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Research on Iterative Diffusion Models of Generative AI Technology

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Abstract:
To explore the causes of the digital divide in the generative AI era and address the limitations of traditional innovation diffusion theory, this study adopts a dual framework of innovation diffusion and reflexivity theory. Using content analysis and indepth interviews, it focuses on DeepSeek from December 2024 to December 2025 to examine the iterative diffusion of generative AI.The study finds that generative AI diffusion features simultaneous technological iteration and adoption driven by audience rational cognition, breaking traditional diffusion laws. Consumers' technological maturity expectations and social factors interact and reinforce each other as core barriers, forming the new digital divide mechanism.Replacing the traditional Sshaped curve model, this study constructs a stepwise upward model of iterative diffusion, clarifies the negative impacts of audience refusal at individual, technical and social levels, and answers three core questions about refusal reasons, laggard factors and related impacts. It confirms that the digital divide is shaped by technological cognition, maturity expectations and social factors.Finally, it proposes improving digital literacy, guiding rational technological expectations and fostering a positive communication environment to bridge the divide. This study enriches the two theories in the digital context, fills the userperspective gap in generative AI research, and provides a new theoretical model and perspective for digital technology innovation diffusion studies.

Keywords:
Technological iteration diffusion, Technological maturity expectation, Social factors, Digital divide, Staged diffusion model

1 Introduction

Generative AI large models are rapidly being adopted across the entire society. At this time, the theory of historical finality has resurfaced. On one hand, early proponents of electronic utopianism and network utopianism believed that generative AI would bring us a utopian world of beauty. On the other hand, early pessimistic theorists such as those who claimed "he audience is dead" and "entertainment is everything" believed that generative AI would lead to large-scale disruption and even destruction. However, we have observed that new technologies do not bring about a relatively uniform impact on the entire society. On the contrary, people's acceptance of the innovation and diffusion of generative AI varies greatly. In the current era when the level of social education has significantly increased, the laggards in the diffusion of such innovations are not necessar-

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ily restricted by educational status as in traditional innovation diffusion. Then what causes the digital divide in the era of generative AI?

2 Literature Review

2.1 Diffusion of innovations

The theory of innovation diffusion was formally proposed by American communication scholar Everett M. Rogers in 1962. It is a classic theory that studies how new things (technologies, ideas, practices, etc.) are gradually recognized, adopted, and popularized by members within a social system over time through certain channels.

In foreign-related research, the diffusion theory originated earliest in 19th-century Europe. The relevant studies of French scholar Gabriel Tarde, German Georg Simmel, as well as diffusion scholars from Germany, Austria, and the UK laid an important foundation for the formation of the theory of innovation diffusion.Tarde (1969) proposed the “logical imitation law”, stating that the new invention is more likely to be imitated by society if it is more similar to the old inventions that have been imitated and institutionalized in the society. The law of innovation diffusion presents as an “S”curve, which he proposed. In domestic-related research, through searching existing literature, it can be known that the research on innovation diffusion in China mainly focuses on theoretical research, influencing factors, technological innovation, etc. Chinese scholars' main areas of research on innovation diffusion are in the aspects of innovation diffusion’s influencing factors and the diffusion of technologies. However, these studies are insufficient in terms of innovative and structural analysis. A technology is not immutable; the process of old technologies being eliminated and new technologies being innovatively diffused again. The adoption of generative AI technology is beyond the explanation of traditional innovation diffusion.

2.2 Reflexivity theory

Reflexivity refers to the process by which social actors continuously reflect on themselves and the social environment they are in. It emphasizes the dynamic relationship between knowledge and society, as well as between the researcher and the research subject.

In related studies abroad, there are representative works such as David Brewer’s book *Knowledge and Social Imaginaries* (2001), and the joint work of Barry Barnes, David Brewer, and John Henry titled *Scientific Knowledge: A Sociological Analysis*. In domestic research, the main publications include articles and books such as *The Resolution of the ‘Reflexivity’ Puzzle and the Future Trend of Scientific Knowledge Sociology* by Wang Yanyu and Ma Liping, and *Reflexivity and the ‘Mannheim Paradox*’ by Xiao Ying, published in 2004. Scholars from both abroad and China have conducted research on the issue of reflexivity, discussing it from a wide range of fields such as scientific sociology, sociology, and in recent years, it has expanded to law and political science. However, no study has explored the interaction mechanism between the iterative and diffusion of generative AI technology from the perspective of reflexive theory, nor has it supported the analysis of the counter-effect of the subjective cognition of the audience on rejection or delay.

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2.3 Generative AI technology

Research on generative AI technology has been conducted from multiple perspectives by the academic community. From the perspective of industry development, generative AI covers multiple fields such as education, healthcare, media, finance, and industry.

From the perspective of the impacts generated by generative AI, domestic scholars have conducted research from the aspects of social culture, economic operation, and technical ethics. For instance, Zhou Haina in *Generative AI and the Cross-Media Reconstruction of Traditional Art: Technological Logic, Cultural Impact, and Ethical Negotiation* argues that the intervention of generative AI in traditional arts such as calligraphy and ink painting has triggered a profound collision between technological logic and humanistic values.

However, these studies have not investigated the phenomenon of generative AI technology iteration from the rational measurement attitude of users, nor have they answered the question of what factors influence the audience to become laggards, nor have they studied from the perspective of innovation diffusion what kind of impact such refusal to use would cause.

3 Research Methods

3.1 Research approach

Conduct a content analysis of popular generative AI models at home and abroad, clearly define the technical iteration time of generative AI models, as well as the technical breakthroughs during the iteration process, and explore the characteristics of their iterations.

3.2 Research methods and specific approaches

3.2.1 Content analysis

3.2.1.1 Research steps

This table outlines the four core steps of a content analysis methodology, from selecting research topics and defining the scope, to establishing analysis units and coding frameworks, and finally to data collection and analysis.

Table 1 Content analysis research steps

Research Step	Specific Content
1. Propose research subtopics and hypotheses	Select the topic
2.Determine the research scope and sampling	Determine the scope of the research sampling
3.Determine the analysis unit and code	Define the concept to be calculated and determine the analysis unit Establish the categories of the analysis content Create an encoding table
4.Subsequent steps of encoding	Training programmers and experimental coding Collecting data Analyze the data Report results

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3.2.1.2 Research questions and hypotheses

R1: What reasons do the users have for refusing to use generative AI?

R2:What factors influence the users to become laggards?

R3:What kind of impact will this refusal to use have?

3.2.1.3 Research subjects

The research involves searching for popular AI technologies both domestically and internationally on Baidu Baike pages. The research period is from December 2024 to December 2025. The main subject of the research is the DeepSeek search results. Information is collected from various sources (sorted by credibility) - DeepSeek's official website, DeepSeek's official app, national science and technology and industry institutions, global top AI research platforms, Baidu Baike, mainstream media and core authoritative media, domestic and international technology development communities, etc. Random sampling is conducted to obtain relevant information about DeepSeek and conduct content analysis.

3.2.1.4 Coding schedule

This coding schedule is a structured framework for analyzing DeepSeek's technological iterative diffusion, organized into four core dimensions: Version update dimension, Technical Attribute Dimension, Publication and dissemination dimension, Application and Impact dimension.

By standardizing the coding of these elements, the schedule ensures consistent, systematic analysis of DeepSeek's evolution, dissemination, and user reception, laying a data-driven foundation for studying generative AI's iterative diffusion.

Table 2 Coding Schedule

Applicable dimension	Elements	Category
Version update dimension	Update time	Specific dates, quarters, years
	Update scale	Bug fixes/detailed optimizations, new features, core technology iterations
Technical Attribute Dimension	Technical breakthrough direction	Natural language understanding (NLU), code generation, multi-modal capabilities, tool invocation
	Capability improvement dimension	Mathematical reasoning, logical reasoning, creative ability, long text processing
Publication and dissemination dimension	Release entity	DeepSeek official team, DeepSeek company
	Communication channel	Official Weibo, GitHub repository, social media, technology media coverage
	Evaluation tendency	Positive, neutral, negative
Application and Impact Dimensions	Application scenario	Enterprise-level services, research assistance, entertainment creation
	User feedback	Functionality practicality, performance satisfaction, ease of use

3.2.1.5 Subsequent steps

(1) Train coders;

(2) Conduct experimental coding, analyze the coding results and make improvements to the coding table;

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(3) Collect data: Encode the analysis content according to the established definitions and coding table;

(4) Measure the reliability among coders, each independent coder uses the same coding tool to code the same content. If the results are consistent, it indicates a high reliability for the content analysis;

(5)Analyze the data and draw conclusions.

3.2.2 In-depth interviews

The author employed purposive sampling and selected 5 individuals who had been using DeepSeek continuously from graduated students and alumni, classmates, graduate students who were currently studying, and neighborhood residents. Additionally, 5 individuals who were aware of the product but refused to use it, 5 individuals who attempted to use it but eventually gave up, were also included in the sample for in-depth interviews.

3.2.2.1 Interview questions

Part 1: Basic information survey of respondents

Q1:What is your age? What is your occupation?

Q2:Have you heard of DeepSeek? If so, could you describe the main functions you know about it?

Q3: Have you used DeepSeek? If yes, what was the duration, frequency and scenarios of your usage? If not, have you ever had the idea of trying it?

Q4:Have you heard of the statement “New technologies that come out are like harvesting (a type of vegetable) for profit”?Do you agree?Why?

Part 2: Survey of DeepSeek users

Q1:When did you start using DeepSeek?Through which channel did you first hear about it? What problems did you mainly solve using it?

Q2:What is your average weekly usage frequency of DeepSeek? How long is each usage session approximately?

Q3:If you continue to use DeepSeek?what values does it provide that other tools cannot replace?

Q4:Have you paid attention to the version updates of DeepSeek?Did a certain update significantly improve or affect your usage experience?

Q5:How dependent are you on DeepSeek in your daily study or work?

Q6:Have you ever had the idea of reducing usage or giving it up?What was the reason?

Q7:What do you think are its main shortcomings?Do those shortcomings affect your continued use?

Part 3: Survey on Rejecters/Non-Users of DeepSeek

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Q1:What was the main reason you did not try using DeepSeek? (Such as unfamiliarity with the functions, concerns about the technology being immature, worries about privacy issues, etc.)

Q2:Have you paid attention to the updates and iterations of DeepSeek's technology? Would this kind of information influence your decision?

Q3:Would the evaluations of DeepSeek from social media and people around you (positive/negative) affect your attitude? Could you provide examples to illustrate?

Q4:Would you be more willing to try if trusted individuals or institutions recommended it?

Q5:What tools would you use to replace the functions that DeepSeek can achieve that you are familiar with?

Part 4: Survey on Those Who Abandoned DeepSeek After Trying

Q1:What was the reason you initially tried using DeepSeek? How long did you use it?

Q2:Before and after you stopped using it, did you pay attention to the updates and iterations of DeepSeek's technology? Did this information influence your decision?

Q3:What made you ultimately decide not to use it? What were the main ideas and concerns?

Q4:Do you worry about what negative impacts using DeepSeek might have on your life/work (such as time cost, information security, skill substitution, etc.)?

Q5:In what situations do you think you might reconsider using it in the future?

3.2.2.3 Interview implementation process

1. Conduct one-on-one in-person and online in-depth interviews, and record the entire process with the respondents'consent. Avoid leading questions.

2. Inform the respondents in advance about the purpose of the interview, the time and the use of the data, and anonymize their information.

3. Inform the respondents in advance about the conceptual meanings involved in the process.

4.Based on the collected information and data, extract key information to support the research topic.

3.2.2.4 Subsequent steps

1. Collect and organize the interview result data.

2. Analyze the data to draw conclusions.

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Table 3 Respondent Information

Number	Age	Gender	Profession
1	21	female	student
2	30	female	administrative staff
3	21	female	student
4	33	female	display division
5	39	female	teacher
6	48	male	administrative staff
7	36	male	architect
8	46	female	operation manager
9	21	female	student
10	21	female	student
11	22	female	sales personnel
12	21	female	student
13	25	male	freelancer
14	26	female	Mining personnel
15	47	male	product manager

Table 4 Coding Schedule

Updates Time	Renewal Circs
2024-12-13	Update scale: Bug fixes / Minor optimizations; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2024-12-26	Update scale: No; Technical breakthrough direction: None; Capability improvement dimension: Mathematical reasoning, logical reasoning, creative ability, long text processing
2025-01-01	Update scale: No; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2025-01-20	Update scale: No; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2025-02-01	Update scale: No; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2025-02-03	Update scale: Bug fixes / Minor optimizations; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2025-02-17	Update scale: No; Technical breakthrough direction: Tool invocation; Capability improvement dimension: Logical reasoning
2025-02-18	Update scale: Bug fixes / Minor optimizations; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning, long text processing
2025-03-01	Update scale: No; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Mathematical reasoning, logical reasoning
2025-03-07	Update scale: Bug fixes / Minor optimizations; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Long text processing
2025-03-17	"Update scale: Bug fixes / Minor optimizations; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning" "
2025-03-28	Update scale: None; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2025-04-08	Update scale: Bug fixes / Minor optimizations; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2025-07-18	Update scale: No; Technical breakthrough direction: None; Capability improvement dimension: Mathematical reasoning, logical reasoning, creative ability, long text processing
2025-08-11	Update scale: No; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning
2025-10-03	Update scale: No; Technical breakthrough direction: Natural Language Understanding (NLU); Capability improvement dimension: Logical reasoning

4 Characteristics of the Diffusion of New Technologies

Based on the results of content analysis, this study has identified a significant flaw in the traditional innovation diffusion process. That is, a technology is not static. During the process of innovation diffusion, it gains high benefits and thus undergoes technological iteration. This leads to the elimination of old technologies and the re-innovation and diffusion of new technologies. This is something that traditional innovation diffusion cannot explain. The essential difference between the diffusion of generative AI technology and traditional in-

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novation diffusion lies in: technological iteration and diffusion occur simultaneously, breaking the traditional pattern of "first diffusion, then iteration". The update and iteration speed of generative AI is extremely fast. The foundation of generative AI is solid. Since Google proposed the Transformer structure in 2017, using the self-attention mechanism to solve the problem of long text dependency, it has become a standard for large models, significantly reducing the threshold for iteration. Secondly, generative AI adopts a modular design, allowing only the optimization of certain performance parts without the need to restructure the entire system. According to the statistics of research led by DeepSeek, the scale of updates is mainly divided into four categories, showing a clear distribution pattern: no large-scale updates, accounting for 50%, the most common type; Bug fixes/technical optimizations, accounting for 31.25%, the secondary update type; Core technology iteration, accounting for 12.5%, the important update type; Core technology iteration and new functions, accounting for 6.25%, the major update type. System updates are mainly maintenance updates (no updates+bug fixes), accounting for 81.25%, indicating that the overall system architecture is stable and mainly focuses on detailed optimizations rather than large-scale restructurings. Thirdly, generative AI uniformly models text, images, and audio, accelerating multi-modal integration, and one iteration can bring improvements in multiple fields of capabilities. In addition, the vast amount of data on the Internet provides trillions of high-quality learning materials for generative AI models, providing them with technical fuel for iteration. Generative AI is not a static technology. Each iteration of generative AI improves on the existing basis, and each update provides a large amount of data and direction for the next iteration, forming an accelerating phenomenon of faster and faster iteration.

Based on the research results obtained from content analysis, we can observe that the update breakthrough mode of the core technology of generative AI DeepSeek in the early stage of development is frequent and continuous. In the fourth quarter of 2024 (October-December), there were 2 updates, accounting for 12.5%, the start-up period; In the first quarter of 2025 (January-March), there were 10 updates, accounting for 62.5%, the peak period of updates.

The rational cognitive perception of the audience dominates the adoption of technology, and the reflexive characteristic is prominent. In the era of generative AI, the audience is no longer merely passively accepting technology; instead, they will make subjective judgments on aspects such as the security and privacy, cost-effectiveness, ease of use, and learning and usage costs of the technology, and then rationally choose to use or reject it. This is the concrete manifestation of the reflexive theory. The new digital divide in the era of generative AI thus emerges.

Generative AI relies on large-scale data training. Therefore, users are concerned about the abuse or leakage of personal data. For example, when e-commerce platforms analyze user behavior through AI, they may cross the privacy boundary. For example, when the elderly use AI tools (such as AI voice tools), they will rationally judge two points - the learning and usage cost and the security risk. They will judge whether complex steps are needed to remember the usage, to generate instructions, whether to recognize dialects; secondly, they will judge whether the AI-recommended information is true and reliable, whether personal privacy will be exposed during the communication of the AI tool, and whether there is the risk of information misguidance. Young groups can quickly adapt to the operation logic of AI tools and have the ability to distinguish the authenticity of AI information; while the elderly, due to a decline in learning ability and a weaker ability to

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distinguish information, are often excluded from AI convenience because of "not knowing how to use" or "not daring to use", forming a usage gap between "digital disadvantaged group" and "digital advantaged group".

5 New Factors Hindering the Iterative Diffusion of New Technologies

The traditional theory of innovation diffusion holds that educational status, economic status, and social status are the core obstructive factors affecting technology diffusion. However, this study reveals that generative AI has rapidly climbed from the "edge position" to the "peak of the expectation expansion period" on the Gartner Technology Maturity Curve in 2023. Besides the traditional factors, the consumer's expectation of technological maturity and the consumer's social factors have become two major new obstructive factors influencing the iterative diffusion of technology. These two factors interact and reinforce each other, jointly determining the technological adoption behavior of the audience and also becoming the formation mechanism of the new digital divide in the era of generative AI.

5.1 Consumers' expectations of technology maturity

From a micro perspective, apart from the original economic status and educational level, the factors influencing users'adoption of generative AI technology also include "expectations of the maturity of new technologies". The maturity expectations of the audience refer to their subjective judgment on the maturity, practicality, and cost-effectiveness of generative AI technology based on their own cognition and external information. This is the result of rational measurement by the audience and a concrete manifestation of the reflexive theory. The maturity curve shows that generative AI is currently in the period of expectation expansion. Consumers tend to underestimate its technical bottlenecks (such as computing power requirements, ethical risks). Users will consider whether this technology will affect our daily life and work, as well as its cost-effectiveness. If it takes too much time, it is not worth using. This is a rational measurement attitude, but it leads to the rejection of the adoption of generative AI technology.

Just this process of technological iteration and diffusion affects consumers' expectations of innovation. A large number of audiences are waiting for the day when the technology matures, and before that, they make up their minds not to adopt this new technology. We observe that as generative AI continues to iterate, a new way of causing knowledge gaps begins to emerge. Users often clearly understand that generative AI is a new technology. However, there is an expectation that "newly emerged technologies are like picking off a slang term for getting rich quickly by exploiting others". Therefore, they often actively refuse to use the new technology.

The interview results of this study show that most informed rejectors and those who gave up after trying have a lower expectation of the maturity of generative AI, believing that the current technology is still in the early stage of development, with problems such as incomplete functions, inaccurate information, and no guarantee of privacy and security, and the time cost for learning and using the technology is too high, and the input and output are not proportional. Therefore, they actively choose to refuse to use the technology. Users use tools to save time and effort and improve efficiency. Since there are already familiar, simple to operate, and smooth process alternative tools, there is no need to spend energy adapting to a more troublesome one, which instead adds burden to themselves.

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The emergence of the maturity expectations factor has led to a new knowledge gap in the generative AI era. This knowledge gap is not caused by differences in information acquisition ability, but is formed by the differences in audience's technical cognition and subjective expectations, and has become the core obstacle to the iteration and diffusion of generative AI technology.

5.2 Consumers' "social" factors

Social factors refer to the influence of social media and the evaluations and feedback from people around on the audience's technological cognition and adoption behavior. This is a typical feature of technology diffusion in the digital age. Influential opinion leaders (such as influencers, industry experts) in social media can significantly enhance the breadth and depth of technology information dissemination. Empirical studies have shown that in the "8.12 Tianjin Explosion" incident, the forwarding behavior of the opinion leader group increased the effect of public opinion information dissemination by 3-5 times. The node centrality index and the information diffusion range were significantly positively correlated ($r = 0.72$, $p < 0.01$). This amplification effect stems from the "trust premium" and "attention aggregation" characteristics brought by their network structure positions.

In social network communities (SNS), the technology information sharing behavior of strong relationship chains (friends, colleagues) will increase the adoption intention of the recipient by 62%. This effect conforms to the "three-degree influence principle" and is particularly significant in the dissemination of health information ($\beta = 0.58$, $p < 0.001$). The interaction between relationship strength and content credibility forms a dissemination amplifier, and its action formula can be expressed as: $E_{amp} = \alpha \cdot R^{1.3} + \beta \cdot C^{0.7}$, where R is the relationship strength and C is the content professionalism.

Social factors have a significant impact on the iterative diffusion of generative AI technology. Their core role is manifested as the "amplifier" and "obstructor" characteristics: On the one hand, positive evaluations from social media and the positive feedback from people around will quickly enhance the popularity of the technology, allowing the audience to form high expectations for the technology, promoting its rapid diffusion and forming a collective adoption phenomenon; On the other hand, negative evaluations from social media and the negative feedback from people around will make the audience form low expectations for the technology, strengthening their attitude of refusing to use it, and hindering the diffusion of the technology, forming a collective rejection feature.

Mass communication facilitates people's access to information, while interpersonal communication is more conducive to changing attitudes. The interview results of this study show that 4 informed rejecters stated that their low cognition and rejection attitude towards DeepSeek mainly originated from the negative evaluations on social media and the negative feedback from people around. Social factors further strengthened their low expectations for the maturity of the technology; while the initial channel for continuous users to come into contact with the technology was mainly social media and recommendations from people around, the positive information dissemination led them to form high expectations for the technology, promoting their attempts and continued use of the technology.

Social factors and the factor of technology maturity expectations show a mutually reinforcing relationship: Negative external social information will strengthen the audience's low expectations for the maturity of the

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technology, further hindering technology diffusion; while positive social information will enhance the audience's high expectations for the maturity of the technology, promoting technology diffusion. The interaction of these two factors leads to the collective and sudden characteristics of the diffusion of generative AI technology.

5.3 New model for technology iteration diffusion

Taking into account these two new factors, we have observed that the adoption of generative AI technology no longer follows the S-shaped curve model. Instead, as the technology progresses through iterations, consumers will suddenly adopt a new technology all at once, then suddenly reject it all at once, and only then will they adopt it again once a better technology emerges. This presents an innovative diffusion route that is step-like and upward.

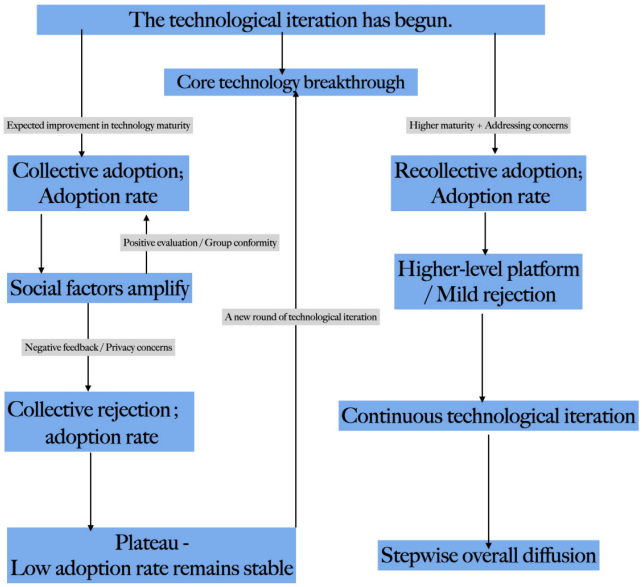


Figure 1 Generative AI technology iterative diffusion logic

The core feature of the stepwise model of generative AI technology iteration and diffusion is that consumers do not gradually and in stages adopt the technology. Instead, as the technology progresses through iterations, they suddenly adopt a new technology at a specific point, then enter a plateau period, and even collectively refuse to adopt it; until a new core breakthrough in the technology solves the core concerns of the audience, the audience will then collectively adopt it again, and the technology adoption rate will achieve a stepwise increase. Overall, the change in the technology adoption rate shows a "stepwise upward" characteristic, rather than the traditional smooth S-shaped curve. The horizontal axis of the model represents time, and the vertical axis represents the technology adoption rate. The core nodes include the core breakthrough of the technology, collective adoption, plateau period, another core breakthrough, and another collective adoption.

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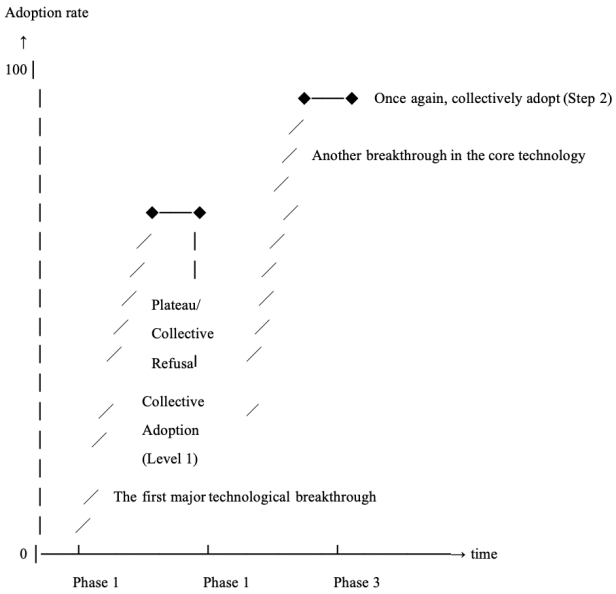


Figure 2 The stepwise model of iterative diffusion of generative AI technology

This model overcomes the shortcomings of the traditional S-shaped curve model for innovation diffusion, breaks through the research premise of "technology remaining unchanged", and can effectively explain the dynamic process where the iteration and diffusion of generative AI technology occur simultaneously. At the same time, it incorporates the subjective cognition of the audience and the influence of social factors, enriching the digital era connotation of the innovation diffusion theory, and providing a new theoretical model for the study of the innovation diffusion of digital technologies.

6 Summary and Reflection

This research is based on the theories of innovation diffusion and reflexivity, using content analysis and in-depth interviews as methods, and focusing on DeepSeek as the research object. It explores the characteristics of the iterative development of generative AI technology, the new obstacles to technology diffusion, and constructs a new model of upwardly progressive technology diffusion. It also analyzes the multiple impacts of the audience's refusal to use technology and ultimately answers the three core research questions proposed in this study, resulting in the following core research conclusions:

First, the core reason for the audience's refusal to use generative AI is no longer solely limited by traditional educational status and economic status, but rather includes low expectations for the maturity of the technology, rational considerations of time costs, multiple concerns about privacy and security, and further reinforcement of their refusal attitude by negative evaluations on social media and negative feedback from people around them.

Second, the core new obstacles to the iterative diffusion of generative AI technology are the consumer's expectations for technology maturity and the consumer's social factors. These two factors interact and reinforce each other, jointly determining the audience's technology adoption behavior. The expectation of technology maturity is the result of rational reflection by the audience and has no direct correlation with traditional fac-

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tors; social factors are amplifiers and obstacles for the dissemination of technical information, which can strengthen the audience's technological expectations and promote or hinder the diffusion of technology.

Third, the behavior of the audience refusing to use generative AI will have multiple negative impacts on the individual audience, technological development, and the social level: at the individual level, it forms a digital capability stratification, missing the benefits of technological development; at the technological level, it forms a feedback barrier, leading to a disconnection between technology iteration and user needs; at the social level, it exacerbates digital stratification, affecting the process of social digital transformation, and further intensifying the digital gap in the era of generative AI.

This research combines the theories of innovation diffusion and reflexivity to construct a dual-theory analytical framework, compensating for the deficiency of traditional innovation diffusion theory in analyzing the subjective cognition of the audience. At the same time, the reflexivity theory is applied to the research on generative AI technology, exploring the counter-effect of the audience's subjective cognition on technology adoption behavior, enriching the application scenarios and digital era connotations of the two theories. First, this research breaks through the existing industrial perspective and social impact perspective of generative AI research, conducting research from the perspective of rational measurement attitudes of users, focusing on the audience's technology adoption behavior and reasons for refusal, exploring the formation mechanism of the new digital gap in the era of generative AI, and filling the gap of existing research that ignores the user perspective. Second, this research breaks through the S-shaped curve model of traditional innovation diffusion, combining the core characteristics and new obstacles of the iterative diffusion of generative AI technology, and constructing a new upwardly progressive technology diffusion model.

The rapid development and popularization of generative AI models is an inevitable result of technological innovation in the digital era. The technology iteration and diffusion process not only changes people's production and lifestyle but also reconfigures the laws of technological diffusion. This study finds that the digital gap in the era of generative AI is no longer determined by traditional educational status and economic status, but is formed by the audience's technological cognition, maturity expectations, and social factors. This new digital gap formation mechanism breaks the inherent cognitive framework of traditional digital gap research and also enables us to have a deeper understanding of the interaction between technological innovation and social acceptance in the digital era.

In the digital era, the audience has transformed from passive recipients of technology to active choosers with independent rational judgment. Their subjective rational cognition and value judgment have become key variables in technology diffusion, and also reveal the deep contradictions between the rapidity of technology iteration and the lag of audience cognition update, as well as the information dissemination nature of the social field and the constructiveness of technological cognition. In the digital age, eliminating new digital divides should no longer be limited to external breakthroughs such as traditional educational resource provision and improvement of economic conditions. Instead, it is necessary to start from enhancing the digital literacy of the audience, guiding them to form a rational and mature expectation for new technologies, and creating a positive social environment for the dissemination of technology. This will enable the two-way adaptation of technological development laws and social acceptance demands. Promote the true realization of inclusive diffusion of generative AI technology, so that the benefits of technological innovation can reach all social

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groups, and make generative AI, through the positive interaction between technological iteration and social acceptance, become an important force for promoting the balanced construction of the digital society and facilitating high-quality social development.

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