

Article

From Affordance to Actualization: A Study on the Nonlinear Mechanisms of Idea Diffusion in AI-Mediated Online Innovation Communities

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Abstract

In online innovation communities, idea diffusion constitutes a core mechanism through which user-generated ideas are transformed into collective innovation outcomes. However, existing research remains fragmented and lacks a process-oriented explanation of how ideas become actionable and trigger diffusion. This study draws on affordance theory to explain how ideas become actionable and drive diffusion in online innovation communities. Cognitive affordance is operationalized as operability and detail richness, entry affordance as actionability signaling and linguistic hedging, and collaborative affordance as mediating structural position and interaction depth. Using text mining and social network analysis on idea-level data and employing a negative binomial regression model, we find that the effects of affordances are inherently nonlinear. While some affordances exhibit positive linear effects, others follow U-shaped relationships, suggesting threshold-dependent activation mechanisms. The results suggest that AI may influence the activation of affordances and alter certain affordance-diffusion relationships under specific conditions. Theoretically, this study advances affordance theory by introducing an activation-based perspective that captures the nonlinear transformation from perceived possibilities to realized actions. It also integrates content and structural dimensions into a unified framework for understanding idea diffusion. Practically, the findings offer insights for platform governance, particularly in designing content structures, participation mechanisms, and AI-assisted tools that effectively facilitate innovation diffusion.

Keywords: affordance theory; idea diffusion; online innovation communities; text analysis; social network analysis; AI moderation; nonlinear effects

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1. Introduction

With advances in digital technology, online innovation communities (OICs) have become a key infrastructure for open innovation, enabling geographically dispersed individuals to collaboratively generate, evaluate, and refine ideas. On such platforms, users simultaneously act as knowledge consumers, producers, and disseminators, forming a dynamic socio-technical system of continuous co-creation [1]. Extensive research suggests that an idea's value does not solely derive from its originality or technological sophistication. Rather, it depends substantially on its diffusion within a community. Specifically,

value increases when the idea can be understood, adopted, reproduced, and further disseminated [2–4]. Therefore, uncovering the mechanisms underlying idea diffusion is crucial for understanding digital innovation ecosystems. Prior research on idea diffusion follows two main streams: content-based studies focusing on linguistic style, emotional expression, and information complexity [5] and network-based studies emphasizing node centrality, structural holes, and interaction ties [6,7]. However, these approaches remain theoretically fragmented. The former centers on information attributes, whereas the latter highlights diffusion structures. Neither offers an integrated framework explaining how information translates into action.

The theory of affordance offers a powerful analytical perspective to bridge this theoretical gap, with its core premise being that individual behavior is shaped by the possibilities for action provided by environmental and technological characteristics [8]. Unlike approaches that treat technology or the environment as factors with a deterministic influence on behavior, this theory emphasizes that objects empower or constrain individual behavior through the affordances they embody; these affordances only translate into actual behavioral outcomes when perceived and enacted by goal-oriented actors [9,10]. In online innovation contexts, ideas are not merely vehicles for informational expression but can be viewed as design objects embedded with potential for action [11]. Therefore, whether users participate in the diffusion of ideas depends on their ability to identify these affordances and actualize them within broader socio-technical contexts [12].

Furthermore, the diffusion of ideas is not a simple linear process. Traditional research, often grounded in the logic of “information overload” or “diminishing returns,” assumes an inverted U-shaped relationship between variables and diffusion [13,14]. However, in digital environments, as information processing capabilities and tool support—particularly AI technologies—improve, users’ approaches to handling complex information are undergoing fundamental changes [15]. In this context, the influence of key factors is often uncertain and nonlinear [16]: at lower levels, these factors may hinder diffusion due to cognitive or coordination constraints; however, once certain thresholds—such as AI literacy, technological maturity, or collaborative conditions—are reached, they become driving forces, thereby forming a U-shaped relationship.

Meanwhile, the rapid development of artificial intelligence (AI) is reshaping the fundamental logic of online innovation. AI transforms the innovation process from linear to dynamic and non-sequential, with human–machine interaction resulting in a complex, multi-stage cyclical structure of knowledge processing [17]. AI not only assists users in understanding information but also directly participates in content generation, thereby altering the degree to which idea diffusion relies on original information and social structures. Therefore, it is necessary to incorporate AI into the analytical framework to explore its moderating role in the relationship between affordance and idea diffusion. We use this as a starting point to develop the following research questions:

RQ1: How do different types of affordance influence idea diffusion?

RQ2: Do these influences exhibit nonlinear characteristics?

RQ3: How does AI usage moderate these relationships?

To address these objectives, this study integrates text analysis with social network analysis to conduct an empirical examination of idea-level data from online innovation communities. Idea diffusion is defined as the extent to which a focal idea is adopted, replicated, modified, and re-created by other community members. Unlike traditional information diffusion, which focuses on information transmission, idea diffusion emphasizes the generation of subsequent creative outputs based on an original idea [18]. Accordingly, the diffusion outcome is operationalized at the idea level, enabling us to examine how idea characteristics influence subsequent adoption and re-creation behaviors. A negative binomial regression model is employed to test the proposed hypotheses.

This study makes three primary contributions. First, from a theoretical perspective, it extends affordance theory from its traditional focus on technological design to the context of idea diffusion in online innovation communities. It broadens the explanatory scope of affordance theory and explores how AI may shape the relationship between affordances and idea diffusion in online innovation communities. Second, from a methodological perspective, this study advances the quantitative operationalization of affordances by combining computational text analysis with network-based structural measures, thereby offering a more integrated approach to capturing both content and relational dimensions. Third, from a practical perspective, the findings provide actionable implications for platform governance, particularly in optimizing content recommendation systems and designing incentive mechanisms that effectively motivate idea contributors in online innovation communities.

2. Literature Review

2.1. *Affordance Theory*

Affordance theory began in ecological psychology as action possibilities from the environment [19]. The stair-climbing experiment used the environmental-to-physical attribute ratio [20]. Later, with relational ontology, affordance became a relational property between animal abilities and environmental features [21]. Prior affordance research suggests that affordances possess three fundamental characteristics: they represent action possibilities related to actors' capabilities, exist independently of whether they are perceived, and remain relatively invariant to users' immediate needs or goals [22]. Environmentally, affordance is inherent, objective in functional possibilities [23]. Later work added technical characteristics, user perception, and social context [24]. In innovation management, a sustainability framework drives adoption via material, organizational, and user agency [25]. In idea research, readability reflects accessibility and affects adoption [26]. Users perceive and use affordances, influencing participation and outcomes [27].

Affordance theory later evolved in information systems and online communities. It is defined as the action possibilities an agent can perceive and realize within a technological environment. It is a structural condition emerging from use [28]. Later work added technical characteristics, user perception, and relational features [29]. In online innovation and knowledge sharing, it splits into three pathways. Cognitive affordance affects comprehension; readability and text features influence idea popularity [26,30]. Entry affordance shapes behavior via technical conditions; ChatGPT reduced simple questions, and undisclosed AI content undermines trust [31,32]. Collaborative affordance facilitates communication; bots alter interaction patterns, and autonomous agents form human-like networks [33,34]. In summary, these three affordances operate on comprehension, technology access, and social interaction, influencing idea diffusion through user perception and implementation.

Affordance theory is a subject-environment framework in information systems and innovation management. Three types appear in online innovation communities: cognitive, entry, and collaborative. The theory links action possibilities to environmental traits, offering a meso-level tool for idea implementation. Cognitive affordance explains adoption. Entry affordance covers resource access and participation. Collaborative affordance focuses on collective integration. A unified framework avoids bias. Although these affordance constructs jointly facilitate idea diffusion, they represent distinct mechanisms operating at different stages of affordance actualization. Operability and detail richness determine whether users can understand and execute an idea by reducing procedural and informational uncertainty, respectively. Actionability signaling and linguistic hedging shape users' willingness to participate by influencing perceived participation legitimacy

and information credibility. Mediating centrality and interaction depth, in contrast, describe collaborative affordances emerging from the social interaction network rather than the textual content itself. Accordingly, each construct captures a unique aspect of the affordance actualization process, minimizing conceptual overlap while providing a complementary explanation of idea diffusion. This study examines how these affordances manifest in product sustainability, idea content, and interaction. Idea texts provide cognitive and entry affordances. Comment networks provide collaborative affordances. This enriches affordance theory in digital idea contexts.

2.2. Idea Diffusion in Online Innovation Communities

In online innovation communities, idea diffusion links individual creation with collective adoption, reflecting both intrinsic innovation attributes and social context. Diffusion theory suggests that the spread of an innovation is ultimately manifested through adoption behaviors among members of a social system rather than through simple information exposure or transmission [35]. Accordingly, the diffusion of an idea is reflected by the extent to which it is adopted, implemented, and utilized by others.

Recent research further suggests that idea diffusion in innovation communities extends beyond information transmission and increasingly involves knowledge reuse and recombination processes [36]. Knowledge recombination theory argues that innovation emerges when existing knowledge elements are adopted, modified, and recombined into new configurations [37]. From this perspective, the influence of an idea is reflected not only in whether it is observed by others but also in whether it stimulates subsequent creative activities, such as adaptation, reproduction, remixing, and derivative innovation. Therefore, idea diffusion can be understood as a process through which original ideas are transformed into subsequent creative outputs through community participation and knowledge recombination.

Consistent with this perspective, empirical studies of online innovation communities increasingly conceptualize idea diffusion through observable adoption and reuse behaviors. Prior research has shown that idea implementation, community adoption, derivative creation, and reuse behaviors are important manifestations of idea influence and diffusion within innovation ecosystems. Ideas that generate higher levels of adoption and reuse tend to exert broader influence and create greater collective value within communities [18,38]. Consequently, idea diffusion should be viewed as a multidimensional process encompassing not only information dissemination but also knowledge transfer, adoption, and creative recombination.

Prior studies have noted that idea diffusion can be characterized not only by the magnitude of adoption but also by its temporal and structural dimensions, including diffusion speed, diffusion scope, and network reach [39]. Classical diffusion research emphasizes relative advantage, compatibility, complexity, trialability, and observability [35,40,41], while recent studies highlight team size, innovation type, platform behavior, network structure, and social signaling [18,42–44]. Small teams tend to propose disruptive ideas, whereas large teams focus on incremental development. Digital platforms have shifted diffusion dynamics, emphasizing interaction, observational learning, and collaborative knowledge creation rather than merely intrinsic innovation attributes.

Network structure has been identified as a critical yet contested determinant of idea diffusion. Some studies suggest that dense and cohesive networks facilitate diffusion by reinforcing social influence and repeated exposure, whereas others emphasize the importance of bridging ties and structural diversity for extending diffusion across disconnected groups [45–47]. These findings indicate that the effects of network structure depend on how diffusion is conceptualized and measured. Diffusion can be operationalized in multiple ways, including the speed of adoption, breadth of reach, cumulative adoption,

or network penetration [48,49]. Consequently, idea diffusion should be understood as a multidimensional process rather than a single outcome, and empirical studies must carefully select measures that align with the specific diffusion aspect under investigation.

2.3. The Role of AI in Online Communities and Open Innovation

AI reshapes both content and interaction in online innovation communities. At the content level, AI reduces repetitive inquiries and increases complex, higher-order questions, enriching the ecosystem [31]. At the interpersonal level, AI agents influence reciprocity and social exchange, while undisclosed AI-generated content may undermine trust in communities valuing originality [32,33]. Autonomous AI agents also embed as non-human digital actors, shaping network evolution and community structure [34].

AI enhances idea generation and knowledge collaboration. Structured human–AI interactions outperform human-only solutions, improving strategic feasibility, financial value, and environmental outcomes [50]. Generative AI facilitates new product development and idea diversity, supporting incremental and radical innovation [51]. AI complements humans across knowledge processes, but effective collaboration depends on trust, role clarity, and AI literacy [52,53]. Poor interpretability and opaque governance mechanisms reduce trust and participation [54], while high AI self-efficacy can enhance innovation but may also trigger displacement concerns when organizational readiness is low [55].

AI-generated ideas differ from human contributions in terms of intrinsic attributes, social signaling, and adoption patterns, creating both opportunities and trust challenges [56]. Although most studies agree that AI enhances idea generation and knowledge collaboration, findings regarding its broader social consequences remain mixed. On the one hand, AI-supported interactions can stimulate creativity and improve problem-solving performance by providing novel inspirations, expanding the search space for solutions, and facilitating human–AI co-creation [50,57,58]. On the other hand, concerns regarding transparency, authenticity, and algorithmic opacity may undermine trust and reduce users' willingness to engage with AI-supported systems, particularly in contexts where human originality and autonomy are highly valued [59–61]. These contrasting findings suggest that AI simultaneously acts as both an enabling and constraining force, with its effects depending on users' perceptions of legitimacy, competence, and governance. Table 1 summarizes prior studies examining the role of AI in idea generation and knowledge collaboration.

Table 1. A Study on the Role of AI in Idea Generation and Knowledge Collaboration.

Dimension	Author (Year)	Key Findings
Content Enhancement	Burtch et al., 2024 [31]	AI reshapes content by reducing repetitive inquiries and increasing complex, higher-order questions, enriching the ecosystem.
Interaction & Trust	Lloyd et al., 2025 [32]	Moderating AI-generated content affects human interactions on platforms like Reddit, impacting community dynamics and participation.
	Safadi et al., 2024 [33]	Bots influence human interaction in online communities, with effects on engagement and social behaviors.
Autonomous AI Agents	Chen et al., 2026 [34]	Large language model-based autonomous agents act as non-human digital actors, shaping network evolution and community structure.
Knowledge Diffusion	Boussiou et al., 2024 [50]	Human–AI collaboration supported by differentiated search strategies produces solutions

		with higher strategic feasibility, financial value, and environmental value than human-only approaches.
	Mariani & Dwivedi, 2024 [51]	Generative AI serves as a key enabler of new product development, idea diversity, and innovation ecosystem evolution.
Knowledge Collaboration	Chowdhury et al., 2022 [52]	Effective collaboration between AI and employees depends on the synergy of factors such as knowledge sharing, AI skills, trust, and clear role definitions.
	Jarrahi et al., 2023 [53]	AI complements humans at every stage of the knowledge process, requiring systematic investment in personnel, skills, infrastructure, and business processes.
Trust, Risk, Conditional Effects	Chow et al., 2026 [56]	Generative AI links affordance availability with trust and knowledge creation processes, transforming technological potential into actionable innovation outcomes.
	van der Waa et al., 2021 [54]	Lack of interpretable understanding of AI decision-making logic can erode user trust, and opaque mechanisms may discourage participation.
Creativity & Inspiration	Kim & Maher, 2023 [57]	AI-based inspiration stimulates human design ideation, expanding the search space for solutions and enhancing creativity.
	Dellermann et al., 2019 [58]	Hybrid intelligence combining humans and AI improves collective problem-solving and knowledge integration.
	Zerilli et al., 2022 [59]	Transparency modulates trust in AI, with opaque systems potentially reducing user engagement.
	Vössing et al., 2022 [60]	Designing transparency in human–AI collaboration enhances trust and effectiveness.
	Moura et al., 2023 [61]	AI-generated art is perceived differently; concerns about originality can reduce perceived value and engagement.

Existing studies have therefore established two important insights. First, idea diffusion is shaped by both content-related characteristics and network structures. Second, AI can influence knowledge creation, trust formation, and user interaction processes. However, these two streams of research remain only partially connected. In particular, little is known about whether AI changes the way platform affordances are translated into diffusion outcomes or whether it influences the nonlinear activation of affordances. Addressing this gap provides the motivation for the present study.

3. Theoretical Analysis and Research Hypotheses

Affordance theory holds that action arises from perceiving environmental possibilities [19]. In information systems, it became a user-technology framework: affordances depend on cognition and context [62]. Recent work shows they are situational and nonlinear [63]: below a threshold, action is hard; above it, behavior activates strongly. Diffusion also requires information to have enough explanatory power [64]. Combining these, idea diffusion is an affordance-driven activation process with thresholds. This paper builds a three-stage model: cognitive (understanding/execution), entry

(participation willingness), and collaborative (sustained interaction). These act sequentially, from information understanding to behavioral participation to group diffusion. Figure 1 illustrates the three-stage model developed in this study.

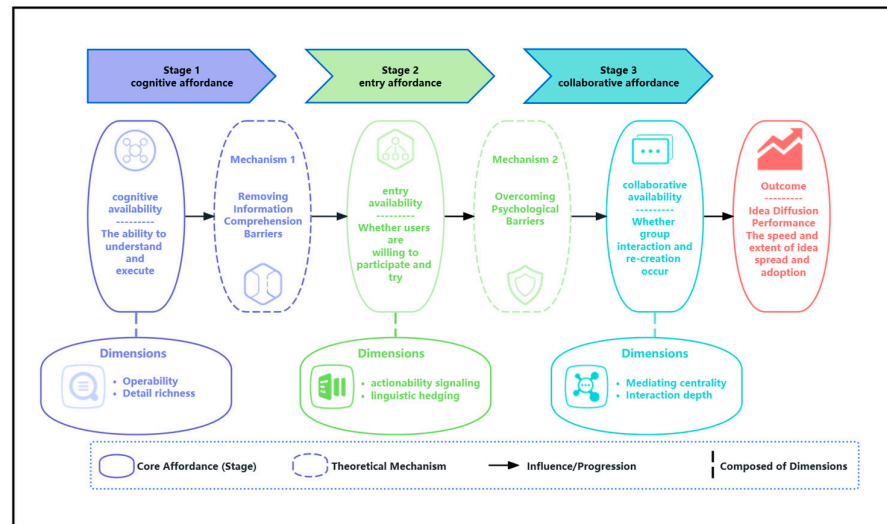


Figure 1. Three-stage model. Notes: This figure presents the three-stage research model. The detailed description of the model is provided in the Supplementary Materials (Hypotheses Model.svg).

Existing affordance research generally assumes a monotonic relationship between affordance characteristics and behavioral outcomes [28]. However, affordance theory views affordances as action potentials rather than guaranteed actions, and their realization depends on users' interpretation, capabilities, and contextual conditions [10,65]. Consequently, increasing affordance levels may not generate proportional increases in idea diffusion, making nonlinear effects theoretically plausible. Importantly, whether a nonlinear relationship takes the form of a U-shaped or an inverted U-shaped pattern depends on the dominant role of the affordance characteristic [66]. When additional information primarily increases cognitive burden, information-overload mechanisms may produce an inverted U-shaped relationship. In contrast, when affordance characteristics function not only as information cues but also as implementation resources that facilitate understanding, adaptation, and reproduction, their enabling value may eventually outweigh their cognitive costs, leading to a U-shaped relationship after a critical threshold is reached [67]. Therefore, the quadratic specifications adopted in this study are theory-driven rather than exploratory and are intended to capture threshold-based affordance activation processes. Furthermore, generative AI may influence these relationships by reducing search, interpretation, and knowledge-integration costs, thereby shifting the activation threshold at which affordance-related resources become behaviorally valuable [68]. Specifically, AI enables users to process, interpret, and apply complex information more efficiently. Consequently, levels of information complexity that might otherwise exceed users' cognitive capacities may remain actionable under AI support, allowing the benefits of affordance-related resources to emerge at different levels of affordance intensity. Consequently, AI is expected to influence the location and strength of existing nonlinear affordance-diffusion relationships rather than independently creating such relationships. This mechanism provides the theoretical basis for examining the moderating role of AI usage in the affordance-diffusion relationship.

Throughout this study, the term “U-shaped relationship” refers specifically to a convex nonlinear relationship whose inflection point lies within the observed data range and whose effect becomes increasingly positive after the threshold is crossed. To avoid ambiguity, all nonlinear effects are described consistently as U-shaped relationships within the observed range.

3.1. The Impact of Cognitive Affordance on Idea Diffusion

Cognitive affordance is the ability to turn information into actionable representations. Affordance is relational, not objective [69]. If an idea text lacks clear action paths, users abandon it even when execution is easy [70,71]. This paper breaks the process into two stages: comprehension and execution. Detail richness provides material, tool, and parameter information to help users form clear cognitive representations. Operability uses action-oriented language to translate cognition into behavior. Together, they form the core of cognitive affordance. Neither alone suffices. Both informational adequacy and action accessibility are needed for effective idea execution and further dissemination. Unlike actionability signaling, detail richness does not explicitly encourage participation but instead increases the informational completeness required for idea understanding.

Detail richness reflects technical completeness in an idea, a key dimension of cognitive affordance supporting comprehension [72]. It appears as the density of specifics (e.g., materials, tools, parameters). Unlike operability (action pathways), detail richness emphasizes information sufficiency and explanatory power, helping users understand components and implementation. Its impact on idea diffusion varies by stage. Traditional cognitive load theory suggests more information increases load [73], inhibiting efficiency. But in digital innovation, information’s role depends on reaching thresholds of interpretability and decision-readiness [74].

When detail richness is low, limited information prevents users from forming a clear cognitive representation. This creates uncertainty about feasibility and value, inhibiting participation and diffusion. As detail richness increases, interpretability improves, but users still need extra cognitive effort before a sufficient level is reached. At this stage, the promotion effect remains limited [75]. When detail richness becomes high, information gains strong diagnosticity. It supports decision-making [76]. Rich descriptions of materials, tools, and parameters reduce uncertainty and enhance replicability and verifiability. This makes it easier for users to imitate, improve, or recreate the idea, significantly promoting idea diffusion.

From an affordance perspective, detailed information shifts from a cognitive burden to an action resource. Insufficient information hinders action, while sufficient information promotes it [77]. Thus, detail richness has a nonlinear, U-shaped effect on idea diffusion.

H1a: *The relationship between detail richness and the diffusion of ideas is U-shaped.*

Operability means an idea has clear action paths and implementation guidelines [78]. Highly actionable ideas contain many action-oriented verbs (e.g., print, assemble). These verbs convey behavioral information and serve as cognitive cues, helping users map abstract concepts into concrete steps. Thus, operational language provides clear procedural information, transforming an idea from a conceptual level into a sequence of perceivable and replicable actions [78].

Operability reduces users’ information processing costs, helping translate ideas into action [79,80]. Cognitive load theory notes limited resources; unclear structures increase load [81]. Actionable language minimizes inference, building clearer representations [82]. Cognitive processing theory shows that explicit action-oriented information shortens the understanding of the decision execution path, improving efficiency [82]. From affordance

theory, operability enhances action feasibility. Seeing a clear path shifts perception from understanding to possible execution [19]. This increases participation in diffusion (e.g., commenting, improving, recreating).

H1b: *Operability has a positive impact on idea diffusion.*

3.2. The Impact of Entry Affordance on Idea Diffusion

Entry affordance concerns crossing psychological and situational thresholds into action [83]. It involves two mechanisms: participation motivation and perceived risk [29,84]. This study selects actionability signaling (communicates accessibility/modifiability, stimulates interaction) and linguistic hedging (reduces certainty/authority, lowers anxiety) as core dimensions [85,86]. Together, they form a complementary motivation-risk regulation: the former promotes willingness, the latter reduces concerns, jointly determining entry feasibility. Unlike detail richness, which concerns information sufficiency, actionability signaling functions through behavioral invitation and perceived participation legitimacy.

In online innovation communities, user participation depends on perceived legitimacy and feasibility [87]. Actionability Signaling uses linguistic cues (e.g., “Feel free to edit”) to lower psychological barriers. Such prompts reduce cognitive uncertainty and action costs, encouraging action [88]. From a social cognitive view, behavior relies on situational and normative signals [89]. When an idea work is labeled “editable” or “recreatable,” its openness is reinforced, promoting re-creation and diffusion [90]. However, this effect is nonlinear and has threshold characteristics.

When actionability signaling is low, the idea appears closed, users doubt eligibility, and participation is inhibited [87]. At a moderate level, openness increases but ambiguity remains, leaving users uncertain and cognitively burdened [91]. When actionability signaling is high, the idea clearly signals being modifiable and participation-friendly, reducing uncertainty and psychological costs, thereby boosting re-creation and idea diffusion [88].

H2a: *Actionability signaling and idea diffusion exhibit a U-shaped relationship.*

Linguistic Hedging reflects the openness of idea content and the scope for exploration. It is a key indicator of participatory space within affordances [92]. Unlike open-ended invitations (which focus on permission to participate), linguistic hedging shows whether an idea offers room for creativity and improvement. Information gap theory suggests that incomplete or ambiguous information motivates people to explore and fill gaps [93]. Linguistic Hedging (e.g., possibly, could be tried, not yet perfected) introduces ambiguity and openness. It transforms an idea from a closed final outcome into a process-oriented entity that can be further developed and optimized.

Linguistic Hedging also has stage-specific effects [92]. When linguistic hedging is low, ideas appear highly certain with little room for improvement. Users struggle to find entry points. This inhibits re-creation and diffusion [94]. As linguistic hedging increases, users see room for improvement. However, if uncertainty is too small to create a clear information gap, motivation remains limited. When uncertainty becomes high, the information gap becomes significant. This stimulates exploration and participation [95]. At that stage, users are more likely to comment, discuss, and even re-create by adding information or proposing improvements. This drives idea diffusion.

H2b: *Linguistic hedging and idea diffusion exhibit a U-shaped relationship.*

3.3. The Impact of Collaborative Affordance on the Diffusion of Ideas

Collaborative affordance is embedded in socio-technical structures, not individual abilities [96,97]. It is the latent potential to connect, activate, and reproduce ideas in a network. Measurement requires two dimensions: structural positional advantages [98] and interactive generative processes [99]. By simultaneously incorporating structural and process dimensions, we can more accurately characterize the formation mechanism of collaborative affordance.

Mediating centrality captures the bridging role of idea publishers in community networks: occupying structural holes and connecting heterogeneous groups [100]. From an affordance perspective, idea diffusion depends on embedding in multi-path information flows. Yet this structural advantage is not linear but exhibits a curvilinear threshold effect [101].

At low-to-moderate mediating centrality, creators move beyond local circles but are not yet stable hubs. Structural hole advantages fail. Two mechanisms dilute affordance: fragmented pathways scatter ideas into noise [102], and rising coordination costs drain creators' energy, reducing participation [103]. Thus, we propose:

H3a: *There is a U-shaped relationship between mediating centrality and idea diffusion.*

From an affordance perspective, technology or platforms do not directly determine behavior. They provide perceptible action possibilities [10]. In online innovation communities, comment replies, threaded discussions, and collaboration tools form the basis of collaborative affordances. Their impact on idea diffusion depends on how users turn these into concrete interactions. Multi-turn interaction is a high-quality, structured form: continuous, multi-tiered response chains around one idea.

Compared to single-turn or shallow interactions, multi-turn interaction is a key manifestation of collaborative affordance. It is more likely to facilitate idea diffusion. At the cognitive level, multi-round communication aids information integration and reduces uncertainty. Sustained interaction creates structural conditions for information accumulation and reorganization [104]. As discussion rounds increase, different participants add interpretations, revisions, and new content. The original idea evolves from a single expression into a multidimensional representation. This process improves comprehensibility and interpretive depth. It lowers cognitive costs for potential audiences. Repeated clarification and correction also reduce uncertainty about the idea's feasibility and value. Thus, users' willingness to share and adopt grows. At the social level, multi-round communication reinforces social identity and normative signals. Compared to low-intensity interactions, multi-round exchanges require more time and cognitive effort. This makes them more visible signals of participation intensity [105].

H3b: *Interaction depth positively influences idea diffusion.*

3.4. The Moderating Role of AI

Affordance theory states that action depends on perceiving and using environmental possibilities. With generative AI, this process becomes human-machine collaborative [106]. AI generates content, completes action paths, and optimizes expressions, altering information processing and cost structures. Recent research suggests that generative AI not only serves as a technological tool but also reshapes how users perceive, interpret, and actualize affordances. By enhancing information processing, knowledge integration, and trust formation, AI can alter the translation of affordance potentials into concrete actions, thereby influencing subsequent innovation outcomes [56]. Hence, AI's moderating role is an intervention in the affordance-to-action conversion mechanism. AI is theorized to

influence the location and strength of existing nonlinear affordance-diffusion relationships rather than independently creating such relationships.

3.4.1. The Moderating Effect of AI Usage on Operability

Operability provides clear, actionable paths and is key to behavioral affordance. Traditionally, ideas with clearer steps promoted diffusion. But generative AI now auto-generates action plans, so users rely less on the original text and more on AI assistance [107]. Thus, the role of the text's operational information in promoting idea diffusion weakens.

AI usage reduces the marginal value of operability in three ways. First, AI substitutes cognitive effort by generating action steps even from vague ideas, diminishing the advantage of highly Operable ones [15,107]. Second, AI lowers the cost of obtaining operational information, reducing the marginal utility of operability [108]. Third, AI-generated solutions are highly standardized, compressing differences in operability and eroding the advantage of highly operable ideas [109].

H4a: *AI usage negatively moderates the relationship between operability and idea diffusion. As the level of AI usage increases, the positive impact of operability on idea diffusion significantly weakens.*

3.4.2. The Moderating Effect of AI Usage on Actionability Signaling

Actionability signaling motivates participation via permission and improvement signals; its effectiveness depends on perceived sincerity. In non-AI contexts, it shows a positive U-shaped relationship: low-level signals signal competence, high-level stimulate action, moderate-level create ambiguity and inhibit diffusion.

Generative AI produces text with higher semantic coherence and clarity [110]. This structural advantage makes even low or ambiguous invitations interpretable, reducing cognitive cost [111]. Thus, at low-to-moderate levels, AI amplifies the linear promotional effect on idea diffusion.

At high levels, actionability signaling relies on content incompleteness to sustain participation. But AI-generated content is highly complete and self-consistent [112], narrowing the space for user intervention. Hence, at high levels, AI weakens the additional contribution, negatively modulating curvature.

H4b: *AI usage positively moderates the first-order effect of actionability signaling and negatively moderates its second-order effect. That is, AI usage generally enhances the marginal effect of open-ended invitations, but simultaneously weakens their U-shaped relationship, causing the curvature to flatten.*

3.4.3. The Moderating Effect of AI Usage on the Structural Position Effect of Mediating Centrality

Mediating centrality reflects an idea's bridging role. Its diffusion advantage comes from connecting structural holes and integrating cross-group information. Traditionally, it shows a positive U-shaped relationship. Low centrality helps diffusion via small, high-trust networks. High centrality enables cross-domain communication through structural holes. Moderate centrality suffers from structural instability.

AI alters how users interpret network signals and information flows, moderating in two ways. First, AI-driven matching and recommendations amplify visibility for bridging positions, strengthening the positive first-order effect of mediating centrality [113]. Second, AI reduces path dependence and substitutes bridges: AI-generated content improves clarity [110], lessening disadvantages for low-centrality users, and cross-structural exposure [113,114] erodes advantages for high-centrality nodes, weakening the right-side increase.

In summary, AI reduces low-centrality disadvantages and high-centrality advantages. It compresses the nonlinear space of mediating centrality on idea diffusion, flattening the U-

shaped curve. Thus, the interaction between AI and the quadratic term of mediating centrality negatively moderates idea diffusion.

H4c: *AI usage positively moderates the first-order effect of mediating centrality and negatively moderates its second-order effect. That is, AI usage enhances the marginal positive effect of Mediating centrality but weakens its U-shaped relationship, thereby reducing the curvature intensity.*

In summary, AI does not simply reinforce or weaken the effects of affordances. Rather, it may influence the conditions under which affordances are translated into behavioral outcomes. On the one hand, AI can affect the marginal effects of affordances through substitution and enhancement mechanisms. On the other hand, it may influence nonlinear affordance-diffusion relationships by facilitating information processing and reducing the cognitive costs associated with complexity and ambiguity. These findings provide preliminary evidence that generative AI may play a role in affordance activation processes within online innovation communities. However, given the relatively limited prevalence of AI-related ideas in the present dataset, these effects should be interpreted as indicative of potential AI-enabled mechanisms rather than definitive evidence of a universal transformation of affordance-behavior relationships. The research framework of this study is presented in Figure 2. The dashed boxes denote the three dimensions of affordance, whereas the solid boxes denote the individual variables.

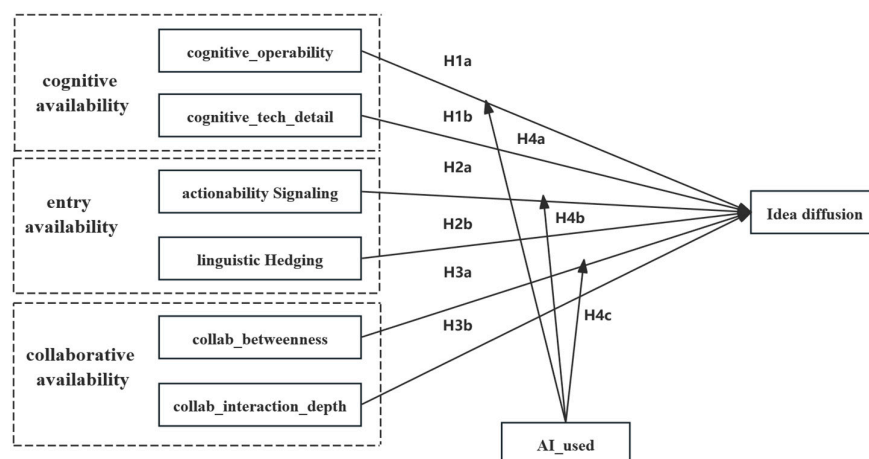


Figure 2. Research Framework Diagram. Notes: The original hypotheses model is provided in the Supplementary Materials (Research Framework.svg).

4. Research Methods

4.1. Data Collection

This study selected the Makerworld community. It is an online innovation community for sharing and creating 3D-printed models. The community covers multiple sections such as 3D printers, art, education, fashion, hobbies and DIY, home use, scale models, props, tools, toys, games, and generator models. Using a Python 3.11 web crawler, the study collected idea content from these sections. Each idea record includes a unique identifier, author ID, text description, attachments, publication time, views, likes, and followers. Comment data includes comment ID, user ID, parent comment ID, and timestamp. This data was used to build a comment interaction network. Between 26 January 2026 and 8 February 2026, the study collected 121,587 idea entries along with their comments and user profiles. After cleaning (removing entries with empty text or only

images), 94,319 valid idea entries remained. After data cleaning, 94,319 valid ideas remained. Among them, 93,381 ideas contained sufficient comment information for network construction. Finally, 66,879 observations with complete information across all variables were retained for the regression analyses.

MakerWorld is an international innovation community in which idea descriptions are written in both Chinese and English, with Chinese constituting the majority of the corpus and English representing a smaller but non-negligible proportion. In addition, a limited number of entries contain multilingual expressions that combine both languages. To ensure consistent processing of multilingual textual data, this study employed Jieba together with a customized dictionary for text preprocessing and tokenization. The customized dictionary incorporated both Chinese domain-specific terminology and frequently occurring English technical terms. The use of Jieba does not imply that the corpus is exclusively Chinese; rather, it serves as a preprocessing tool within a multilingual text-processing pipeline designed to ensure consistent treatment of both Chinese- and English-language content.

4.2. Variable Design and Measurement

4.2.1. Dependent Variable

Recent empirical research in online innovation and user-generated idea communities has increasingly treated idea adoption and subsequent creative use by peers as a reflection of idea diffusion rather than as an index of individual user productivity. In a large-scale empirical study of user ideas submitted to an online innovation platform, Qin [38] operationalize idea adoption as the outcome of interest and demonstrate that objective indicators, including related posts, likes, and comments, significantly affect the likelihood that a focal idea will be adopted by others, enriching the measurement of idea diffusion in digital communities. This approach aligns with theoretical perspectives on idea diffusion within online social and innovation networks, where the spread of an idea is evidenced by its uptake and recombination by peers rather than the sheer productivity of its originator [115]. By focusing on how often a focal idea triggers subsequent adoption or reproduction behaviors, platform-based metrics such as the number of reproductions operationalize the core aspects of diffusion.

On the MakerWorld community, idea diffusion occurs when a focal idea is adopted and recreated by other users. Specifically, when a user views an idea and uses its associated images, parameters, or design elements to produce their own version, this reproduction contributes to the idea's diffusion. The greater the number of such reproductions, the more widespread and influential the idea is within the community. In this study, we employ an objective website-based measure to capture idea-level diffusion: the total number of times a focal idea has been recreated by other users, denoted as *make_count* [18]. When a user views and adopts an idea, they may replicate it using associated images, parameters, or design elements. Each such reproduction is counted in *make_count*, capturing the extent to which the idea has diffused through the community. This operationalization reflects the influence and propagation of a specific idea, rather than the creative output or productivity of its original creator. This measurement strategy captures the propagation and influence of individual ideas within the community, in contrast to measures of individual users' creative productivity.

4.2.2. Independent Variables

Operability

Operability measures how easily an idea guides hands-on action via action-oriented language. This study uses the proportion of action verbs to measure operability. Operability reflects the physical manipulation a 3D-printed model requires. More action verbs mean the idea is more likely to inspire practical action [116]. This indicator captures informational completeness rather than behavioral invitation. The calculation steps are as follows:

- Text preprocessing: Remove non-textual content (HTML tags, symbols, emojis). Keep plain text. Use Jieba for Chinese word segmentation. Remove stop words and single-character words.
- Build an action word list. Base it on common 3D printing and crafting behaviors. Include terms such as “print,” “assemble,” “carve,” “join,” “bond,” “sand,” “spray,” and “drill.”
- Calculate action word frequency. Segment each cleaned idea text. Count words in the action list as Action Count. Count total words as Total Words.
- Compute Operability. Operability (cognitive_operability) = Action Count/Total Words. See Formula (1). The calculation procedure and corresponding code are provided in the Supplementary Materials (Build_Action_Density_Index.py).

$$\text{cognitive_operability} = \frac{\text{Action Count}}{\text{Total Words}} \quad (1)$$

Detail Richness

This study measures detail richness in idea texts by the proportion of technical terms. Technical information completeness and accuracy are key for reproduction [117]. Technical density is defined as the ratio of technical terms to total words [118]. Calculation steps:

- Text preprocessing is the same as for operability.
- Build a technical term list for 3D printing and model making (e.g., “PLA,” “nozzle,” “layer height,” “support”).
- Count technical terms in each cleaned idea text as Tech Count. Total words = Total Words.
- Detail richness (cognitive_tech_detail) = Tech Count/Total Words (Formula (2)). Higher ratio means richer technical details and better guidance. For transparency and reproducibility, the detailed calculation procedure and Python code used to construct this index are provided in the Supplementary Materials (Technical_Density.py).

$$\text{cognitive_tech_detail} = \frac{\text{Tech Count}}{\text{Total Words}} \quad (2)$$

Actionability Signaling

This study measures actionability signaling with a composite index. It captures linguistic cues that lower participation barriers and guide users from bystanders to participants. Three dimensions are used: open-ended invitations, modifiability prompts, and comment guidance [119–121]. Unlike detail richness, this measure captures explicit participation cues rather than technical information. Stronger signals promote idea re-creation and diffusion. Calculation steps:

- Text preprocessing is the same as for operability.
- Compute open-ended invitation proportion. Build a glossary of invitation phrases (e.g., “Feel free to try,” “Can be modified,” “We welcome your feedback”). For each

idea text, count glossary matches (Invite Count) and total sentences (Total Sentences). Open Invite = Invite Count/Total Sentences (Formula (3)). For transparency and reproducibility, the detailed calculation procedure and Python code used to construct this index are provided in the Supplementary Materials (Invitation_Indicators.py).

$$\text{Open Invite} = \frac{\text{Invite Count}}{\text{Total Sentences}} \quad (3)$$

- Compute the modifiability hint ratio. Build a list of modifiability hint phrases. Examples include “needs optimization,” “could be improved,” “incomplete,” “needs refinement,” “not yet completed,” “adjustable,” “customizable,” and “replaceable.” Count how many times these phrases appear in each idea text. Record this as a modify count. The modify hint metric is the modify count divided by the total number of sentences. See Formula (4). For transparency and reproducibility, the detailed calculation procedure and Python code used to construct this index are provided in the Supplementary Materials (Modifiability.py).

$$\text{Modify Hint} = \frac{\text{Modify Count}}{\text{Total Sentences}} \quad (4)$$

- Calculate the Comment Induction Index. This index measures how much an idea text semantically stimulates user comments. It does not just count comments. It identifies comments highly relevant to the idea’s theme by calculating semantic similarity between the idea description and comment content. Steps:
 - a. Encode each idea text using a multilingual sentence vector model (e.g., paraphrase-multilingual-MiniLM-L12-v2) to obtain sentence vector C.
 - b. Encode all comments for that idea text to obtain comment vectors R1, R2, ..., Rn.
 - c. Compute cosine similarity between C and each Ri using Equation (5).

$$\text{sim}(C, R_i) = \frac{C \cdot R_i}{\|C\| \|R_i\|} \quad (5)$$

- d. Set a similarity threshold θ (here, $\theta = 0.6$). Count comments with similarity above the threshold. Denote this as guided comments.
- e. The comment guide index is the ratio of guided comments to total comments on the idea (Equation (6)). The index ranges from 0 to 1. A higher value means a stronger semantic link between the idea text and comments, and better guidance toward discussions related to the idea’s theme. For transparency and reproducibility, the detailed calculation procedure and Python code used to construct this indicator are provided in the Supplementary Materials (Comment_Guidance.py).

$$\text{Comment Guide} = \frac{\text{Guided Comments}}{\text{Total Comments}} \quad (6)$$

- Combining the three indicators: Since the three indicators share the same unit of measurement (all being ratios), this study employs an equally weighted average to calculate the composite actionability signaling, as shown in Equation (7). To ensure consistency in the direction of the indicators, all three are positive indicators; a higher value indicates stronger actionability signaling.

$$\text{Action Signaling} = \frac{1}{3} (\text{Open Invite} + \text{Modify Hint} + \text{Comment Guide}) \quad (7)$$

In the actual calculations, this study utilized the Python programming language and the sentence_transformers library to load the pre-trained model, compute the comment guidance indices for all ideas in batches, and periodically save intermediate results to ensure computational stability.

Linguistic Hedging

Uncertainty expressions in idea texts affect perceived action affordance [122]. This study uses TF-IDF to quantify linguistic hedging (words expressing speculation, tentativeness, or non-affirmation). Higher weighted density means more ambiguity, weaker perceived affordance, and lower action likelihood. Calculation steps:

- Text preprocessing is the same as for operability.
- Build an ambiguous term list (e.g., “possibly,” “maybe,” “probably,” “estimate,” “try,” “suppose,” “uncertain”).
- For each term, compute IDF as shown in Equation (8): $IDF(w) = \log((N + 1)/(df(w) + 1)) + 1$ (smoothing to avoid zero denominator), where N = total documents, $df(w)$ = document frequency of term w . TF is calculated per document.

$$IDF(w) = \log\left(\frac{N + 1}{df(w) + 1}\right) \quad (8)$$

- For each idea text, compute the weighted term frequency sum: multiply the term frequency of each fuzzy term by its IDF, then sum the results. This is shown in Equation (9), where $tf_j(w)$ is the frequency of term w in document j , and $IDF(w)$ is its inverse document frequency.

$$\text{Weighted Sum}_j = \sum_{w \in \text{FuzzyWordList}} tf_j(w) \times IDF(w) \quad (9)$$

- The linguistic hedging index is the ratio of the weighted term frequency sum to the total number of words in the document (Equation (10)). A higher index value means a higher density of uncertainty-expressing language in the idea text, and thus greater information ambiguity. For transparency and reproducibility, the detailed calculation procedure and Python code used to construct this indicator are provided in the Supplementary Materials (Uncertainty.py).

$$\text{Linguistic Hedging} = \frac{\text{Weighted Sum}}{\text{Total Words}} \quad (10)$$

Mediating Centrality

This study measures the mediating centrality of idea content using the mean mediating centrality in the comment network [39]. Mediating centrality reflects how users act as bridges between participants. It shows their ability to facilitate information flow [123]. A higher mean mediating centrality means a few key nodes control interaction paths. Information depends on individual users, leading to lower affordance for collaboration. A lower mean means the network is more decentralized. Information flows more evenly, resulting in higher affordance for collaboration [124]. Calculation steps:

- Construct the comment network. For each idea, extract all users who commented as nodes. Establish directed edges based on reply relationships. If user A replies to user B, add an edge from A to B. Each idea has its own independent comment network. For transparency and reproducibility, the detailed calculation procedure and Python code used to construct this indicator are provided in the Supplementary Materials (Comment_Network.py).

- Compute node mediating centrality. Mediating centrality measures how often a node lies on shortest paths between other nodes. For node v in a network, the formula is given in Equation (11).

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (11)$$

Here, σ_{st} denotes the total number of shortest paths from node s to node t , and $\sigma_{st}(v)$ denotes the number of these shortest paths that pass through node v . To facilitate cross-network comparisons, mediating centrality is typically normalized to the interval $[0, 1]$.

- Calculate the mean mediating centrality of the network: Compute the arithmetic mean of the normalized mediating centrality for all nodes in the network, as shown in Equation (12):

$$\text{Avg Between} = \frac{1}{n} \sum_{v \in V} C_B(v) \quad (12)$$

- Compute the mediating centrality indicator for the idea. The mean mediating centrality of each idea's comment network is used as the measure, denoted as `collab_betweenness`. This value ranges from 0 to 1. A smaller value indicates a more decentralized network and higher affordance for collaborative action.

In calculations, Python's NetworkX library models the comment reply network for each idea. The `nx.betweenness_centrality` function computes standardized mediating centrality for each node. The mean is then taken as the idea's mediating centrality indicator (stored as `collab_betweenness`).

Interaction Depth

Comment depth measures interaction depth as the length of reply chains from the root comment. More levels and continuity mean stronger multi-round dialogue. Higher average depth indicates more thorough communication [125]. This study operationalizes interaction depth as the average comment level, a key indicator of collaborative affordance. Calculation steps:

- Construct the comment network: The specific steps are the same as those for constructing the comment network based on mediating centrality.
- Define comment hierarchy (depth): Set the depth of root comments with no reply targets to 1; for each reply comment, its depth equals the depth of the parent comment it replies to plus 1, as shown in Equation (13):

$$\text{depth}(\text{reply}) = \text{depth}(\text{parent}) + 1 \quad (13)$$

Here, parent refers to the parent comment being replied to.

- Calculate the average comment depth: For all comments on each idea, calculate the arithmetic mean of each comment's depth, as shown in Formula (14):

$$\text{Avg Depth} = \frac{1}{m} \sum_{i=1}^m \text{depth}_i \quad (14)$$

Here, m represents the total number of comments under the post, and depth_i represents the depth value of the i -th comment.

- Calculate the post's interaction depth metric: Use the average comment depth for each post as its interaction depth measurement, denoted as `collab_interaction_depth`. This metric ranges from $[1, +\infty)$, with higher values indicating deeper comment hierarchies and greater potential for multi-round interactions.

In the actual calculation, this study uses the Python programming language to sort comment timestamps and recursively trace reply relationships, calculate the depth of each comment, and finally compute the average to obtain the interaction depth metric for each post.

4.2.3. Moderating Variables

This study measures AI usage by detecting AI-related terms in idea texts. AI usage means creators mention or use generative AI tools for creation, content generation, or optimization. In online innovation communities, explicitly stating AI use signals a human–machine collaboration. This may change how users perceive operability, actionability signaling, and mediating centrality. The measurement steps are as follows:

- Text Preprocessing: The text preprocessing steps for AI usage are the same as those for Operability.
- Construction of an AI Keyword Glossary: Based on common terminology, tool names, and technical concepts in the generative AI field, an AI keyword glossary is constructed. This covers general terms (such as “AI,” “artificial intelligence,” and “large models”), internationally renowned AI tools (such as “ChatGPT,” “GPT-4,” “Claude,”), domestic AI tools (e.g., “Kimi,” “DeepSeek,” “Doubao,”), technical concepts (e.g., “machine learning,” “deep learning,” “neural networks,”), as well as Chinese and English abbreviations and aliases.
- Matching AI keywords: Use regular expressions to construct matching patterns, matching keywords at word boundaries (\b) and ignoring case. Search each idea text; if at least one AI keyword appears in the description, the idea is deemed to use AI and assigned a value of 1; otherwise, it is assigned a value of 0. As shown in Formula (15):

$$AI_used_i = \begin{cases} 1, & \text{If the description text for Idea } i \text{ contains any AI keywords} \\ 0, & \text{Otherwise} \end{cases} \quad (15)$$

- Generate interaction terms: To examine the moderating role of AI usage on the relationship between affordance variables (operability, actionability signaling, mediating centrality, etc.) and idea diffusion, interaction terms between AI usage and each affordance indicator were constructed. The calculation of the interaction terms is shown in Equation (16):

$$Interaction_i = AI_used_i \times Affordance_i \quad (16)$$

Here, $Affordance_i$ represents a specific affordance metric for the i -th idea (e.g., operability, actionability signaling, mediating centrality, etc.). For the moderating effects of quadratic terms (such as the square of actionability signaling or the square of mediating centrality), the interaction terms are constructed as the product of AI_used and the respective quadratic terms.

In the calculations, Python’s pandas and re libraries were used to match keywords in each idea’s description. This generated a binary variable AI_used . This variable was then multiplied by each affordance metric to create interaction terms, which were included in the regression model.

It is important to note that the binary moderator AI_used captures observable signals of AI involvement disclosed within idea descriptions rather than directly measuring actual AI-assisted creation behavior. Given the absence of platform-level records indicating whether AI tools were used during the creation process, keyword matching provides a practical approach for identifying ideas that explicitly reference AI technologies.

However, this measure appears in a relatively small proportion of the full sample (approximately 0.9% of all idea entries), meaning that statistical inference concerning moderation effects involving AI_used is based on a limited effective sample size. Prior research on rare events and low-prevalence predictors has documented that interaction estimates involving such predictors can be less stable and may exhibit reduced statistical power [126]. Consequently, the interpretation of the moderating role of AI usage should be framed in terms of the subset of idea entries that explicitly reference AI tools rather than generalized to the entirety of the MakerWorld community. To support the consistency of the interaction patterns, additional robustness checks — such as bootstrapped confidence intervals and subgroup analyses within the AI_used subsample — were conducted, but these conclusions remain conditioned on both the limited representation and the fact that AI_used reflects disclosed AI involvement rather than actual usage.

4.2.4. Control Variables

Given the platform’s current state, this study selects control variables from two perspectives. One is the characteristics of the idea content itself. The other is the characteristics of the content creators. These variables may influence the diffusion of idea content. However, they are not the primary focus of this study.

Characteristics of the Idea Content

Idea content characteristics include likes, description length, and publication time. Likes reflect initial popularity [127], denoted as likes. Description length is total characters in the idea text, denoted as description_length [30]. Publication time controls for time effects on visibility and diffusion, denoted as publish_time [128].

Creator Characteristics

Creator characteristics include the number of followers. Followers indicate the creator’s social capital and influence. This study uses followers as a control variable, denoted as followers [129].

Table 2 lists the variables and their measurement indicators. The dependent variable is idea diffusion. This measure captures the extent to which a user’s creative contribution stimulates subsequent creations within the community. Independent variables are grouped into three dimensions: cognitive affordance, entry affordance, and collaborative affordance. Additionally, a moderating variable indicates whether AI tools are explicitly mentioned in the description. A set of control variables is also included to account for potential confounding factors.

Table 2. Research Variables and Measurement Indicators.

Variable Type	Variable Name	Definition	Measurement Method
Dependent variable	make_count	Idea diffusion	Total number of times a focal idea has been recreated by other users
Independent variable	cognitive affordance	cognitive_operability	Operability
			Total number of action verbs ÷ Total number of words
		cognitive_tech_detail	Detail richness
			Total number of technical terms ÷ Total number of words
	entry affordance	action_signaling	actionability signaling
			Equal-weighted average of open-ended invitations, modifiability hints, and comment guidance index

	linguistic_hedging	linguistic_hedging	TF-IDF weighted density of hedging terms (weighted term frequency sum ÷ total number of words)
	collab_betweenness	Mediating centrality	Mean betweenness centrality of nodes in the comment network (lower values indicate a more decentralized network)
	collab_interaction_depth	Interaction depth	Average comment depth in the comment network (root comment depth = 1, reply depth increments by 1)
	AI_used	whether AI tools are used	Explicit mention of AI keywords in the description (1 = yes, 0 = no)
Control Variables	likes	number of likes	Number of likes received by each idea
	followers	number of followers	Number of followers of the idea publisher
	publish_time	publication time	Specific publication date of the idea
	description_length	description length	Total number of characters in the idea description

The descriptive statistics for the relevant data are shown in Table 3.

Table 3. Descriptive statistics.

Variable	Mean	SD	Min	Median	Max
cognitive_operability	0.285	0.255	0.000	0.125	1.000
cognitive_tech_detail	0.088	0.089	0.000	0.071	1.000
action_signaling	0.022	0.071	0.000	0.000	4.778
linguistic_hedging	0.007	0.032	0.000	0.000	0.556
collaboration_betweenness	0.012	0.048	0.000	0.000	0.333
collaboration_interaction_depth	1.010	0.062	1.000	1.000	2.375
likes_log	3.148	1.408	0.000	3.135	8.729
followers_log	4.091	2.406	0.000	4.060	10.334
description_length_log	3.608	1.200	0.000	3.714	8.411
publish_time_log	690.162	180.822	0.000	695.0000	1026.000
AI_used	0.009	0.097	0.000	0.000	1.000
make_count	71.453	110.651	0.000	30.000	934.000

Figure 3 shows Spearman correlations. make_count correlates strongly with followers_log ($r = 0.68$, $p < 0.001$). description_length_log correlates modestly with make_count ($r = 0.13$, n.s.) but negatively with cognitive_operability ($r = -0.47$, $p < 0.001$). collab_betweenness and collab_interaction_depth are positively correlated ($r = 0.41$, $p < 0.001$). likes_log correlates with collab_betweenness ($r = 0.39$) and followers_log ($r = 0.48$). These results justify the control variables and assess multicollinearity.

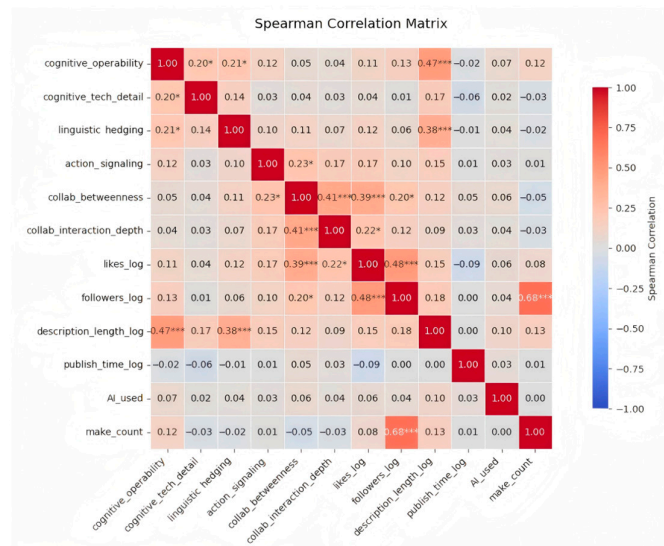


Figure 3. Spearman correlation matrix. Notes: *** $p < 0.001$, * $p < 0.05$.

4.3. Model Design

The dependent variable is idea diffusion (make_count). Because the variance of make_count substantially exceeds its mean, the dependent variable exhibits overdispersion, making the Poisson model unsuitable. Accordingly, a negative binomial regression model is employed, which relaxes the equidispersion assumption by incorporating an additional error term (ϵ_i) to capture unobserved heterogeneity. Equation (17) presents the estimation model.

$$\ln(\mu_i) = \beta_0 + \sum \beta_k X_{ik} + \epsilon_i \quad (17)$$

This study follows a theoretically grounded approach rather than a purely exploratory one. Prior research in information systems and innovation literature suggests that the relationship between platform affordances and creative outcomes is often non-monotonic, as increasing levels of affordances may initially facilitate idea development but eventually generate cognitive overload, coordination costs, or diminishing marginal returns [130,131]. Accordingly, all focal affordance variables are modeled using both linear and quadratic specifications to test theoretically derived threshold and curvilinear effects predicted by affordance activation theory, rather than introducing nonlinear terms on an exploratory basis [132].

To comprehensively examine the main effects of cognitive affordance, entry affordance, and collaborative affordance, as well as their squared effects and the interaction effects of the moderator variable AI_used (including linear and squared interactions), this study constructs the following negative binomial regression model, as shown in Equation (18):

$$\begin{aligned}
\ln(\mu_i) = & \beta_0 + \beta_1 \text{cognitive_operability}_{ic} + \beta_2 \text{cognitive_tech_detail}_{ic} \\
& + \beta_3 \text{Action_Signaling}_{ic} + \beta_4 \text{Linguistic_Hedging}_{ic} \\
& + \beta_5 \text{collab_betweenness}_{ic} + \beta_6 \text{collab_interaction_depth}_{ic} \\
& + \beta_7 \text{AI_used}_{ic} \\
& + \beta_8 \text{cognitive_operability}_{ic}^2 + \beta_9 \text{cognitive_tech_detail}_{ic}^2 \\
& + \beta_{10} \text{Action_Signaling}_{ic}^2 + \beta_{11} \text{Linguistic_Hedging}_{ic}^2 \\
& + \beta_{12} \text{collab_betweenness}_{ic}^2 + \beta_{13} \text{collab_interaction_depth}_{ic}^2 \\
& + \beta_{14} \text{cognitive_operability}_{ic} \text{AI_used}_{ic} + \beta_{15} \text{cognitive_tech_detail}_{ic} \text{AI_used}_{ic} \\
& + \beta_{16} \text{Action_Signaling}_{ic} \text{AI_used}_{ic} + \beta_{17} \text{Linguistic_Hedging}_{ic} \text{AI_used}_{ic} \\
& + \beta_{18} \text{collab_betweenness}_{ic} \text{AI_used}_{ic} + \beta_{19} \text{collab_interaction_depth}_{ic} \text{AI_used}_{ic} \\
& + \beta_{20} \text{cognitive_operability}_{ic}^2 \text{AI_used}_{ic} + \beta_{21} \text{cognitive_tech_detail}_{ic}^2 \text{AI_used}_{ic} \\
& + \beta_{22} \text{Action_Signaling}_{ic}^2 \text{AI_used}_{ic} + \beta_{23} \text{Linguistic_Hedging}_{ic}^2 \text{AI_used}_{ic} \\
& + \beta_{24} \text{collab_betweenness}_{ic}^2 \text{AI_used}_{ic} + \beta_{25} \text{collab_interaction_depth}_{ic}^2 \text{AI_used}_{ic} \\
& + \gamma_1 \ln(\text{likes})_i + \gamma_2 \ln(\text{followers})_i \\
& + \gamma_3 \ln(\text{description_length})_i + \gamma_4 \ln(\text{publish_time})_i + \epsilon_i
\end{aligned} \tag{18}$$

μ_i denotes the expected level of idea diffusion for the i -th focal idea, measured as the expected number of derivative 3D models subsequently generated by other users. Superscript c denotes centering. AI_used_i^c is the centered binary variable. β_1 – β_6 are linear main effects; β_7 is the moderator's main effect. β_8 – β_{13} are squared terms for nonlinear tests; β_{14} – β_{19} are linear interaction terms; β_{20} – β_{25} are squared interaction terms for AI's nonlinear moderation. γ_1 – γ_4 are control coefficients. ϵ_i is the error term.

5. Results

5.1. Hypothesis Testing

This study used Python for data analysis and hypothesis testing. Table 4 presents the results of the negative binomial regression models. Model 1 includes only control variables. Model 2 adds all linear main-effect independent variables to Model 1. Model 3 further includes moderator variables. Model 4 includes all linear interaction terms. Model 5 adds all squared terms and squared interaction terms to Model 4.

Table 4. Results of the negative binomial regression.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
AI_used_c			−0.159 ***	−0.243 ***	−0.663 ***
cognitive_tech_detail_c		−0.284 ***	−0.283 ***	−0.280 ***	−0.434 ***
cognitive_tech_detail_c_sq					1.010 ***
cognitive_tech_detail_c_sq_x_AI					−4.764
cognitive_tech_detail_x_AI				0.629	0.291
collaboration_betweenness_c		−1.861 ***	−1.853 ***	−1.860 ***	−7.348 ***
collaboration_betweenness_c_sq					20.609 ***
collaboration_betweenness_c_sq_x_AI					−23.221 ***
collaboration_betweenness_x_AI				0.627	6.881 ***
collaborative_interaction_depth_c		−0.647 ***	−0.648 ***	−0.644 ***	−1.966 ***
collaborative_interaction_depth_c_sq					3.173 ***
collaboration_interaction_depth_c_sq_x_AI					−4.198 *
collaboration_interaction_depth_x_AI				−0.427	1.211
description_length_log	0.036 ***	0.018 ***	0.018 ***	0.018 ***	0.032 ***

action_signaling_c					−0.899 ***	−0.893 ***	−0.908 ***	−2.015 ***
action_signaling_c_sq								5.139 ***
action_signaling_c_sq_x_AI								−13.684 *
action_signaling_x_AI							2.732 **	5.878 **
Linguistic Hedging c					−0.605 ***	−0.605 ***	−0.601 ***	−1.232 ***
linguistic_hedging_c_sq								0.767 ***
linguistic_hedging_c_sq_x_AI								28.013
linguistic_hedging_x_AI							0.499	−1.772
followers_log	0.501 ***	0.500 ***	0.500 ***	0.500 ***	0.500 ***	0.500 ***	0.500 ***	0.500 ***
likes_log	−0.370 ***	−0.358 ***	−0.357 ***	−0.357 ***	−0.357 ***	−0.357 ***	−0.357 ***	−0.345 ***
cognitive_operability_c					0.171 ***	0.174 ***	0.175 ***	0.131 ***
cognitive_operability_c_sq								0.439 **
cognitive_operability_c_sq_x_AI								7.963 ***
cognitive_operability_x_AI							0.271	−0.544 *
publish_time_log	−0.0003 ***	−0.0003 ***	−0.0003 ***	−0.0003 ***	−0.0003 ***	−0.0003 ***	−0.0003 ***	−0.0003 ***

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. For transparency and reproducibility, the detailed data analysis procedure and Python code used for the squared-term analysis are provided in the Supplementary Materials (Complete_Data_Analysis_All_Squared_Terms.py).

Based on Model 5 in Table 4, this study tested the genuine U-shaped relationship between each variable and idea diffusion. Equation (19) gave the inflection point of each quadratic term. If an inflection point lies within the variable's observed range, the nonlinear relationship holds; otherwise, the variable changes monotonically. Table 5 shows the results.

$$x^* = -\frac{\beta_1}{2\beta_2} \quad (19)$$

Table 5. Table for Determining Inflection Points and Value Ranges of Quadratic Effects.

Variable	Min	Max	x- Coefficient	x ² - Coefficient	Inflection Point	Within Range
cognitive_operability	0.000	1.000	0.131	0.439	−0.149	No
cognitive_tech_detail	0.000	1.000	−0.434	1.010	0.215	Yes
action_signaling	0.000	4.778	−2.015	5.139	0.196	Yes
linguistic_hedging	0.000	0.556	−1.232	0.767	0.803	Yes
Collaboration_ betweenness	0.000	0.333	−7.348	20.609	0.178	Yes
collaboration_ interaction_depth	1.000	2.375	−1.966	3.173	0.310	No

As shown in Table 5, inflection points for cognitive_tech_detail, Actionability Signaling, linguistic_hedging, and collab_betweenness lie within their value ranges. This confirms a positive U-shaped relationship with idea diffusion, supporting those hypotheses. In contrast, the inflection points for cognitive_operability (−0.149) and collab_interaction_depth (0.310) are below their minima (0 and 1). Thus, these two variables increase monotonically within the observed range, without a full U-shape. Detailed hypothesis tests follow.

5.1.1. The Impact of Operability

Detail richness has a negative linear term ($\beta = -0.434, p < 0.001$) and a positive quadratic term ($\beta = 1.010, p < 0.001$), indicating a U-shaped relationship with idea diffusion. Low technical detail inhibits diffusion; crossing a threshold promotes understanding and re-creation, confirming Hypothesis H1a. Its inflection point lies within the observed range (Figure 4). The green background represents the range of values of the independent variable. The same interpretation applies to the subsequent figures.

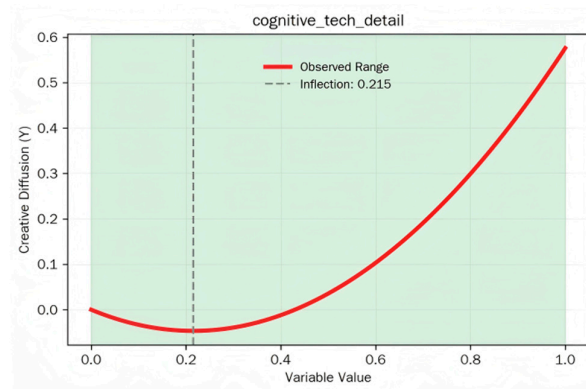


Figure 4. Comparison of the Detail Richness U-Curve and the Observation Range.

Operability has a positive linear term ($\beta = 0.131, p < 0.001$) and a positive quadratic term ($\beta = 0.439, p < 0.01$), theoretically forming a U-shaped curve. However, its inflection point (-0.149) is below the observed minimum (0). Thus, within the data range, operability monotonically increases idea diffusion, confirming Hypothesis H1b (Figure 5).

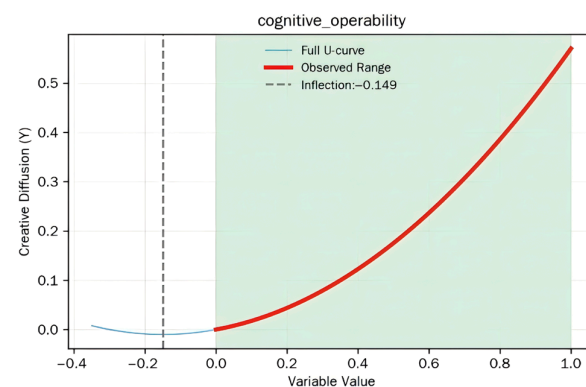


Figure 5. Comparison of the Operability U-Curve and the Observation Range.

5.1.2. The Effect of Entry Affordance

Actionability signaling has a negative linear term ($\beta = -2.015, p < 0.01$) and a positive quadratic term ($\beta = 5.139, p < 0.01$), supporting a U-shaped relationship. Low levels inhibit participation; high levels activate action, confirming Hypothesis H2a. Its inflection point lies within the observed range (Figure 6).

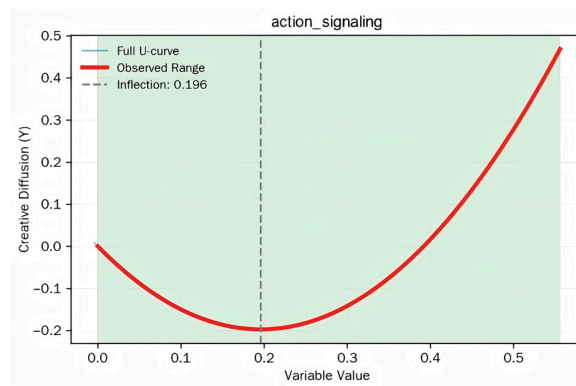


Figure 6. Comparison of the Actionability Signaling U-Curve and the Observation Range.

Linguistic hedging shows a negative linear term ($\beta = -1.232$, $p < 0.01$) and a positive quadratic term ($\beta = 0.767$, $p < 0.01$), indicating a U-shaped effect. Moderate uncertainty promotes diffusion; too little or too much hinders it, confirming Hypothesis H2b. Its inflection point lies within the observed range (Figure 7).

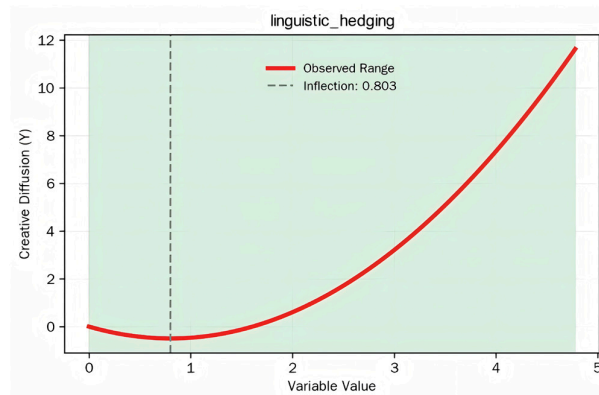


Figure 7. Comparison of the Linguistic Hedging U-Curve and the Observation Range.

5.1.3. The Impact of Collaborative Affordance

Mediating centrality has a negative linear term ($\beta = -7.348$, $p < 0.01$) and a positive quadratic term ($\beta = 20.609$, $p < 0.01$), indicating a positive U-shaped relationship with idea diffusion. Structural advantages emerge only after crossing a threshold, confirming Hypothesis H3a. Its inflection point lies within the observed range, showing a complete U-shaped curve (Figure 8).

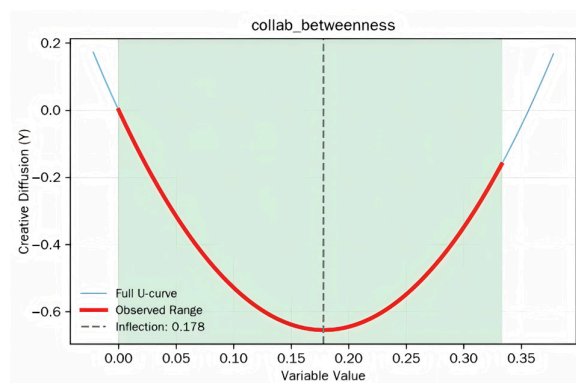


Figure 8. Comparison of the Mediating Centrality U-Curve and the Observation Range.

The linear term for interaction depth is negative ($\beta = -1.966$, $p < 0.01$) and the quadratic term positive ($\beta = 3.173$, $p < 0.01$), theoretically forming a U-shaped curve (Figure 9). However, the inflection point (0.310) is below the observed minimum (1.000). Thus, within the data range, interaction depth increases monotonically, strengthening idea diffusion. This confirms Hypothesis H3b.

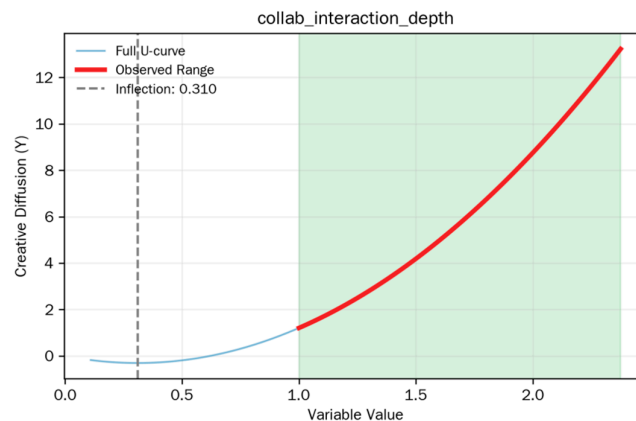


Figure 9. Comparison Chart of the U-shaped Curve of Interaction Depth and Observation Range.

5.1.4. Moderating Effects of AI Usage

Moderation of AI Usage on Actionability signaling

The linear interaction was significantly positive ($\beta = 5.878$, $p < 0.05$) and the squared interaction significantly negative ($\beta = -13.684$, $p < 0.1$). AI usage enhances the linear effect but flattens the U-shaped curvature. H4a supported.

Moderation of AI Usage on Operability

The operability $\times$ AI usage interaction was significantly negative ($\beta = -0.544$, $p < 0.1$), weakening operability's positive effect on idea diffusion. Users relied more on AI-generated paths, reducing the text's own operability value. This supports H4b.

Moderation of AI Usage on Mediating centrality

The linear interaction was positive ($\beta = 6.881$, $p < 0.01$) and the squared interaction negative ($\beta = -23.221$, $p < 0.01$). AI usage strengthens the marginal positive effect while compressing nonlinear space. H4c supported. Figures 10–12 show the moderation diagrams.

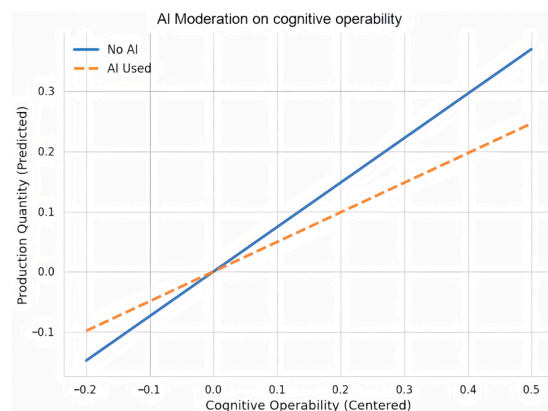


Figure 10. Diagram of the Operability Moderation Effect.

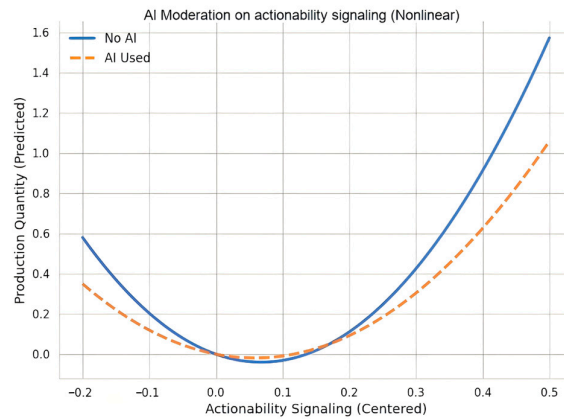


Figure 11. Graph of the Actionability Signaling Moderation Effect.

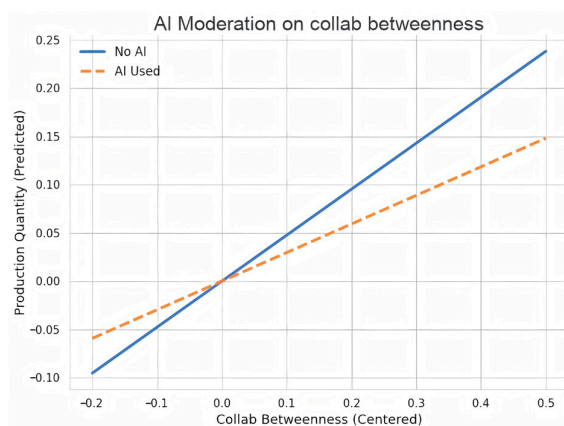


Figure 12. Diagram of the Moderating Effect of AI Usage on Mediating Centrality.

Beyond the hypothesized paths, this study proposes no directional hypotheses for AI usage interactions with detail richness, linguistic hedging, or interaction depth (including squared terms). However, generative AI may affect technical detail density, uncertainty expression, and user interaction patterns, potentially influencing idea diffusion. Thus, we exploratively examined interactions between AI_used and these variables and their squares.

Moreover, the results suggest that AI may influence the activation of affordances and alter certain affordance-diffusion relationships. However, given the relatively small proportion of AI-related ideas in the sample, these findings should be interpreted as preliminary evidence of potential AI-enabled mechanisms.

5.2. Robustness Tests

5.2.1. Bootstrap Test

To assess the robustness of the parameter estimates and correct for any potential bias, this study employed the percentile bootstrap method. Based on the original sample ($N = 93,381$), the number of bootstrap repetitions was set to 5000, with 4662 successful convergences yielding valid estimates. The bootstrap estimation results are shown in Table 6.

Table 6. The Results of Bootstrap Test.

Variable	Effect Size	SE	95% CI	
			Lower	Upper
likes_log	−0.345	0.004	−0.352	−0.337
followers_log	0.5	0.008	0.495	0.504
description_length_log	0.032	0.005	0.023	0.041
publish_time_log	0	0	0	0
cognitive_operability_c	0.131	0.024	0.084	0.180
cognitive_tech_detail_c	−0.434	0.066	−0.562	−0.308
Linguistic Hedging c	−1.232	0.120	−1.505	−1.032
action_signaling_c	−2.015	0.332	−2.635	−1.352
collaboration_betweenness_c	−7.348	0.264	−7.849	−6.809
collaborative_interaction_depth_c	−1.966	0.204	−2.371	−1.569
cognitive_operability_c_sq	0.439	0.204	0.056	0.831
cognitive_tech_detail_c_sq	1.01	0.229	0.571	1.485
linguistic_hedging_c_sq	0.767	0.227	0.400	1.273
action_signaling_c_sq	5.139	1.352	2.400	7.749
collaboration_betweenness_c_sq	20.609	0.946	18.669	22.385
collaborative_interaction_depth_c_sq	3.173	0.394	2.421	3.968
AI_used_c	−0.663	0.176	−0.986	−0.286
cognitive_operability_x_AI	−0.544	0.319	−1.122	0.118
cognitive_tech_detail_x_AI	0.291	0.848	−1.38	1.977
linguistic_hedging_x_AI	−1.772	1.893	−5.217	2.324
action_signaling_x_AI	5.878	3.384	0.601	14.412
collab_betweenness_x_AI	6.881	2.295	1.432	10.436
collaboration_interaction_depth_x_AI	1.211	1.511	−2.448	3.491
cognitive_operability_c_sq_x_AI	7.963	2.499	2.389	12.122
cognitive_tech_detail_c_sq_x_AI	−4.764	5.396	−17.926	3.757
linguistic_hedging_c_sq_x_AI	28.013	15.498	−2.740	57.629
action_signaling_c_sq_x_AI	−13.684	15.424	−57.173	4.381
collab_betweenness_c_sq_x_AI	−23.221	8.347	−36.079	−3.796
collab_interaction_depth_c_sq_x_AI	−4.198	2.923	−8.456	3.360

Bootstrap results show robustness. Intervals for cognitive_operability_c [0.084, 0.180], collab_betweenness_c_sq [18.669, 22.385], action_signaling_c_sq [2.400, 7.749] exclude zero, matching original directions. For moderators: cognitive_operability_x_AI [−1.122, 0.118] slightly crosses zero ($p = 0.049$ near significant); its squared term [2.389, 12.122] positive. collab_betweenness_x_AI [1.432, 10.436] and its square [−36.079, −3.796] exclude zero. action_signaling_x_AI [0.601, 14.412] and its square [−57.173, 4.381] include zero ($p = 0.016$ significant, lower bound near critical). There are no sign reversals, and the estimates are robust.

5.2.2. Quantile Regression Analysis

To examine whether the effects of the explanatory variables remain consistent across different levels of idea diffusion, this study conducted a quantile regression analysis, selecting three representative quantiles: 0.25, 0.5, and 0.75. The results of the quantile regression analysis are presented in Table 7.

Table 7. Results of quantile regression.

Variable	0.25	0.5	0.75
AI_used_c	0.077 (2.465)	0.796 (4.290)	0.127 (9.867)
cognitive_tech_detail_c	0.000 *** (0.848)	0.000 *** (1.526)	0.000 *** (3.455)
cognitive_tech_detail_c_sq	0.000 *** (2.959)	0.000 *** (4.914)	0.000 *** (9.616)
cognitive_tech_detail_c_sq_x_AI	0.340 (73.618)	0.547 (115.316)	0.868 (202.750)
cognitive_tech_detail_x_AI	0.117 (12.047)	0.689 (22.901)	0.251 (52.925)
collab_betweenness_c	0.000 *** (3.907)	0.000 *** (7.199)	0.000 *** (16.644)
collab_betweenness_c_sq	0.000 *** (14.276)	0.000 *** (25.878)	0.000 *** (58.779)
collab_betweenness_c_sq_x_AI	0.070 (95.581)	0.150 (172.619)	0.968 (394.982)
collab_betweenness_x_AI	0.068 (26.636)	0.127 (48.561)	0.931 (109.550)
collab_interaction_depth_c	0.000 *** (2.752)	0.000 *** (4.311)	0.000 *** (9.009)
collab_interaction_depth_c_sq	0.000 *** (5.251)	0.000 *** (7.558)	0.000 *** (14.387)
collab_interaction_depth_c_sq_x_AI	0.311 (49.131)	0.071 (63.570)	0.023 * (122.893)
collab_interaction_depth_x_AI	0.340 (23.288)	0.144 (33.214)	0.094 (70.160)
description_length_log	0.000 *** (0.059)	0.000 *** (0.106)	0.347 (0.244)
action_signaling_c	0.000 *** (4.191)	0.000 *** (7.492)	0.000 *** (16.837)
action_signaling_c_sq	0.000 *** (16.365)	0.000 *** (29.387)	0.000 *** (65.260)
action_signaling_c_sq_x_AI	0.795 (131.643)	0.737 (167.364)	0.535 (307.733)
action_signaling_x_AI	0.581 (36.922)	0.686 (56.637)	0.835 (116.502)
linguistic_hedging_c_sq_c	0.000 *** (1.036)	0.000 *** (1.913)	0.000 *** (4.372)
linguistic_hedging_c_sq_c_sq	0.001 *** (2.644)	0.000 *** (4.034)	0.001 ** (10.699)
linguistic_hedging_c_sq_c_sq_x_AI	0.257 (270.212)	0.149 (405.107)	0.978 (1111.141)
linguistic_hedging_c_sq_x_AI	0.035 * (28.338)	0.424 (49.048)	0.829 (116.155)
followers_log	0.000 *** (0.024)	0.000 *** (0.050)	0.000 *** (0.133)
likes_log	0.000 *** (0.047)	0.000 *** (0.088)	0.000 *** (0.215)
cognitive_operability_c	0.000 *** (0.323)	0.000 *** (0.570)	0.000 *** (1.285)

cognitive_operability_c_sq	0.003 ** (2.443)	0.618 (4.468)	0.494 (10.376)
cognitive_operability_c_sq_x_AI	0.847 (34.982)	0.123 (60.059)	0.033 * (135.581)
cognitive_operability_x_AI	0.999 (4.718)	0.668 (8.059)	0.245 (17.542)
publish_time_log	0.000 *** (0.000)	0.000 *** (0.001)	0.137 (0.001)

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Quantile regression shows the squared terms remained significant across all quantiles ($p < 0.01$ or $p < 0.001$), confirming the U-shaped relationship is robust. collab_betweenness_c_sq_x_AI was marginally significant at $q = 0.25$ ($p = 0.070$), direction consistent; cognitive_operability_c_sq_x_AI was positive at $q = 0.75$ ($p = 0.033$), matching the main regression. linguistic_hedging_x_AI was significant only at $q = 0.25$ ($p = 0.035$), indicating AI's moderation of linguistic hedging appears mainly at low diffusion levels. Overall, the key U-shape and AI's nonlinear moderating effects are stable across quantiles.

5.2.3. Model Stability Across Time

A 2025 subsample ($n = 57,712$; 61.8%) was used to re-estimate the negative binomial model (Table 8). Results were highly consistent with the full sample. AI usage had a significant negative main effect ($\beta = -0.704$, $p < 0.001$). Detail richness ($\beta = -0.707$, $p < 0.01$), mediating centrality ($\beta = 21.681$, $p < 0.01$), and linguistic hedging ($\beta = 3.120$, $p < 0.01$) all showed nonlinear patterns: initial negative followed by a U-shape. The interaction effect of Linguistic Hedging and AI remained significantly positive ($\beta = 10.075$, $p < 0.001$).

Table 8. Results of the Negative Binomial Regression on the 2025 Subsample.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
AI_used_c			−0.194 ***	−0.309 ***	−0.704 ***
cognitive_tech_detail_c		−0.174 ***	−0.174 ***	−0.170 ***	−0.274 ***
cognitive_tech_detail_c_sq					0.707 **
cognitive_tech_detail_c_sq_x_AI					−2.180
cognitive_tech_detail_x_AI				0.487	−0.859
collab_betweenness_c	−1.893 ***	−1.880 ***	−1.885 ***	−7.619 ***	21.681 ***
collab_betweenness_c_sq					−33.127 ***
collab_betweenness_c_sq_x_AI				0.448	9.217 ***
collab_interaction_depth_c	−0.666 ***	−0.668 ***	−0.663 ***	−1.966 ***	3.100 ***
collab_interaction_depth_c_sq					−3.936
collab_interaction_depth_c_sq_x_AI				−0.185	1.291
description_length_log	0.023 ***	0.013 **	0.013 ***	0.014 ***	0.029 ***
action_signaling_c		−0.803 ***	−0.789 ***	−0.825 ***	−1.439 ***
action_signaling_c_sq					3.120 **
action_signaling_c_sq_x_AI					−23.551 ***
action_signaling_x_AI				3.475 **	10.075 ***
linguistic_hedging_c	−1.079 ***	−1.081 ***	−1.069 ***	−1.684 ***	1.426 ***
linguistic_hedging_c_sq					17.395
linguistic_hedging_c_sq_x_AI				1.336	0.014

followers_log	0.509 ***	0.507 ***	0.508 ***	0.507 ***	0.507 ***
likes_log	−0.383 ***	−0.368 ***	−0.367 ***	−0.367 ***	−0.354 ***
cognitive_operability_c		0.099 ***	0.104 ***	0.106 ***	0.022
cognitive_operability_c_sq					0.945 ***
cognitive_operability_c_sq_x_AI					8.709 ***
cognitive_operability_x_AI				0.354	−0.630
publish_time_log	−0.001 ***	−0.001 ***	−0.001 ***	−0.001 ***	−0.001 ***

Notes: *** $p < 0.001$, ** $p < 0.01$.

A direct comparison (Table 9) of Tables 4 and 8 shows minor fluctuations for a few weak variables, but all core findings—negative AI usage effects, U-shaped relationships, and moderating/mediating effects—are highly consistent in direction and significance. Thus, the results are robust across time.

Table 9. Comparison of the Full Sample with the 2025 Coefficients.

Variable	Full Sample Coefficient	2025 Subsample Coefficient	Direction	Significance	
AI_used_c	−0.663 ***	−0.704 ***	√	√ (both $p < 0.001$)	
action_signaling_c	−2.015 ***	−1.439 ***	√	√ (both $p < 0.001$)	
action_signaling_c_sq	5.139 ***	3.12 **	√	√ (both $p < 0.001$)	
action_signaling_c_sq_x_AI	−13.684 *	−23.551 ***	√	√ (both $p < 0.05$)	
action_signaling_x_AI	5.878 **	10.075 ***	√	√ (both $p < 0.01$)	
linguistic_hedging_c	−1.232 ***	−1.684 ***	√	√ (both $p < 0.001$)	
linguistic_hedging_c_sq	0.767 ***	1.426 ***	√	√ (both $p < 0.001$)	
linguistic_hedging_c_sq_x_AI	28.013	17.395	√	√ (both n.s.)	
linguistic_hedging_x_AI	−1.772	0.014	×	√ (both n.s.)	
cognitive_operability_c	0.131 ***	0.022	√	×	(inconsistent)
cognitive_operability_c_sq	0.439 **	0.945 ***	√	√ (both $p < 0.01$)	
cognitive_operability_c_sq_x_AI	7.963 ***	8.709 ***	√	√ (both $p < 0.001$)	
cognitive_operability_x_AI	−0.544 *	−0.63	√	×	(inconsistent)
cognitive_tech_detail_c	−0.434 ***	−0.274 ***	√	√ (both $p < 0.001$)	
cognitive_tech_detail_c_sq	1.01 ***	0.707 **	√	√ (both $p < 0.001$)	
cognitive_tech_detail_c_sq_x_AI	−4.764	−2.18	√	√ (both n.s.)	
cognitive_tech_detail_x_AI	0.291	−0.859	×	√ (both n.s.)	
collab_betweenness_c	−7.348 ***	−7.619 ***	√	√ (both $p < 0.001$)	
collab_betweenness_c_sq	20.609 ***	21.681 ***	√	√ (both $p < 0.001$)	
collab_betweenness_c_sq_x_AI	−23.221 ***	−33.127 ***	√	√ (both $p < 0.001$)	
collab_betweenness_x_AI	6.881 ***	9.217 ***	√	√ (both $p < 0.001$)	
collab_interaction_depth_c	−1.966 ***	−1.966 ***	√	√ (both $p < 0.001$)	
collab_interaction_depth_c_sq	3.173 ***	3.1 ***	√	√ (both $p < 0.001$)	
collab_interaction_depth_c_sq_x_AI	−4.198 *	−3.936	√	×	(inconsistent)
collab_interaction_depth_x_AI	1.211	1.291	√	√ (both n.s.)	
description_length_log	0.032 ***	0.029 ***	√	√ (both $p < 0.001$)	
followers_log	0.5 ***	0.507 ***	√	√ (both $p < 0.001$)	
likes_log	−0.345 ***	−0.354 ***	√	√ (both $p < 0.001$)	
publish_time_log	−0.0003 ***	−0.001 ***	√	√ (both $p < 0.001$)	

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; n.s. = not significant. √ = consistent direction; × = inconsistent direction.

5.3. Endogeneity Tests

5.3.1. Sources of Endogeneity

The OLS model controls for idea characteristics, publication time, and creator attributes, but endogeneity may persist. To address this, we use two-stage least squares (2SLS) with instrumental variables (IV). One-period lagged values of detail richness and actionability signaling serve as IVs. These lagged variables correlate with current values but do not directly affect current idea diffusion.

5.3.2. Endogeneity Tests and Instrument Validity

The Wu-Hausman test shows OLS and IV estimators differ systematically ($F(2, 66,865) = 39.90, p < 0.001$), rejecting exogeneity. IV is needed. Weak instrument test: first-stage partial F-statistics are 2631.6 (Detail richness) and 138.83 (Actionability signaling), far above Stock-Yogo ($F > 10$), rejecting weak instruments. Shea's R^2 are 0.138 and 0.010. Correlations between IVs and endogenous variables are 0.375 (lagged Detail richness) and 0.102 (lagged Actionability signaling), as expected.

5.3.3. Results After Correcting for Endogeneity

Table 10 compares OLS and 2SLS. OLS coefficients for detail richness and actionability signaling on idea diffusion are -0.254 and -1.077 (both $p < 0.01$). After endogeneity correction, 2SLS absolute values rise to -0.913 and -12.488 ($p < 0.01$), directions unchanged. OLS underestimated negative effects due to endogeneity. Other controls are consistent. IVs satisfy correlation and exogeneity; 2SLS results are reliable.

Table 10. OLS and 2SLS Estimation Results for Factors Influencing the Diffusion of Ideas.

	Variable	OLS	2SLS
Independent Variables	Cognitive cognitive_operability	0.3727 *** (0.020)	0.4117 *** (0.022)
	affordance cognitive_tech_detail	-0.2536 *** (0.055)	-0.9125 *** (0.171)
	Entry linguistic_hedging	-1.1390 *** (0.074)	-1.0402 *** (0.130)
	affordance action_signaling	-1.0769 *** (0.152)	-12.488 *** (1.789)
	Collaborati collab_betweenness	-1.8589 *** (0.100)	-1.4910 *** (0.112)
Moderating Variables	ve collab_interaction_de	-0.6890 *** (0.077)	-0.5500 *** (0.073)
	affordance pth		
	AI_used	-0.2243 *** (0.048)	-0.1919 *** (0.046)
Control Variables	likes	-0.0006 *** (0.00003)	-0.0006 *** (0.00003)
	followers	0.0002 *** (0.00000)	0.0002 *** (0.00000)
	publish_time	-0.0001 *** (0.00003)	-0.0001 *** (0.00003)
	description_length	0.00003 (0.00005)	-0.00008 (0.00005)
	Constant	4.5521 *** (0.080)	4.5396 *** (0.076)
	Observations	66,879	66,879
	R ²	0.089	0.011
	Endogeneity test	Wu-Hausman $F(2, 66,865)=39.90$ ***	
	Weak instrument test	First-stage F-statistics: 2631.6 (Detail richness), 138.83 (Actionability Signaling)	

Notes: Standard errors in parentheses. *** $p < 0.001$.

The weak instrument test F-values exceed the Stock-Yogo critical value of 10, rejecting the null of weak instruments.

6. Discussion

Drawing on affordance theory, this study develops a framework encompassing cognitive, entry, and collaborative affordances to explain idea diffusion in online innovation communities, with a focus on nonlinear effects and the moderating role of AI. Using text and social network analysis with a negative binomial model, we identify six key variables and examine their effects. The results reveal distinct and nonlinear patterns across affordance types. Operability and interaction depth exhibit positive linear effects, whereas detail richness, actionability signaling, linguistic hedging, and mediating centrality follow U-shaped relationships, indicating threshold-dependent activation processes. Moreover, AI usage significantly moderates these relationships by attenuating some first-order effects and flattening nonlinear patterns, suggesting a structural reshaping rather than a simple amplification role. Overall, idea diffusion is best understood as a threshold-based activation process, in which large-scale dissemination emerges only after affordances surpass critical levels.

6.1. Consistency with Prior Literature

Our findings are broadly consistent with prior research, while also extending existing theoretical perspectives. The observed U-shaped relationships for detail richness, actionability signaling, linguistic hedging, and mediating centrality lend support to the threshold-based view of affordance actualization, suggesting that the effects of affordances unfold only after surpassing critical activation points [63,64]. These results also resonate with information-gap theory, which posits that moderate levels of uncertainty may inhibit engagement, whereas sufficiently high levels can stimulate exploratory behavior [92,93].

In addition, the U-shaped effect of mediating centrality is consistent with prior findings on the nonlinear role of network positions in diffusion processes [101,102], reinforcing the view that structural advantages do not translate into influence in a strictly linear manner.

Importantly, our findings further extend this literature by suggesting that the use of generative AI may influence these relationships. Rather than simply strengthening or weakening existing effects, AI appears to affect both linear and nonlinear affordance-diffusion relationships, indicating that algorithmic support may play a role in shaping how affordances are translated into diffusion outcomes. These findings provide preliminary evidence that AI may influence affordance activation processes within online innovation communities and highlight the potential importance of algorithmic mediation in innovation diffusion.

6.2. Practical Implications

The findings offer practical insights for online innovation platforms, community managers, and idea contributors.

- (1) Optimizing idea expression. Focus on actionable content and high-quality details. Idea diffusion depends on information richness, structure, and action inferability. Platforms should shift from content quantity to structural quality. Standardize idea expression frameworks to clarify pathways and steps. Use modular templates (problem, path, steps). Showcase high-quality cases to reduce uncertainty. AI auto-completion can improve low-quality inputs, boosting shareability.
- (2) Designing participation mechanisms. Focus on effective openness. Openness has a threshold effect, not a linear increase. Make participation signals explicit (e.g., improvement, forking, collaboration). Provide structured entry points (e.g., version

- branches, re-creation channels). Clear, structured mechanisms stimulate participation better than ambiguous designs.
- (3) Using AI tools. Improve efficiency without excessive substitution. AI may weaken re-engagement and co-creation. Position AI as cognitive enhancement, not replacement. Adopt a hybrid model: AI generation plus user re-editing. Preserve user modification to maintain ownership. Ensure transparency of AI suggestions so users can control AI influence, preventing automation-driven disengagement.

6.3. Limitations and Future Directions

Although this study has conducted a systematic exploration in theory and methodology, several limitations remain. Future research should address them.

First, the findings should be interpreted within the contextual boundaries of the MakerWorld platform. Although MakerWorld provides a rich empirical setting for examining idea diffusion in AI-mediated online innovation communities, platform-specific characteristics such as user composition, governance mechanisms, participation norms, and technological infrastructure may influence the observed affordance-diffusion relationships. Consequently, the generalizability of the findings to other innovation communities should be interpreted with caution. Future research could extend the present framework to multiple innovation platforms and compare whether the nonlinear activation patterns of affordances remain consistent across different technological and institutional environments. Such comparative analyses would help strengthen the external validity of the proposed framework.

Second, limitations remain in the operationalization of key constructs. This study measures affordance characteristics primarily through text-mining techniques, social-network indicators, and platform-generated behavioral metrics. While these approaches provide objective and scalable measurements, they may not fully capture users' subjective perceptions and interpretations of affordances. In addition, AI involvement is identified through the presence of AI-related keywords within idea descriptions. This approach captures disclosed references to AI technologies rather than directly observing AI-assisted creation behavior. Consequently, the measure may be subject to both false positives and false negatives. Some creators may mention AI-related concepts without substantively using AI during the creation process, whereas others may rely heavily on AI tools without explicitly reporting such usage. Therefore, the AI_used variable should be interpreted as an observable signal of AI involvement rather than a direct measure of actual AI-assisted content creation. Future research could combine computational measures with surveys, experiments, platform metadata, or behavioral logs to develop more comprehensive measurements of both perceived affordances and AI-assisted innovation activities.

Third, the representativeness of the AI-related subsample warrants careful consideration. Only a small proportion of ideas in the dataset explicitly referenced AI-related tools or technologies. Although the robustness analyses generally support the main findings, the relatively limited size of the AI subgroup may constrain the statistical power and stability of moderation estimates. Moreover, several interaction effects exhibit varying levels of significance across robustness tests and subsamples, suggesting that the influence of AI may depend on contextual conditions and user characteristics. Therefore, the moderating effects identified in this study should be interpreted as evidence of potential AI-enabled mechanisms rather than definitive proof that AI universally reshapes affordance-diffusion relationships. Future research could examine communities with higher levels of AI adoption, compare different stages of AI diffusion, and employ larger AI-related samples to further validate the robustness and boundary conditions of these effects.

Fourth, the mechanisms through which AI influences the actualization of affordances require deeper investigation. In this study, AI is conceptualized as a moderating factor that affects the translation of affordance potential into diffusion outcomes. However, different forms of AI may influence innovation processes through distinct pathways. For example, generative AI may support idea elaboration, content creation, and technical problem-solving, whereas recommendation algorithms may shape information exposure, visibility, and network connectivity. Future research could distinguish among different categories of AI technologies and investigate how they differentially influence cognitive, entry, and collaborative affordances, thereby providing a more nuanced understanding of AI-mediated innovation processes.

Finally, although this study advances understanding of nonlinear affordance effects by identifying U-shaped relationships, real-world innovation processes may involve more complex nonlinear dynamics than those captured by quadratic specifications. Affordance activation may exhibit multiple thresholds, asymmetric effects, higher-order nonlinearities, or interactions among different affordance dimensions. Moreover, the process through which affordances are transformed into actual diffusion outcomes may evolve over time as users accumulate experience and technological support. Future research could employ more flexible analytical approaches, such as generalized additive models, semiparametric regression, machine-learning techniques, or longitudinal designs, to explore richer nonlinear patterns and further illuminate how affordances are actualized into idea diffusion outcomes in AI-mediated innovation environments.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/systems14070838/s1>, Supplementary_File_1_Code: Build_Action_Density_Index.py: construction of the operational verb density index; Comment_Guidance.py: construction of the comment guidance index; Comment_Network.py: construction of the comment network; Complete_Data_Analysis_All_Squared_Terms.py: complete data analysis including all squared terms; Determinacy.py: measurement of determinacy language; Image_Helper.py: construction of image/attachment assistance indicators; Invitation_Indicators.py: construction of invitation indicators; Modifiability.py: measurement of modifiability; Network_Indicators.py: construction of network indicators; Supportiveness.py: measurement of supportiveness; Technical_Density.py: construction of technical density indicators; Total_Comments.py: calculation of total comments; Uncertainty.py: measurement of uncertainty language. Supplementary_File_2_Figure: Hypotheses Model.svg: Three-stage model figure; Research_Framework.svg: Research Framework Diagram.

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the authors can provide aggregated data, variable definitions, keyword dictionaries, and analysis scripts for academic research purposes, subject to platform policies and ethical requirements.

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