Postprint: An Integrated Qualitative Simulation and Empirical Study on the Influencing Mechanism of Information Subscription Intention in Mass Reading Platforms

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Abstract

[Purpose/Significance] This study aims to employ the Qualitative Simulation (QSIM) method to investigate the influencing factors of online information subscription intention and their underlying mechanisms. By constructing a relational model of factors affecting information subscription intention, it seeks to uncover the evolutionary patterns and trends of online information subscription behavior, thereby facilitating a deeper understanding of the mechanisms influencing user subscription patterns and providing a decision-making basis for function formulation in mass reading platforms. [Method/Process] First, based on a review of relevant behavioral research theories, six major factors influencing subscription intention are identified: subscription content quality, subscription cost, external influence, subscription demand, subjective perception, and personal characteristics. Subsequently, a preliminary relational model of influencing factors is constructed through structured interviews, and questionnaire surveys and empirical data collection are conducted to refine this preliminary model. Finally, the QSIM algorithm is utilized to drive the interaction and evolution among the various factors in the model, and through observation and analysis, the evolutionary characteristics and patterns of each influencing factor on subscription intention are determined. [Results/Conclusions] The qualitative simulation method can effectively describe and monitor the changing process of subscription behavior characteristics. The results indicate that subscription content quality, subscription demand, and external factors exert a positive influence on subscription intention, while subscription cost exerts a negative influence, albeit with a relatively minor impact magnitude.

Full Text

Research on the Influence Mechanism of Information Subscription Intention on Public Reading Platforms Based on Integrated Qualitative Simulation and Empirical Analysis

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Abstract

[**Purpose/Significance**] This study aims to investigate the influencing factors and mechanisms of online information subscription intention using the Qualitative Simulation (QSIM) method. By constructing a relational model of factors affecting information subscription intention, we seek to uncover the evolutionary patterns and trends of online information subscription behavior, thereby deepening our understanding of the underlying influence mechanisms and providing a decision-making basis for the functional development of public reading platforms.

[**Method/Process**] First, based on a review of relevant behavioral research theories, we identified six key factors influencing subscription intention: subscription content quality, subscription cost, external influence, subscription demand, subjective feelings, and personal characteristics. We then constructed a preliminary influencing factor relationship model through structured interviews, which was subsequently refined via questionnaire surveys and empirical data collection. Finally, the QSIM algorithm was employed to drive the interaction and evolution among factors in the model, allowing us to observe and analyze the evolutionary characteristics and patterns of each influencing factor on subscription intention.

[**Result/Conclusion**] The qualitative simulation method can effectively describe and monitor the changing process of subscription behavior characteristics. Among the findings, subscription content quality, subscription demand, and external factors positively influence subscription intention, while subscription cost negatively affects subscription intention, albeit with a relatively small impact magnitude.

Keywords: public reading platform; subscription intention; empirical research; QSIM; influence mechanism
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1 Introduction

By 2019, 79.3% of Chinese citizens were reading through terminals such as PCs, mobile phones, and Kindle e-books on public reading platforms like Douban Reading, Amazon, and WeChat Reading [1]. Overall, compared to digital libraries, people tend to prefer public reading platforms, a preference determined by the strong professional and academic nature of digital library resources [2]. Reading methods on public platforms can be either complete or fragmented; reading materials can be either popular or professional; and reading processes can be either random or subscription-based [3]. For the "subscription" behavior, the frequency of popular resource subscriptions is often higher than that of professional resource subscriptions. Moreover, factors such as platform resource heterogeneity, subscription process diversity, and user experience differences significantly impact subscription intention. The relationships among these influencing factors are complex and difficult to quantitatively describe in terms of mechanism and pattern of change.

According to organizational behavior research, subscription behavior exhibits both group and process characteristics: group behavior changes follow discernible patterns, making such trends predictable [5]. Based on this premise, simulating the process of this typical "subscription" behavior can help us understand its change mechanism, derive possible reading patterns and trends, and thereby guide the promotion of public reading.

The QSIM simulation method (Qualitative Simulation), proposed by B. Kuipers [6] in 1986 based on complex systems theory, is a causal reasoning algorithm that uses group behavioral characteristics to simulate real-world problems. Its core idea is to start from the initial state of variables and, following certain reasoning rules based on causal principles, derive subsequent states of each variable in the system to predict all possible future behaviors of the system. QSIM has been widely applied in management fields, with its effectiveness and utility having been validated [7-12].

This study aims to employ this method to investigate the interaction mechanisms and evolutionary patterns among influencing factors of information subscription behavior on public reading platforms. First, we construct an influencing factor model for online information subscription intention based on literature research and structured interviews. Then, we refine the model using questionnaire surveys and platform data, and utilize QSIM to drive the evolution of relationships among factors. Finally, by assigning different values to decision variables for reasoning, analysis, and discussion, we uncover patterns of online information subscription behavior to provide decision-making recommendations for platform marketing and methodological insights for information behavior research.

2 Theoretical Foundation and Literature Review

2.1 Literature Review

Current qualitative simulation theory research is relatively mature internationally, with numerous achievements in applications spanning biology, medicine, physics, management, economics, and other fields. K. Yu et al. [7] used QSIM algorithms to conduct qualitative simulations of group safety behaviors among coal miners, revealing development trends and evolution patterns. F. Guerrin [8] applied QSIM to describe and simulate biological domain knowledge. F. E. Cellier et al. [9] simulated the human cardiovascular system, providing new methods for medical research. Lou Shuai et al. [10] introduced QSIM algorithms in systems engineering to simulate components of water resource systems for predicting subsequent changes. Zhu Hou et al. [11] proposed an evolutionary model based on QSIM-ABS simulation to address limitations of classical public opinion evolution models. Xia Gongcheng et al. [12] constructed an employee turnover process model and simulated turnover behavior using QSIM for prediction. Hu Bin [13] improved upon Kuipers' QSIM method in studying group work behaviors, effectively explaining and predicting behavioral change processes. Additionally, QSIM has been extensively used in enterprise management and economics to guide economic decision-making practices [14-15].

Subscription is a typical online information behavior, with information behavior research encompassing information needs, information seeking, information use, and information transfer [16]. L. P. Ayres et al. pioneered information behavior research by studying users' information-seeking behaviors [4]. T. H. Lee [17] identified that perceived and recognized mobile service performance is an important factor hindering graduate students' use of mobile libraries through observation and interviews. A. Sukhhu [18] explored factors influencing travelers' willingness to exchange tourism information by constructing a social network structural equation model. J. Rowley et al. [19] investigated factors affecting adults' credibility judgments of online health information through questionnaires. P. Pluye et al. [34] used quantitative evaluation of information-seeking results to guide qualitative interviews, combining quantitative and qualitative data to compose clinical profiles of information-seeking outcomes, significantly reducing doctors' information retrieval costs. H. R. Jamali et al. [35] studied the role of Google in physicists' and astronomers' information-seeking behaviors using semi-structured interviews and questionnaires. C. Gan et al. [23] compared four commonly used models in mobile user behavior research (TAM, TPB, DTPB, and UTAUT) to analyze the role of perceived usefulness and behavioral intention in mobile library user adoption.

Domestic research on online information behavior began relatively later. Literature reviews reveal four main categories: basic issues of online information behavior, behavioral pattern research, research methodology, and influencing factors. Wang Yan et al. [39] provided a comprehensive introduction to relevant elements of online information behavior, offering a potential conceptual framework for subsequent research. Wang Qiuwen et al. [38] explored online information consumption behavior patterns in the Web 2.0 environment. Wu Dan et al. [36] compared subsequent click behaviors between mobile and PC users based on university library log data mining to guide platform construction. Deng Xiaozhao [20] studied Internet users' information retrieval behavior, with conclusions effectively guiding retrieval platform optimization. Zha Xianjin et al. [37] noted that online information behavior research commonly employs questionnaire surveys, log analysis, and statistical analysis, effectively summarizing methodological choices for future research. Zhang Shuai et al. [21] analyzed factors influencing users' online knowledge payment behavior through structured interviews using qualitative analysis software, providing theoretical foundations for subsequent knowledge payment platforms. He Wei et al. [22] combined structural equation modeling with the UTAUT model to analyze how information quality, service quality, and perceived risk affect users' intention to use mobile libraries. Xu Kaiying et al. [26] studied influencing factors of mobile library user adoption behavior using structural equation modeling and questionnaires.

Evidently, domestic and international scholars predominantly employ network measurement and mathematical models to study user behavior [22-26], focusing on user acceptance behavior, satisfaction, continuous usage behavior, sharing behavior, and various facet behaviors (searching, browsing, clicking). Most research concentrates on individual behavior [41] and static quantitative studies, with fewer studies employing qualitative simulation for dynamic behavioral evolution analysis [42]. Therefore, this paper attempts to introduce QSIM into behavioral analysis to drive dynamic factor evolution and uncover patterns of online information subscription behavior change.

2.2 QSIM Qualitative Simulation

B. Kuipers [6] proposed the QSIM algorithm based on Qualitative Differential Equation (QDE) theory to simulate processes of described objects. QDE includes two components: variables (typically system parameters) and constraints (descriptions of relationships between different parameters in the system). In group behavior simulation, QSIM generates all possible subsequent states based on each variable's initial state, then filters out unreasonable states according to constraints among variables, thereby simulating group behavior.

2.2.1 Qualitative State Given a system's qualitative differential equation and its initial state at time t_0, the QSIM algorithm predicts possible system behaviors in the form of a state tree. A specific system behavior consists of all states along a path from the root node (initial state) to a leaf node (terminal state). For system analysis, we first select a finite set of distinguishable time points and landmark values within intervals. Landmark values refer to function values at significant points of the inferable function f: [a,b] $\rightarrow$ * that have symbolic meaning, expressed as:

time: $\{t_0 < t_1 < t_2 < \ldots < t\ \}$
landmark value: $\{l_0 < l_1 < l_2 < \ldots < l\ \}$

Thus, the qualitative state of a variable during time period t can be represented as QS(f,t) → QS<qval,qdir>(f,t) or QS(f,t ,t $_1$); where t , t $_1$ are distinguished time points—points where variable states undergo sudden changes. The qualitative state is represented as a binary group:

qval = lf(t) = l if f(t) = l
qdir = inc if f'(t) > 0
std if f'(t) = 0
dec if f'(t) < 0

Where qval is the landmark value of inference function f at time t (the qualitative value of each variable), and qdir represents the binary change direction and speed at time t.

2.2.2 Qualitative State Transition QSIM is essentially causal reasoning. As time progresses, system states continuously change due to interactions among variables. Since time progression involves transitions between distinguished time points and intervals, variable qualitative state transitions also consist of two parts: I-transitions and P-transitions. P-transitions represent state changes from "distinguished time point" to "distinguished time interval," while I-transitions represent changes from "distinguished time interval" to "distinguished time point," typically occurring after a period of accumulation. The logical descriptions of I-transitions and P-transitions are shown in [Figure 1: see original paper].

In the reasoning process, each state change corresponds to different rules, generating different subsequent states [27]. The QSIM algorithm includes six constraint relationships: ADD, MULT, MINUS, DERIV, M+, M-, representing addition, multiplication, inverse, differentiation, monotonic increase, and monotonic decrease, respectively. This paper only involves monotonic increase constraints (same change trend) and monotonic decrease constraints (opposite change trend).

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3 Empirical Research

Early subscription models primarily involved newspapers or magazines, where users regularly obtained printed publications through paid subscriptions. With the continuous development of network information technology, online subscriptions have become increasingly common. The general model involves service providers offering online information, audio-visual media, and other content for paid consumption [28]. In this model, service providers attract users by offering limited free content while adopting membership marketing strategies to provide personalized services that meet diverse user needs. This study incorporates both free and paid subscription forms into subscription behavior research to comprehensively simulate user online information subscription behavior.

Due to platform differences and individual user variations, online information subscription behavior is influenced by multiple factors. These influencing factors can essentially be viewed as dynamic characteristic variables affecting subscription outcomes. Qualitative simulation requires consideration of relationships among variables, which this study quantifies through empirical methods.

3.1 Conceptual Model Development

Through literature review, we summarized influencing factors of information behavior (see) and used structured group interviews to explore relationships among these factors. Thirty interviewees from different professions were randomly divided into groups, with members scoring relationships between variables using {-2, -1, 0, +1, +2}, where "+" represents positive influence, "-" represents negative influence, and numerical values represent influence magnitude (larger values indicating stronger influence). After scoring, group means were calculated to construct a preliminary influencing factor relationship model (see [Figure 2: see original paper]). In the figure, "+" indicates that the tail factor positively affects the arrow-pointing factor (tail factor enhancement leads to arrow factor enhancement), "-" indicates negative influence, and numbers indicate influence strength. For example, the arrow from subscription content quality to subjective feelings with a "+" sign indicates that improved content quality enhances user subjective feelings, with a strength of 1.

Since all influencing factors of online information subscription intention are latent variables, we designed a questionnaire based on existing literature, selecting appropriate measurement variables. The questionnaire included demographic questions and scale items, all using a five-point Likert scale (1-5 representing "strongly disagree" to "strongly agree"). Survey participants were individuals who had used subscription platforms, with no geographical restrictions. A total of 396 questionnaires were distributed, yielding 265 valid responses. The sample included 108 males and 157 females (relatively balanced gender ratio), with ages 18-24 comprising the largest group (72.5%) and students accounting for 66.8% of respondents (reflecting that young people are primary platform users). Most respondents held bachelor's (39.6%) or master's degrees (37.4%).

3.2 Structural Equation Model Analysis

3.2.1 Reliability and Validity Analysis For reliability analysis, we measured questionnaire reliability using Cronbach's alpha coefficient: higher alpha indicates better reliability, with values above 0.8 indicating high reliability. For validity analysis, we used KMO values and factor loading coefficients: higher KMO indicates better validity, with values above 0.8 indicating high validity; factor loading coefficients (absolute values > 0.4) indicate correspondence between items and factors. Analysis yielded a Cronbach's alpha of 0.887, with all measurement items above 0.87, indicating high data reliability. The KMO value was 0.883, with all factor loadings above 0.4, demonstrating that measurement items effectively captured latent variables with high validity.

3.2.2 Model Path Hypothesis Testing and Structural Model Determination We used independent samples t-tests and one-way ANOVA to analyze differences in gender, age, occupation, academic background, education level, and subjective feelings to explore the influence of personal characteristics. Results showed that only age had a significant effect on subjective feelings, with users aged 25-30 reporting the most positive subjective experiences. Since other demographic variables showed no significant differences, we concluded that personal characteristics have minimal impact on subjective feelings.

Using the online SPSSAU platform for path analysis on questionnaire data, we validated model assumptions and refined the conceptual model. After multiple iterations based on analysis results, we obtained the revised path coefficients and relationship model (see [Figure 3: see original paper]). Solid lines represent paths existing in the initial model and validated by questionnaire data; dashed lines represent paths not initially hypothesized but confirmed by data. "**" indicates significance at $p < 0.01$. Path coefficients > 0 indicate positive influence, while < 0 indicate negative influence.

3.3 Model Revision with Empirical Data

Given the subjectivity of questionnaire data, we crawled user behavior data from online subscription platforms to objectively revise the two most important paths: "subscription content quality" and "subscription cost" to "subscription intention." Data were collected from VIP works on the "Jinjiang Literature City" platform, capturing fields including "work name," "author," "word count," "work score," and "total favorites." After excluding derivative works and works published after December 31, 2018, we obtained 4,464 valid records.

Jinjiang Literature City uses serial streaming pricing based on word count, so we used "word count" as the measure of subscription cost (including economic and time costs—more words indicating higher cost). "Work score," calculated from clicks, reviews, and ratings, served as the measure of subscription content quality (higher scores indicating higher quality). "Current favorites count" measured subscription intention (more favorites indicating stronger subscription intention). Regression analysis in SPSS (see) yielded $F = 12361.752$, $P < 0.001$, indicating a significant regression equation. Subscription cost negatively affected subscription intention (β = -0.045 $<$ 0), while subscription content quality positively affected subscription intention ($\beta = 0.926 > 0$).

Based on platform data and questionnaire results, we further revised the model: subscription cost negatively affects subscription intention with a path coefficient of -0.045; subscription content quality positively affects subscription intention with a path coefficient of 0.926. For subsequent qualitative simulation, we divided path coefficients into two levels using the mean after removing extreme values: "+" (or "-") for general influence and "2+" (or "2-") for strong influence. This yielded the qualitative model of influencing factor relationships for online information subscription intention (see [Figure 4: see original paper]).

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4 Qualitative Simulation of Online Information Subscription Behavior

4.1 Qualitative Representation of Variables and Reasoning Algorithm

4.1.1 Qualitative Representation of Variables Variables in this study are divided into decision variables and state variables. Decision variables are external inputs to the system that decision-makers can adjust based on system states; state variables are internal system variables that can only change through interactions among variables and their own previous states [33]. From the qualitative model in [Figure 4: see original paper], we defined X_1 (subscription content quality) and X_2 (subscription cost) as decision variables, and X_3 (external influence), X_4 (subscription demand), X_5 (subjective feelings), and X_7 (subscription intention) as state variables with the following values and meanings:

X_3: -1 = low external influence, 0 = moderate external influence, 1 = high external influence
X_4: -1 = weak subscription demand, 0 = moderate demand, 1 = strong demand
X_5: -1 = poor subjective feelings, 0 = neutral feelings, 1 = positive feelings
X_7: -1 = weak subscription intention, 0 = moderate intention, 1 = strong intention

State variable change directions are {2-, -, 0, +, 2+}, where "2-" indicates rapid decrease, "-" indicates slow decrease, "+" indicates slow increase, and "2+" indicates rapid increase. According to equation (4), l = {-1, 0, 1} and qdir = {2-, -, 0, +, 2+}. For example, QS(X_3, t , t $_1$) = <(-1,0), +> indicates that X_3 has a value of (-1,0) in time interval (t , t $_1$) with a slow upward trend, representing relatively strong subscription demand with slowly increasing tendency.

For decision variables, we use unary representation , such as QS = {<->, <0>, <+>}, representing "decrease," "no change," and "increase" in subscription content quality or cost.

4.1.2 Reasoning Algorithm The algorithm steps [33] are:

1. Set simulation stage number n and define change direction of decision variables at each stage

2. Determine subsequent state transitions for each state variable using state transition tables

3. Filter or merge inconsistent direction transitions for state variables

4. Filter jump behaviors (state transitions must be smooth and continuous)

5. Summarize remaining transitions to form reasonable stage interpretations

6. Exit when reaching simulation stage n, otherwise return to step 2

In step 2, for one-to-one variable relationships, the state change direction is determined by the cause variable's change direction and the strength marked on the relationship line. For many-to-one relationships, we first determine each cause variable's contribution to the result variable's change direction based on its own change direction and relationship strength, then sum all contributions. The final change direction is forced to convert to {2+, +, 0, -, 2-}: if the weighted sum is ≥ 2+, it converts to "2+"; if ≤ 2-, it converts to "2-".

4.2 Simulation Example

This simulation uses variables X from the qualitative model in [Figure 4: see original paper], assuming simulation stages n = 9: time: {$t_0 < t_1 < t_2 < … < t_9$}.

4.2.1 Initial State ($t = t_0$) Decision variable states QS(X_1, t $_1$, t) = <-> (X_2 similarly) indicate that the platform takes measures to reduce subscription content quality (or increase cost) based on the previous stage. If QS(X_1, t $_1$, t) = <0>, the platform maintains previous quality levels; if <+>, it improves quality.

At initial time t_0, state variable values and meanings are shown in :

QS(X_3, t_0) = <0,0>: moderate external influence maintained
QS(X_4, t_0) = <0,0>: moderate subscription demand with no change
QS(X_5, t_0) = <0,0>: neutral subjective feelings remaining stable
QS(X_7, t_0) = <0,0>: moderate short-term subscription intention

4.2.2 Simulation from $t = t_0$ to $t = t_1$ Given decision variable initial states QS(X_1, t_0, t_1) = <-> and QS(X_2, t_0, t_1) = <+>.

(1) From $t = t_0$ to $t = (t_0, t_1)$: Variables transition from distinguished time points to intervals using P-transitions.

X_3: <0,0> → <(-1,0), ->, <0,0> under combined influence of X_1 and X_2. X_1's influence on X_3 is 2+, giving force ω_1 = 2-; X_2's influence is +, giving ω_2 = +. Combined contribution is -, so external influence may either decrease from "moderate" to "lower" with slowly decreasing trend, or remain unchanged.

X_4: <0,0> → <(-1,0), 2-> under combined influence of X_1 and X_3. Total force is 2-, so subscription demand shifts from "moderate" to "weaker" with rapidly decreasing trend.

X_5: <0,0> → <(-1,0), 2-> under combined influence of X_1 and X_4. Total force is 2-, so subjective feelings shift from "neutral" to "poor" with rapidly decreasing trend.

X_7: <0,0> → <(-1,0), 2-> under combined influence of X_1, X_2, X_3, X_4. Total force is 2-, so subscription intention shifts from "moderate" to "weaker" with rapidly decreasing trend.

After merging inconsistent behaviors, state variables show:

X_3: <(-1,0), ->, <0,0>
X_4: <(-1,0), 2->
X_5: <(-1,0), 2->
X_7: <(-1,0), 2->

(2) From $\mathbf{t = (t_0,\ t_1)}$ to $\mathbf{t = t_1}$: Variables transition from intervals to distinguished time points using I-transitions. Since state variables were already influenced by decision variables at (t_0, t_1), I-transitions primarily consider state variable changes.

X_3: <(-1,0), -> → <-1,0>, <(-1,0), ->, <0,0> under influence of X_1 and X_2. With no change in X_1 and X_2, force is 0, but external influence may suddenly shift from "lower" to "low" at distinguished time points, stabilizing at the lowest level.

X_4: <(-1,0), 2-> → <-1,0>, <(-1,0), -> under influence of X_1 and X_3. With three possible X_3 states, total force on X_4 is either 0 or -, giving two possible demand changes.

X_5: <(-1,0), 2-> → <-1,0> under influence of X_1 and X_4.
X_7: <(-1,0), 2-> → <-1,0> under combined influence of X_1, X_2, X_3, X_4.

After merging, state variables show:

X_3: <-1,0>, <(-1,0), ->, <0,0>
X_4: <(-1,0), 2->, <-1,0>
X_5: <(-1,0), 2->, <-1,0>
X_7: <(-1,0), 2->, <-1,0>

4.2.3 Simulation from $\mathbf{t = t_0}$ to $\mathbf{t = t_9}$ The above describes first-stage variable changes. To understand evolutionary patterns and influence mechanisms, we assign different values to decision variables at different time nodes for causal reasoning simulation. Subsequent stages follow the same reasoning process as $t_0 \rightarrow t_1$. Due to space limitations, we summarize qualitative simulation results across stages in .

4.3 Simulation Results Analysis and Discussion

Stages 1-2: For products with certain external influence and user demand, when content quality decreases and cost increases, external influence, user demand, and subjective feelings all deteriorate, with demand and feelings decreasing rapidly, causing subscription intention to decline rapidly. Since subscription cost positively affects external influence, external influence declines slowly during (t_0, t_1) and may maintain its original state because cost investments through promotions create positive influence. However, if the platform maintains this quality and cost level, other variables continue declining to their lowest points.

Stages 3-4: Based on stage 2, maintaining content quality while reducing cost causes subscription intention to rise from its lowest point to the (-1,0) interval with a slow upward trend, potentially reaching a moderate state at t_3. Maintaining this cost level stabilizes subscription intention at a moderate state over time (stage 4). This suggests that when content quality is poor, appropriately reducing pricing can maintain subscription intention. However, the model shows cost reduction further decreases external influence, demand, and subjective feelings, which would reduce subscription intention. Realistically, at the lowest quality level, the law of diminishing marginal returns [40] means cost reduction has minimal effect on external influence, but with unchanged demand and feelings, cost reduction significantly improves subscription intention.

Stage 5: To further improve subscription intention, the platform can increase content quality while maintaining low pricing. This causes external influence to slowly rise from its lowest point due to quality and cost effects. Although the rise is slow, the progressive influence relationships cause demand and subjective feelings to rise rapidly from their lowest points. Subscription intention shifts from stable moderate state to first slow then rapid increase, as initial direct effects of quality and cost are followed by further effects mediated through external influence, demand, and feelings.

Stages 6-7: Maintaining stage 5's quality and pricing causes subscription intention to stabilize at its highest point first; external influence stabilizes at moderate state; demand and subjective feelings remain in the rapidly rising (0,1) interval before stabilizing at their highest points (stage 7). This shows that when measures cause subscription intention to peak first, maintaining the status quo allows other factors to eventually stabilize at maximum values through market adjustment, saving platform resources.

Stage 8: Further improving content quality and increasing cost on top of stage 7 causes external influence to slowly rise from moderate to maximum, while demand, subjective feelings, and subscription intention maintain their highest levels without declining due to higher pricing. This indicates platform maturity: even raising prices for greater profit won't cause large-scale user loss or decreased subscription intention.

Stage 9: Continuing stage 8's high quality and pricing maintains external influence's slow rise to maximum, while demand, subjective feelings, and subscription intention remain stable at peak levels.

Through multi-stage qualitative simulation using QSIM, we can observe in detail how each influencing factor changes, thereby mastering the influence mechanism of online information subscription behavior. For platform marketing, decision-makers can adopt appropriate measures at different stages to attract more users, increase platform stickiness, generate greater profits, and provide better user experiences.

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5 Conclusions and Recommendations

5.1 Research Conclusions

This study identified factors influencing online information subscription intention through literature review, constructed a conceptual model via structured interviews, refined the model using questionnaire and platform data, and employed QSIM to drive factor interactions for dynamic multi-stage causal reasoning simulation. Main conclusions include:

1. Factors influencing user intention can be described not only through static models but also through dynamic interaction and evolution processes, as intention formation is inherently a process. This study provides a method for describing these dynamic evolution processes.
2. Results show subscription intention is influenced by multiple factors that also interact with each other. Intention changes result from cumulative effects of other factors in complex ways. For example, content quality directly and positively affects subscription intention while also indirectly influencing it through positive effects on demand and external influence. Subscription cost directly and negatively affects intention but also indirectly influences it through positive effects on external influence.
3. Qualitative simulation can clearly demonstrate the dynamic change processes of influencing factors. Integrating qualitative simulation with empirical testing enables more comprehensive analysis of information subscription intention mechanisms. QSIM results show that factors affecting user intention are always dynamically changing and influencing each other. External influence demonstrates relatively strong stability, playing a stabilizing role for subscription intention.

5.2 Recommendations

Based on empirical relationships, this study introduces qualitative simulation to drive factor interactions across time periods, obtaining change processes under different decisions, which has significance for platform marketing. Public reading platforms can adopt corresponding measures to enhance user subscription intention and generate more subscription behaviors:

1. **Improve content quality to enhance reading appeal.** High-quality reading content attracts more users to reading activities and generates subscription behavior. Increase content diversity and reduce homogenization to create platform IP cultural products and maximize content value.

2. **Focus on user needs for precise recommendations.** Using AI algorithms to extract and analyze various user behavior data during subscription processes can identify reading needs for precise content recommendations, triggering potential needs and enhancing subscription intention.

3. **Strengthen promotion to build good reputation.** External influence positively affects subscription demand. Platforms can build good external reputation to stimulate subscription demand and stabilize/improve subscription intention.

4. **Emphasize process observation for timely decision guidance.** Public reading platforms can conduct process qualitative simulation, comprehensively considering interactions among various factors to analyze and predict change trends. Platform marketing decisions can use simulation results to identify optimal input combinations and timing for maximum benefit with minimum cost.

Limitations

This study has some limitations. In QSIM reasoning, variable value spaces only include "high," "moderate," and "low," which is overly simplistic to reveal complex external influence and internal decision processes in subscription behavior. Additionally, due to platform restrictions, crawler data only validated two paths, somewhat affecting model accuracy. Future research should integrate multi-platform, multi-type data for more comprehensive model path validation and expand variable qualitative value spaces to deeper explore user behavior patterns.

References

[1] Chinese Internet Data Information Center. China Press and Publication Research Institute: 17th National Survey on Citizens' Reading [EB/OL]. [2020-05-22]. http://www.199it.com/archives/1040053.html.
[2] Yang Zheng, Liu Linxiao. Research on Communication Influence of Public Libraries in the Big Data Era—Analysis from the Perspective of Audience Behavior [J]. Publishing Wide Angle, 2019(12): 40-42.
[3] Peng Qian. Analysis of Graduate Students' Academic Reading Behavior and Needs [D]. Wuhan: Central China Normal University, 2017.
[4] Wilson TD. Human information behavior [J]. Informing Science: the

International Journal of an Emerging Transdiscipline, 2000, 3(2): 49-56.
[5] Adizes I. Management styles [J]. California Management Review, 1976, 19(2): 5-20.
[6] Kuipers B. Qualitative simulation [J]. Artificial Intelligence, 1986, 29(3): 289-338.
[7] Yu K, Cao Q, Zhou L. Study on qualitative simulation technology of group safety behaviors and the related software platform [J]. Computers & Industrial Engineering, 2019, 127: 1037-1055.
[8] Guerrin F, Dumas J. Knowledge representation and qualitative simulation of salmon redd functioning. Part I: qualitative modeling and simulation [J]. Biosystems, 2001, 59(2): 75.
[9] Cellier FE, Sanz V. Mixed quantitative and qualitative simulation in Modelica [C]//Casella F. Proceedings of the 7th International Modelica Conference. Linköping: Linköping University Electronic Press, 2009(43): 86-95.
[10] Lou Shuai, Wang Huimin, Niu Wenjuan, et al. Water resources management decision process simulation based on QSIM algorithm [J]. Systems Engineering, 2013, 31(12): 18-29.
[11] Zhu Hou, Hu Bin. Information and emotion-driven public opinion evolution QSIM-ABS simulation [J]. Journal of the China Society for Scientific and Technical Information, 2016(3): 310-316.
[12] Xia Gongcheng, Hu Bin, Zhang Jinlong. Employee turnover behavior prediction based on qualitative simulation [J]. Journal of Management Sciences in China, 2006, 9(4): 81-94.
[13] Hu Bin, Dong Shengping. Qualitative simulation method for group work behavior [J]. Journal of Management Sciences in China, 2005(2): 77-85.
[14] Berndsen R. Causal ordering in economic models [J]. Decision Support Systems, 1995, 15(2): 157-165.
[15] Wei Xiaochao, Hu Bin. Empirically-driven qualitative simulation and optimization of mobile banking user behavior [J]. Journal of Systems Engineering, 2013, 28(1): 75-82.
[16] Wilson TD. Models in information behavior research [J]. Journal of Documentation, 1999, 55(3): 249-270.
[17] Lee TH. Adoption factors and problems of mobile library services for graduate students: case study of University of Wisconsin Milwaukee library [C]//Xia L, Khoo M. IConference 2016 Proceedings. Philadelphia: iSchools, 2016.
[18] Sukhhu A, Zhang T, Bilgihan A. Factors influencing information-sharing behaviors in social networking sites [J]. Services Marketing Quarterly, 2015, 36(4): 317-334.
[19] Rowley J, Johnson F, Sbaffi L. Gender as an influencer of online health information-seeking and evaluation behavior [J]. Journal of the Association for Information Science and Technology, 2015, 68(1): 36-47.
[20] Deng Xiaozhao. Research on Internet users' information retrieval and browsing behavior [J]. Journal of Intelligence, 2003, 22(6): 653-658.
[21] Zhang Shuai, Wang Wentao, Li Jing. Research on influencing factors of users' online knowledge payment behavior [J]. Library and Information Service,

2017(10): 94-100.
[22] He Wei, Li He. Empirical study on mobile library user intention [J]. Library and Information Service, 2015, 59(7): 39-47.
[23] Gan C. Understanding behavioral intention in using mobile library: a comparison of four models [J]. Library Journal, 2017, 36(1): 59-66.
[24] Yoon HY. User acceptance of mobile library applications in academic libraries: an application of the technology acceptance model [J]. The Journal of Academic Librarianship, 2016, 42(6): 687-693.
[25] Hong W, Thong JYL, Wong WM, et al. Determinants of user acceptance of digital libraries: an empirical examination of individual differences and system characteristics [J]. Journal of Management Information Systems, 2001, 18(3): 97-124.
[26] Xu Kaiying, Cui Wei, Hong Xudong, et al. Influencing factors of library mobile reading user adoption behavior [J]. Library and Information Service, 2017, 61(15): 43-50.
[27] Hu Bin. Principles and Applications of Qualitative Simulation of Group Behavior [M]. Wuhan: Huazhong University of Science and Technology Press, 2006: 37-95.
[28] Wang CL, Zhang Y. Subscription to fee-based online services: what makes consumers pay for online content? [J]. Journal of Electronic Commerce Research, 2005, 6(4): 304-311.
[29] Xia Qianlong, Shi Guohong. Analysis of influencing factors of library mobile information service quality based on AHP-fuzzy comprehensive evaluation [J]. Journal of the China Society for Scientific and Technical Information, 2014, 33(8): 860-871.
[30] Asai S. Determinants of library subscription prices of economic journals [J]. Finance and Management Sciences, 2018, 6(1): 1.
[31] Wei Qunyi, Yao Yuan, Li Yiting. Empirical study on influencing factors of WeChat library user intention [J]. Library and Information Service, 2018, 62(5): 68-75.
[32] Nikou S, Bouwman H. Ubiquitous use of mobile social network services [J]. Telematics and Informatics, 2014, 31(3): 422-433.
[33] Shao Zufeng, Hu Bin. Qualitative simulation of employee quality-performance relationship [C]//Editorial Office of Chinese Journal of Management Science. Proceedings of 2004 Chinese Management Science Academic Conference. Beijing: Chinese Society of Optimization, Overall Planning and Economic Mathematics, 2004: 388-391.
[34] Pluye P, Grad R, Repchinsky C, et al. Four levels of outcomes of information-seeking: a mixed methods study in primary health care [J]. Journal of the American Society for Information Science and Technology, 2013, 64(1): 108-125.
[35] Jamali HR, Asadi S. Google and the scholar: the role of Google in scientists' information-seeking behaviour [J]. Online Information Review, 2010, 34(2): 282-294.
[36] Wu Dan, Jin Xin, Wang Linlin. Comparative analysis of subsequent click behavior between mobile and non-mobile library users [J]. Library and

Information Service, 2016, 60(18): 27-34.
[37] Zha Xianjin, Zhang Jinchao, Yan Yalan, et al. Review of current status and development trends of online information behavior research [J]. Journal of Library Science in China, 2014, 40(4): 100-115.
[38] Wang Qiuwen, Zheng Jianming. Research on online information consumption behavior patterns in Web 2.0 environment [J]. New Century Library, 2012(5): 23-26, 1.
[39] Wang Yan, Deng Xiaozhao. Discussion on basic issues of network user information behavior [J]. Library and Information Service, 2009, 53(16): 35-39.
[40] Zhang Kunlun. New exploration of the law of diminishing marginal utility [J]. Modern Finance and Economics: Journal of Tianjin University of Finance and Economics, 2004(4): 8-10.
[41] Gao Chunling, Lu Xiaojun, Zheng Yongbao. Differential analysis of user mobile reading behavior based on individual characteristics—taking Liaoning Normal University as an example [J]. Library and Information Service, 2013, 57(9): 70-74.
[42] Shi Xiao. Research on personal Internet banking usage intention based on integrated qualitative simulation and empirical analysis [D]. Wuhan: Huazhong University of Science and Technology, 2010.

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Research on the Influence Mechanism of Information Subscription Intention on Public Reading Platforms Based on Qualitative Simulation and Empirical Analysis

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Abstract: [Purpose/significance] This paper aims to study the influencing factors and mechanism of online information subscription intention using qualitative simulation (QSIM). By constructing a relationship model of influencing factors of information subscription intention and exploring the evolution law and trend of online information subscription behavior, this study seeks to deeply understand the influence mechanism of user subscription patterns and provide decision-making basis for public reading platform function development. [Method/process] Firstly, based on relevant behavioral research theories, six influencing factors were summarized: subscription content quality, subscription cost, external influence, subscription demand, subjective feelings, and personal characteristics. A rough influencing factor relationship model was constructed through structured interviews and refined via questionnaire surveys and empirical data collection. Finally, the QSIM algorithm drove interactions and evolution among factors to determine evolution characteristics and patterns. [Result/conclusion] Qualitative simulation can effectively describe and monitor the change process of subscription behavior characteristics. Subscription content quality, subscription demand, and external factors positively affect subscription intention; subscription cost negatively affects subscription intention but with small impact.

Keywords: public reading platform; subscription intention; empirical research; QSIM; impact mechanism

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