Grounded Theory Analysis of the Formation Mechanism of Herd Selection Behavior on Online Learning Platforms: Postprint

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Abstract

[目的/意义] This study investigates the formation mechanism of herd selection behavior in online learning platforms, aiming to provide references for platform construction and service optimization. [方法/过程] From the student perspective, the grounded theory method is employed to conduct three-stage coding analysis on interview data, clarifying the interaction mechanisms among categories and constructing a formation mechanism model of herd selection behavior in online learning platforms. [结果/结论] Perceived benefits, user needs, social influence, and information encountering directly influence the formation of herd selection behavior in online learning platforms, while platform quality and platform reputation exert indirect influence through the mediating role of perceived benefits. Based on these findings, several targeted recommendations for service optimization of online learning platforms are proposed from the user, context, and platform levels.

Full Text

A Grounded Analysis of the Formation Mechanism of Herd Choice Behavior on Online Learning Platforms

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Abstract: [Purpose/Significance] This study explores the formation mechanism of herd choice behavior on online learning platforms to provide references for platform construction and service optimization. [Method/Process] From the student perspective, grounded theory was employed to conduct three-level coding analysis of interview data, clarifying the interaction mechanisms among categories and constructing a theoretical model of herd choice behavior formation on online learning platforms. [Result/Conclusion] Perceived benefits, user demands, social impacts, and information encounters directly influence the formation of herd choice behavior on online learning platforms, while platform quality and platform reputation indirectly affect this behavior through the mediating role of perceived benefits. Based on these findings, targeted recommendations for optimizing online learning platform services are proposed from user, contextual, and platform levels.

Keywords: online learning platforms; herd behavior; herd choice; grounded theory
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The integration of internet technology with traditional education has facilitated the emergence and development of online education, expanding both physical teaching scenarios and online library services. As of December 2020, China's online education user base reached 342 million, accounting for 34.6% of all internet users, with mobile online education users totaling 341 million, representing 34.6% of all mobile internet users [1]. Particularly since the COVID-19 outbreak in 2020, online education has been gradually adopted and promoted in universities, secondary schools, and primary schools worldwide as a primary alternative and compensatory measure. The widespread adoption of online education has reshaped traditional teaching models, contributing to the resolution of educational resource inequality [2] and the achievement of educational equity goals [3], while demonstrating effects equal to or even better than traditional classroom instruction [4]. Online learning platforms, as carriers of online education, have become favored by users for their advantages in transcending temporal and spatial limitations, broadening user perspectives, improving resource utilization efficiency, and enhancing learning enthusiasm. They have formed a dual-pillar situation alongside offline physical classrooms and become a primary application of mobile libraries. The continuous development of online learning platforms has accelerated the transformation of education in the new era, with smart education representing the future trend of educational informatization [5] and a major contemporary proposition requiring urgent resolution [6]. However, the survival and development of online learning platforms depend on user support and trust; platforms lacking an audience base will inevitably face elimination. Users' attitudes and behavioral tendencies toward online learning platforms significantly influence their survival and development, making in-depth research on user platform selection behavior crucial.

Herd behavior is a widespread social phenomenon where individuals tend to

do what the majority does, even when they believe they should act differently [7]. Research indicates that herd behavior occurs more readily in cyberspace [8] and appears in users' online learning processes [9], suggesting that herd phenomena may also exist in platform selection. Moreover, students are essential for both online and traditional education [4]. Therefore, this study examines the antecedents and pathways of herd choice behavior among online learning platform users from the student perspective, aiming to enrich herd behavior theory, guide user behavior, optimize platform services, and promote healthy platform development.

2 Literature Review

2.1 Research on Online Learning Platform Usage Behavior

Online learning platform usage behavior constitutes learning behavior for students and teaching behavior for instructors. Numerous scholars have investigated this topic. For instance, A. Tarhini et al. [12] examined students' adoption and use of web-based learning systems, finding that work-life quality, perceived ease of use, perceived usefulness, computer self-efficacy, social norms, and facilitating conditions significantly positively influenced adoption, with work-life quality having the strongest effect. S. Gao and Y. Yang [13] developed a model of MOOCs usage intention, discovering that perceived usefulness, perceived ease of use, and mimetic pressure significantly affected usage intentions. R. Rusli et al. [14] investigated university students' attitudes toward MOOCs, revealing that most students fully recognized MOOCs' existence, functions, advantages, and services, and could achieve growth in knowledge, soft skills, and personality through social learning. Wu Jilan and Shang Shanshan [15] examined factors influencing MOOCs platform usage, finding that course instruction, website design, tacit skill knowledge, tacit cognitive knowledge, and tacit social knowledge learning significantly positively affected learner usage, with tacit skill and social knowledge learning being more important than instruction and design. Wang Jianya et al. [16] conducted a meta-analysis of 64 domestic and international studies on online learning user behavior, identifying strong correlations between user and system factors and usage behavior, moderate correlations with social influence, with perceived convenience, perceived entertainment, and usage attitude having the greatest impact, while computer anxiety, personal innovation, and information quality had weaker effects. Zhu Hongcan and Duan Gangping [17] analyzed the impact of online reviews on usage intention, finding that review usefulness significantly positively influenced learners' intentions and moderated the relationships between popularity, review source expertise, and usage intention, while usefulness was itself positively affected by source expertise, credibility, popularity, two-sided reviews, and third-party recommendations.

2.2 Research on Post-Usage Behavior on Online Learning Platforms

After using online learning platforms, user experience influences continued or discontinued usage. Factor analysis represents important empirical research on

continuous usage. One study on cloud-based learning applications confirmed that computer self-efficacy, enjoyment, perceived ease of use, perceived usefulness, and user cognition—all usability factors—positively correlated with continuous usage intention [19]. Another study on mobile learning platforms indicated that perceived ease of use, perceived usefulness, perceived mobile value, expectation confirmation, and satisfaction directly or indirectly affected continuous usage intention [20]. Positive experiences may lead to sustained use, while negative experiences may prompt migration to other platforms. Such migration between platforms constitutes switching behavior [21]. Y. Liao et al. [22] found that learners' switching intention was influenced by "push effects," "pull effects," and "anchoring effects." Fang Jiaming et al. [23] further discovered that in the push effect dimension, system quality and relationship quality of traditional platforms reduced migration intention; in the pull effect dimension, functional and emotional deficiencies in new platforms enhanced migration intention; and in the anchoring effect dimension, emotional commitment, usage habits, and switching costs created behavioral inertia.

2.3 Review

Existing research has extensively explored online learning platform usage and post-usage behaviors. However, selection precedes usage, and few studies have examined selection behavior. D. Yang et al. [24] found that learners preferentially chose courses already selected by others, indicating herd tendencies in course selection. W. Wang et al. [9] observed herd behavior in MOOCs, noting that since learners could choose low-cost or free courses, they likely imitated others' choices, potentially leading to herd choice behavior. Nevertheless, research on platform selection behavior remains scarce, with even fewer in-depth investigations into herd choice behavior. Do herd phenomena truly exist in platform selection? If so, what are their formation antecedents and pathways? What strategic implications exist for platforms? To address these questions, this study systematically analyzes the formation mechanism of herd choice behavior from the student perspective using grounded theory.

3 Research Design

3.1 Research Method

Grounded theory is a method for constructing theory by coding raw data based on existing theories, literature, and researchers' knowledge and experience [25]. It effectively builds theory from empirical data [26], particularly suitable for theoretical construction when research topics are underdeveloped [27], and has been applied across numerous domains [28-30]. Given the limited research on herd choice behavior in online learning platforms and the method's convenience for coding and data analysis, this study employs grounded theory to explore the formation mechanism. To simplify coding procedures, this research utilizes NVivo software, which demonstrates high compatibility with this method and has been widely applied across fields [31-32].

3.2 Data Collection

3.2.1 Interview Outline Design Semi-structured interviews facilitate flexible, comprehensive, and authentic understanding of respondents' views. This study adopted semi-structured interviews for data collection. Before formal interviews, a preliminary outline was developed based on literature review and researcher experience. Two pilot interviews were conducted to refine the draft, resulting in the final interview outline shown in .

Interview Outline

Section	Content
Introduction	Respondents' answers have no right or wrong; please answer based on personal experience and thoughts; interviews will be recorded, and we will comply with confidentiality regulations and assume legal responsibility
Terminology Definition	Definition and examples of herd choice behavior and online learning platforms
Respondent Information	Gender, age, education, major, etc.
Core Questions	Have you exhibited herd choice behavior in selecting online learning platforms? Please provide examples. What factors did you consider when herd choosing platforms? Please elaborate. Under what circumstances did you herd choose platforms? Please elaborate. What are your feelings or experiences about herd choice behavior? Please elaborate. What other factors influenced your herd choice?

3.2.2 Sample Selection This study employed purposive sampling [33] and theoretical saturation sampling [34] as selection criteria. For purposive sampling, criteria included: 1) familiarity with herd choice behavior on online learning platforms; 2) maximum information provision for the research question; 3) clear understanding of interview questions and ability to articulate views; 4) consent to be interviewed and recorded after understanding the purpose and confidentiality provisions. For theoretical saturation, the criterion was when respondents could no longer provide new categories or relationships, with validation conducted on at least three additional participants. Following these

principles and considering gender, major, and data collection convenience, 17 respondents were ultimately selected.

3.2.3 Data Collection Due to the pandemic, data collection (including outline design, pilot interviews, formal interviews, and transcription) spanned nearly three months, with all interviews conducted online. All interviews were recorded with participant permission. Interview content was adjusted, supplemented, and probed based on responses. After interviews, recordings were initially transcribed using speech recognition software, then manually proofread and corrected to create standardized documents. To avoid misinterpretation, transcriptions were confirmed by respondents themselves, with confirmed documents serving as raw data for analysis. The 17 confirmed documents were labeled A-Q sequentially, totaling 48,860 words.

4 Grounded Analysis

4.1 Open Coding

In the open coding stage, raw data were coded sentence-by-sentence, extracting 345 reference points. Using "native concepts," these were conceptualized into 58 initial concepts such as friend recommendation, group integration, browsing encounter, and group size, as shown in .

Examples of Conceptual Coding

Raw Data	Initial Concepts
H: If many people around me use this platform, I tend to choose the platform that more people around me use	Group size, choosing based on audience
N: If I see many positive comments, I might choose to try it	Comments, choosing based on positive review quantity
B: If the price difference is huge, I might need to consider…	Price consideration
D: When everyone uses it, there might be more topics for discussion when communicating together	Group integration, common topics
A: When reading literature, other scholars might mention such learning platforms	Reading encounter, academic references

Raw Data	Initial Concepts
G: Some advertisements recommend these platforms, saying which have high download numbers, making you likely to choose platforms with high downloads	Browsing encounter, advertising, choosing based on download volume

Note: Letters represent respondents.

These initial concepts were further categorized into 14 basic categories: others' comments, information encounters, course strength, user demands, etc. (see).

Categorization Coding Details

Basic Category	Initial Concepts	Definition Basis
Choosing popular platforms	Choosing based on download volume, audience size, usage volume	Users tend to choose platforms with higher downloads or usage, even when they believe they shouldn't; based on Banerjee's herd behavior theory [7]
Choosing highly recognized platforms	Choosing based on recommendation frequency, ratings, positive review quantity	Users tend to choose platforms with more recommendations, better ratings, or more positive reviews, even when they believe they shouldn't
Others' comments	Evaluations, comments, ratings, user feedback	The extent to which other users positively evaluate used platforms; Park et al. define online reviews as positive/negative evaluations of purchased products [35]
Others' recommendations	Teacher recommendations, friend recommendations, peer recommendations	Frequency of other users recommending platforms based on personal experience

Basic Category	Initial Concepts	Definition Basis
Group norms	Group integration, common topics, not falling behind	The constraining and influencing power of users' groups
Information encounters	Entertainment encounters, browsing encounters, reading encounters	The extent to which users accidentally encounter platform-related information; Erdeloz defines information encountering as accidentally finding interesting information while searching for other topics [37]
Platform reputation	Platform awareness, word-of-mouth, perceived credibility	The extent to which users consider platforms well-known and credible in oral communication; Whyte defines word-of-mouth as consumer oral communication [38], while Schmitt et al. distinguish pure word-of-mouth as spontaneously generated [39]
Promotion efforts	Promotion intensity, advertising	Users' perception of platform promotional efforts
Course strength	Course resources, quality, design, instructors, fees, target audience, expertise	Platform advantages in course quality, instructors, target audience, domain, fees
Platform design	Platform attributes, interface design, functional features	The completeness of functions and user-friendliness of interfaces
Demand matching	Course demand matching, preference matching, audience matching	The extent to which platforms meet user needs

Basic Category	Initial Concepts	Definition Basis
Perceived usefulness	Helpfulness, value, high content quality	The extent to which platform information positively impacts learning/work; Sussman et al. define perceived usefulness as the degree to which using specific information improves learning/work [40]
Perceived interest	Interesting, engaging, lively content	The extent to which platform information creates enjoyment; Zhao Ying et al. define perceived interest as the interestingness of MOOC content [41]
User demands	Learning needs, personal needs	The extent to which users develop needs or desires for platforms; Zeng Jianxun defines user demands as needs or desires arising within a certain period [42]

4.2 Axial Coding

In axial coding, basic categories were refined into seven main categories: social influence, platform reputation, perceived benefits, information encounters, etc., further integrated into dimensions of herd behavior, user, platform, and context (see).

Axial Coding Results

Main Category	Basic Categories	Connotation
Herd choice behavior	Choosing popular platforms, choosing highly recognized platforms	Users' tendency to choose platforms selected by the majority, even when believing they shouldn't, including choosing popular and highly recognized platforms
Perceived benefits	Perceived usefulness, perceived interest, demand matching	Expected benefits and returns from platform selection [43], manifested in three aspects; higher usefulness, interest, and demand match increase perceived benefits
User demands	User demands	The extent of users' needs or desires for platforms, varying across contexts
Platform reputation	Word-of-mouth, promotion intensity	The extent to which users consider platforms sincere and well-known [44], manifested in word-of-mouth and promotion; better word-of-mouth and greater promotion enhance reputation
Platform quality	Course strength, platform design	Platform characteristics in courses and design; stronger courses and more user-friendly design increase perceived quality

Main Category	Basic Categories	Connotation
Information encounters	Information encounters	The extent of accidentally encountering platform-related information, varying across contexts
Social influence	Others' comments, others' recommendations, group norms	The influence of specific people or organizations on herd choice [45], manifested in three aspects; more positive comments, recommendations, and stronger group norms increase positive social influence

4.3 Selective Coding

In selective coding, relationships among the seven main categories were identified through comparative analysis:

1. **Platform quality → Platform reputation**: Course strength and platform design directly affect platform reputation. For example, respondent Q noted: "NetEase Cloud Classroom's TED series is very distinctive and has continued. I think it's already their label and is well-known" (course strength → word-of-mouth).
2. **Platform reputation → Perceived benefits**: Word-of-mouth and promotion intensity directly affect perceived benefits. For example, respondent K stated: "Larger platforms give me higher credibility. Platforms like Tencent, Alibaba, and NetEase feel more credible, and their content quality is more guaranteed" (word-of-mouth → perceived usefulness).
3. **Social influence → Herd choice behavior**: Others' comments, recommendations, and group norms directly affect herd choice. For example, respondent F explained: "People around me recommended it after using it. Since we have similar needs and they all use it, it's probably good. Their recommendations must meet their needs, so choosing this saves me the effort of finding and comparing platforms" (others' recommendations → choosing popular/recognized platforms).
4. **Information encounters → Herd choice behavior**: Information encounters directly affect herd choice. For example, respondent A men-

tioned: "When entertaining myself on Zhihu or other websites, I see recommendations. If a platform appears frequently, I might choose to use it" (information encounters → choosing recognized platforms).

5. **Platform quality → Perceived benefits**: Course strength and platform design directly affect perceived benefits and indirectly affect them through platform reputation. Perceived benefits directly influence herd choice through demand matching, perceived usefulness, and perceived interest. For example, respondent C noted: "Since learning is often boring, if the resources interest me, I might choose this platform" (course strength → perceived interest → choosing recognized platforms).

6. **User demands → Herd choice behavior**: User demands directly affect herd choice. For example, respondent N stated: "First, it's my own demand. If I'm preparing for an exam, I have this need and will then choose it" (user demands → choosing recognized platforms).

The resulting storyline: Under the direct influence of social influence, information encounters, user demands, and perceived benefits, users exhibit herd choice behavior on online learning platforms. Perceived benefits are influenced by platform quality and platform reputation, with platform reputation having direct effects and platform quality having both direct effects and indirect effects through platform reputation. Based on this storyline, "herd choice behavior on online learning platforms" was identified as the core category, and a formation mechanism model was constructed (see [Figure 1: see original paper]).

[Figure 1: see original paper] Formation Mechanism Model of Herd Choice Behavior on Online Learning Platforms

4.4 Theoretical Saturation Test

Theoretical saturation is achieved when raw data no longer provide new categories or relationships, with validation conducted on three or more additional cases [46]. This study used theoretical saturation as the sampling criterion, stopping interviews when no new categories emerged. Saturation was reached at the 14th respondent, after which three additional participants were interviewed for validation, yielding no new categories or relationships, thus confirming theoretical saturation.

5 Conclusion and Discussion

5.1 Research Conclusions

As a product of internet-traditional education integration in the new information technology environment, online learning platforms have attracted multidisciplinary attention. However, research on herd choice behavior remains limited. Through grounded analysis of interview data, this study identifies influencing factors and constructs a theoretical model. Findings reveal that herd choice

behavior is prevalent among students selecting online learning platforms, influenced jointly by user demands, perceived benefits, social influence, information encounters, platform quality, and platform reputation. User demands, perceived benefits, social influence, and information encounters have direct effects; platform quality and platform reputation have indirect effects through perceived benefits; platform quality directly affects platform reputation; platform reputation directly affects perceived benefits; and platform quality both directly and indirectly (through platform reputation) affects perceived benefits.

5.2 Research Contributions

This study makes three primary contributions. First, while previous research examined herd information commenting on bullet-screen video websites [47], herd choice in online courses [9], and herd shopping behavior [48], few studies have investigated herd choice behavior on online learning platforms. This research fills this gap from the student perspective, advancing theoretical development in online learning platforms and herd behavior, and providing foundations and scale design references for future studies. As carriers of online education and extensions of physical teaching scenarios and library services, these findings also enrich educational and library science research.

Second, previous research focused on contextual and user factors influencing herd behavior [49-50] while neglecting platform factors. This study systematically extracts influencing factors from contextual, user, and platform dimensions, identifying the important role of previously overlooked categories like information encounters. Third, using grounded theory, this research comprehensively reveals the interaction mechanisms among different influencing factors, deepening understanding of online platform selection and herd behavior, and providing valuable insights for platform development, service optimization, and user behavior guidance.

5.3 Practical Implications

User-level factors (perceived benefits and user demands) directly influence herd choice behavior. Perceived benefits affect behavior through demand matching, perceived usefulness, and perceived interest. Platform quality and platform reputation (platform-level factors) indirectly influence herd choice through perceived benefits. Platform quality operates through course strength and platform design, while platform reputation operates through word-of-mouth and promotion intensity.

Regarding **user demands and demand matching**, platforms must not only stimulate learning needs but also accurately grasp implicit demands, providing targeted services. Artificial intelligence and user profiling can analyze historical big data to depict mainstream groups' potential needs, optimizing platform services accordingly. Regarding **perceived usefulness and interest**, platforms should adopt user-preferred formats to introduce platform efficacy, content, and

teaching teams, creating psychological impact and enhancing users' perception of usefulness and interest.

Contextual factors (social influence and information encounters) directly affect herd choice behavior. Social influence operates through others' comments, recommendations, and group norms. First, group norms matter—forming group norms is crucial for platform development, as user scale creates potential influence. Platforms should therefore focus on expanding their user base. Second, others' comments and recommendations matter—platforms must value "opinion leaders." Authoritative or well-known users' opinions often lead mass attitudes, and their endorsements stimulate demand. Platforms can invite renowned teachers or celebrities to teach or endorse, creating influence. Third, information encounters matter—promotion is necessary. Multiple communication channels and media should familiarize users with the platform, creating potential influence when needs arise. Platforms can collaborate with high-attention WeChat public accounts, Weibo influencers, or Douyin for subtle advertising impact.

Regarding **platform quality**, course strength and platform design are key. Platforms should emphasize content importance, optimizing course design through clear categorization, refined content, and condensed class hours; invite renowned teachers to enhance authority; improve content relevance and diversity; implement evaluation mechanisms; and optimize payment and access mechanisms. Platform design should improve usability, intelligence, interface color schemes, and layout.

Regarding **platform reputation**, word-of-mouth and promotion intensity matter. Platforms should diversify communication channels, increase advertising frequency, and enhance influence through collaborations with prestigious universities, renowned teachers, and celebrity endorsements to increase awareness.

5.4 Limitations and Future Directions

This study has several limitations. First, it does not differentiate platform types, though users may perceive comprehensive and specialized platforms differently. Future research should analyze herd behavior across different platform types to understand characteristics, differences, and influence patterns. Second, the study excludes educators and does not analyze demographic characteristics. Future research should incorporate educator perspectives and examine gender, education, age, and other variables. Third, the grounded theory model lacks quantitative validation, limiting robustness. Future studies should employ regression analysis and structural equation modeling for quantitative empirical testing.

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Author Contributions:
Zha Xianjin: Overall research design, partial writing, finalization;
Zhang Kun: Data collection, data analysis, partial writing;
Yan Yalan: Data analysis, partial writing.

Note: Figure translations are in progress. See original paper for figures.