivation across repeated interactions by distinguishing early-stage versus later-stage interaction within a usage session. Second, identify behavioral indicators of changing effort allocation that are directly observable in interaction logs—most notably prompt length (as a proxy for prompt effort) and inter-interaction interval (as a proxy for interaction pacing). Third, examine whether these motivational dynamics are temporally contingent, testing whether the later-stage shift intensifies as generative AI becomes more embedded in everyday life and consumers' expectations become more routinized.

The significance of this study is both theoretical and practical. Theoretically, it extends technology-use research beyond static adoption frameworks by foregrounding temporal dynamics and experience-dependent motivation in consumer–AI interaction. It also complements recent evidence that generative AI is increasingly integrated into work and consumption-related tasks, making the sustainability of user effort a central issue rather than a peripheral one (e.g., documented impacts of generative AI assistance on performance and behavior). Practically, the findings caution against overreliance on novelty-driven engagement strategies and suggest that sustaining long-term value from generative AI requires adaptive interaction design—interfaces and support features that recognize motivational fatigue, reduce unnecessary effort costs, and align system behavior with evolving user expectations.

2. RELATED LITERATURE

Consumer Interaction with Intelligent Technologies

Prior research on consumer interaction with intelligent technologies has largely centered on technology adoption and early-stage usage (Altrichter & Benoit, 2025; Cheng & Jiang, 2020; Li et al., 2023; Wu et al., 2024). Classic acceptance frameworks identify perceived usefulness and perceived ease of use as fundamental determinants of consumers' willingness to engage with new technologies (Davis, 1989). Within AI-enabled services, studies further demonstrate that trust, perceived intelligence, and system transparency play critical roles in shaping consumers' initial acceptance and evaluations of algorithmic systems (Hasan et al., 2021; Wu et al., 2024). While this literature provides important insights into why consumers adopt and initially engage with AI technologies, it generally conceptualizes post-adoption motivation as relatively stable. Continued use is often treated as a homogeneous outcome, with limited attention to how consumers' effort, engagement intensity, or interaction strategies evolve once AI systems become familiar and embedded in routine activities.

Experiential Responses and Social Interaction with AI

A second stream of research draws from consumer psychology and human–computer interaction to examine experiential and social responses to intelligent systems. Building on the Computers Are Social Actors (CASA) paradigm, scholars show that consumers frequently respond to interactive technologies as if they possessed human-like or social attributes, leading to greater engagement, emotional involvement, and compliance—particularly during early interactions (Jin & Youn, 2023; Reeves & Nass, 1996). In AI-mediated service encounters, social cues such as responsiveness, and anthropomorphic design have been shown to enhance perceived warmth, enjoyment, and user cooperation (Li et al., 2023; Poushneh, 2021). However, this body of work predominantly relies on short-term experiments or single-session interactions, implicitly assuming that the effects of social cues and perceived agency persist over time. As a result, it offers limited insight into whether these engagement-enhancing mechanisms remain effective—or potentially attenuate—as consumers accumulate experience and shift from exploratory to routine interaction with AI systems.

Repeated Use, Habit Formation, and Declining Novelty

Studies on cognitive absorption and habit formation indicate that familiarity reduces uncertainty and exploratory behavior, encouraging more routinized and efficiency-oriented interaction patterns (Agarwat & Karahanna, 2000; Limayem et al., 2008). In digital and mobile contexts, repeated exposure often leads users to conserve cognitive resources while maintaining functional use, reflecting an adjustment in effort rather than disengagement. As novelty diminishes, users increasingly rely on learned shortcuts and simplified interaction strategies. Continued use does not necessarily correspond to sustained motivation or high engagement intensity, highlighting the need to distinguish frequency of use from quality of engagement.

Effort Allocation and Cognitive Economy

From a theoretical perspective, effort-based and cognitive resource allocation frameworks provide a useful lens for interpreting these behavioral shifts. Cognitive economy and bounded rationality theories posit that individuals are motivated to minimize mental effort once tasks become familiar, especially when similar outcomes can be achieved with lower cognitive input (Kahneman, 1973; Simon, 1955). Applied to generative AI, these perspectives suggest that repeated interaction may prompt consumers to recalibrate effort and interaction strategies—for example, by simplifying prompts, reducing exploratory behavior, or spacing interactions further apart—rather than discontinuing use altogether. Such adaptation reflects a shift toward instrumental, efficiency-oriented engagement consistent with effort minimization principles.

Despite these insights, existing literature offers limited understanding of how consumer motivation evolves within users across repeated interactions with generative AI. Most studies focus on adoption decisions or treat continued use as a uniform outcome, overlooking gradual changes in effort allocation and interaction pacing. By integrating technology adoption research with effort-based theories, the present study addresses this gap and advances a dynamic account of consumer motivation in repeated human–AI interaction.

Methodology

This study adopts an empirical, observational research design to examine how consumer motivation and effort allocation evolve across repeated interactions with generative artificial intelligence (AI). Rather than focusing on adoption or discontinuance decisions, the analysis centers on within-user behavioral dynamics, capturing how interaction effort and pacing change as users accumulate experience with a generative AI system. The empirical strategy exploits the sequential nature of interaction logs and compares users' behavior within usage sessions, distinguishing between early-stage and later-stage interactions. This within-user, within-session design allows us to isolate experience-driven behavioral changes while minimizing confounding effects arising from stable individual characteristics, such as baseline ability, preferences, or general attitudes toward AI.

Data Collection

The data consist of interaction-level records generated from consumer use of a generative AI system over a multi-year observation window. Each record contains a time-stamped user prompt and the corresponding system response, allowing us to reconstruct fine-grained interaction sequences at the individual level. To capture meaningful repeated interaction rather than sporadic experimentation, the sample is restricted to users who engage in multiple interactions during the observation period. Interactions are first sorted chronologically for each user. Following common practice in studies of digital interaction and conversational behavior, interactions are grouped into usage sessions based on temporal proximity: interactions separated by less than one hour are treated as belonging to the same session, while gaps exceeding one hour indicate the start of a new session. Within each session, interactions are ordered sequentially, enabling the analysis of how user behavior evolves over the course of continued engagement within a single conversational context. All data are anonymized prior to analysis, and no personally identifiable information is included. The study focuses exclusively on behavioral patterns rather than semantic content or output quality, thereby reducing privacy concerns.

Measures

To capture experience accumulation within a session, we construct a Later Stage indicator based on the interaction order within each session. Specifically, interactions occurring beyond a predefined threshold in the session sequence are classified as later-stage interactions, while earlier interactions serve as the baseline early stage. This operationalization reflects a shift from exploratory to more experienced interaction within the same usage episode.

User effort investment is proxied by Prompt Length, measured as the length of the user's input prompt. Prompt length serves as a widely used behavioral indicator of cognitive effort, reflecting the extent to which users elaborate instructions, provide contextual details, or specify constraints in their interaction with the AI system. Shorter prompts are interpreted as lower effort investment, particularly when usage persists.

To capture changes in interaction rhythm, we measure Inter Interaction Interval, defined as the time elapsed (in minutes) between consecutive interactions within the same session. For each session, the first interaction has no preceding interval and is coded as missing. Longer intervals indicate slower interaction pacing and reduced immediacy of engagement.

Results

Descriptive Statistics and Mean Differences

Table 1 presents descriptive statistics and mean comparisons between early-stage and later-stage interactions. Following the session-based interaction structure, interactions are classified into early and later stages based on whether their section order exceeds a within-session threshold of 13, corresponding to the average number of interactions per session. This cutoff captures the transition from initial, exploratory interaction to more experienced engagement within a session.

Table 1. Descriptive Statistics of Interaction Indicators by Usage Stage

	Early Stage	Later Stage	Diff (Late-Early)	T_Stat	P_Value
Prompt length	163.897	57.913	-105.984	-7.256	0.000

Interaction interval	5.515	0.789	-4.725	-12.032	0.000

The mean-difference analysis reveals clear behavioral contrasts between stages. Compared with early-stage interactions, later-stage interactions exhibit significantly shorter prompt length, indicating lower input effort. At the same time, later-stage interactions are characterized by significantly shorter inter-interaction intervals, suggesting a faster interaction pace relative to earlier exchanges.

Fixed Effects Regression Analysis

To further isolate within-user behavioral changes and rule out confounding factors, we estimate a series of fixed effects regression models. In these models, Prompt Length and Interaction Interval are regressed on the Later Stage indicator, exploiting within-user variation across interaction stages. All models include user fixed effects to control for time-invariant individual characteristics, as well as year fixed effects and content-type fixed effects to account for temporal variation and systematic differences across interaction contexts. In addition, we control for the quality of the system's previous response, capturing potential feedback effects whereby higher-quality outputs may mechanically reduce subsequent user effort or delay follow-up interactions.

Across specifications, the coefficient on Later Stage is negative and statistically significant for PromptLength, indicating that users provide shorter prompts in later-stage interactions even after accounting for prior response quality and contextual fixed effects. Similarly, Later Stage is negative and statistically associated with Interaction Interval, implying shorter delays between successive interactions as users progress within a session. These results remain stable when standard errors are clustered at the user level. To assess the robustness of the findings to alternative operationalizations of interaction stage, we replace the binary Later Stage indicator with SectionOrder, a continuous measure capturing the sequential position of an interaction within a session. The results remain qualitatively unchanged: higher section order is associated with shorter prompt length and shorter inter-interaction intervals.

Table 2. Fixed-Effects Regression Results on Effort Indicators

Variable	Prompt Length		Interaction Interval	
	(1)	(2)	(3)	(4)
Later Stage	-63.346***		-1.568***	
	(19.130)		(0.566)	
Section Order		-0.335**		-0.011*
		(0.169)		(0.006)
Controls	Yes	Yes	Yes	Yes
Content Type	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,225	1,225	1,225	1,225
R^2	0.450	0.447	0.150	0.147

Temporal Heterogeneity Across Years

We also examine whether the later-stage effects differ across calendar years. Figure 1 presents coefficient estimates of Later Stage from year-specific regressions. The results reveal pronounced temporal heterogeneity. In 2023, the estimated effect of Later Stage on prompt effort is small and statistically insignificant. In contrast, the effect becomes substantially negative and statistically significant in 2024, indicating a stronger decline in effort during later-stage interactions. This divergence suggests that motivational adaptation intensifies as generative AI usage becomes more mature and routinized. Rather than reflecting short-term novelty decay within sessions alone, the later-stage effect appears to interact with broader temporal dynamics in the adoption and normalization of generative AI.

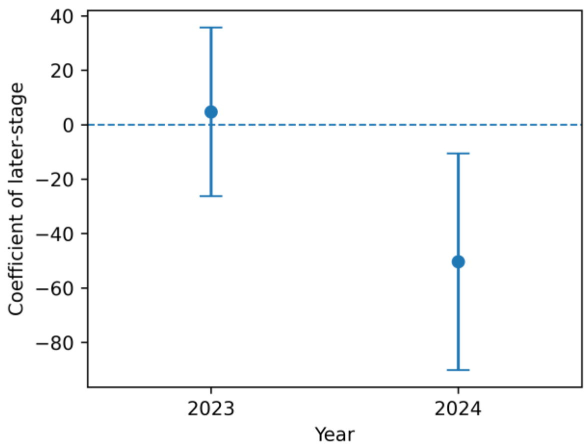

Figure 1a. Heterogeneous Effect of Later Across Years (Prompt Length)

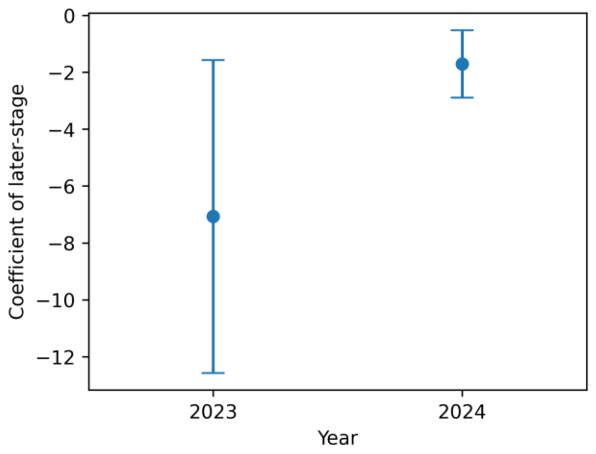

Figure 1b. Heterogeneous Effect of Later Across Years (Interaction Interval)

3. DISCUSSION

This study examines how consumer motivation and effort allocation evolve across repeated interactions with generative artificial intelligence (AI), moving beyond adoption-centric perspectives to focus on within-user behavioral dynamics. Across multiple analyses, the results consistently show that later-stage interactions are characterized by shorter prompts and shorter inter interaction intervals, even when overall usage persists. Together, these patterns indicate a shift toward lower input effort and faster interaction pacing as users accumulate experience with generative AI.

A central implication of these findings is that later-stage behavioral change reflects effort economization rather than disengagement. Although users provide shorter prompts, they also interact more rapidly, suggesting a transition toward streamlined and routinized use rather than withdrawal. Consumers continue to rely on generative AI but do so in a more economical and instrumental manner, minimizing unnecessary elaboration while maintaining task completion.

This behavioral pattern aligns with theories of cognitive economy and bounded rationality, which argue that individuals seek to conserve mental effort once tasks become familiar and predictable (Kahneman, 1973; Simon, 1955). It also extends prior research on continued technology use and habit formation, which shows that familiarity promotes routinization and efficiency-oriented behavior (Agarwat & Karahanna, 2000; Limayem et al., 2008). By focusing on interaction-level effort and pacing, the present study demonstrates that sustained use can coexist with declining effort intensity and accelerated interaction rhythms.

The findings further suggest that experiential and social motivations may be stage-dependent. While early interactions may encourage richer input and exploratory engagement, repeated exposure appears to shift users toward goal-oriented efficiency. As interaction becomes routinized, consumers rely less on elaborate prompts and engage more rapidly with the system, indicating that instrumental considerations increasingly dominate interaction behavior. This temporal perspective helps reconcile mixed findings in prior research regarding the persistence of social presence and perceived intelligence effects in human–AI interaction.

Finally, this study documents meaningful temporal heterogeneity across calendar years. The later-stage reduction in prompt effort is weak and statistically insignificant in 2023 but becomes pronounced in 2024, suggesting that interaction routinization intensifies as generative AI technologies move from early diffusion to more mature and normalized use. As generative AI becomes a familiar and reliable utility, consumers increasingly prioritize speed and efficiency over exploration, leading to faster and more economical interaction patterns rather than reduced usage. By highlighting this year-level heterogeneity, the study underscores the importance of situating human–AI interaction within broader processes of technological diffusion and normalization, rather than treating observed behaviors as time-invariant.

4. CONTRIBUTIONS

This study makes several contributions to consumer research on human–AI interaction. First, it moves beyond adoption-centric frameworks by conceptualizing consumer motivation as experience-dependent and dynamic, shaped by repeated interaction rather than fixed post-adoption states. Second, it integrates effort-based theories from cognitive psychology and consumer economics into the study of generative AI, offering a behavioral account of how users economize cognitive resources while maintaining engagement. Third, by documenting temporal heterogeneity, the study highlights the role of technological maturity in shaping interaction strategies.

From a managerial perspective, the findings caution against relying solely on novelty, anthropomorphism, or rich interaction to sustain long-term engagement. As users gain experience, they increasingly value efficiency and speed. AI systems that fail to adapt to this shift may impose unnecessary cognitive costs. Instead, designers and platform managers should consider interaction designs that support streamlined use—such as concise prompt templates, adaptive defaults, or context-aware suggestions—that align with users' evolving preferences for efficient and instrumental interaction.

Limitations and Future Research

This study has limitations that suggest avenues for future research. First, while behavioral proxies provide valuable insights into effort allocation, future work could combine interaction data with self-reported measures to capture subjective motivation more directly. Second, the analysis focuses on within-session dynamics; future studies could examine longer-term trajectories across months or years at the individual level. Finally, exploring how system-side adaptations interact with user effort dynamics remains a promising direction for understanding sustainable human–AI collaboration.

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