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Cognitive Load, Cognitive Friction, and Continuous Use Intention: An Exploratory Sequential Mixed-Methods Study of Digitally Disadvantaged Users in Rural Digital Public Reading Services

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Research Article

Keywords: digitally disadvantaged users, cognitive load, cognitive friction, continuous use intention, mixed-methods research

Posted Date: November 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11338298/v1

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Additional Declarations: No competing interests reported.

Abstract

Purpose. Digital public reading services combine the attributes of digital libraries and public services, yet platform availability does not guarantee that digitally disadvantaged users can achieve meaningful digital participation. This study distinguishes two interaction costs—cognitive load, the information-processing demands of reading, input, navigation, comprehension, and memory, and cognitive friction, the resistance experienced when system consequences are opaque, unpredictable, uncontrollable, or difficult to recover from—and examines how they and utility expectations shape continuous use intention. Methods. An exploratory sequential mixed-methods design with four phases: (1) qualitative exploration, coding 24 semi-structured interviews and 12 brainstorming records into five thematic dimensions; (2) quantitative verification, administering 20 measurement items to 234 digitally disadvantaged users; (3) statistical testing via confirmatory factor analysis and structural equation modeling; and (4) experimental evaluation through a within-subject A/B test (n = 18) of an interface optimization scheme derived from the significant paths. Results. The five-factor measurement model met fit criteria; cognitive load and cognitive friction emerged as distinguishable constructs. Utility expectations negatively predicted cognitive load, which positively predicted cognitive friction; both negatively predicted continuous use intention, with a significant chain mediation (utility expectations → cognitive load → cognitive friction → continuous use intention). The optimized interface raised task completion from 63.9% to 88.9%, reduced mean successful-task time by 30.81 s, and outperformed the baseline on usability measures. Conclusion. Continuous use intention is jointly constrained by utility expectations and the two interaction costs; the “construct–user problem–design goal–interface strategy” translation path can inform interface optimization for inclusive digital public services.

1 Introduction

Digital public services have expanded from government websites and institutional databases to mobile reading, agricultural knowledge, health information, policy interpretation, skills training, and the dissemination of local culture. Digital reading platforms are therefore no longer merely technical facilities that move collections online; they are public interactive systems through which users acquire knowledge, handle everyday problems, and maintain social connections. Rural digital reading platforms carry the dual attributes of digital libraries and public services: they must provide diverse content resources such as books, videos, agricultural techniques, policies, health information, and activity information, while also helping target users quickly identify the value of the service under constraints of limited time and limited operational resources [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]. Prior digital library research has shown that users differ in retrieval goals, evaluation criteria, use paths, and content preferences [11, 12]; low-literacy users and digital novices may also rely on images, voice, and task-oriented entry points to complete mobile interactions [13]. In light of these user differences, this study does not treat successful search as the sole use path and additionally attends to service entry points such as recommendations, voice, cards, short audiovisual content, acquaintance sharing, and settings assistance. Only when diverse service entry points are converted into understandable, controllable, recoverable, and sustainable digital participation can the practical value of digital public services be realized: users must be able to

recognize information, complete input, judge feedback, handle errors, understand permissions and charges, and trust that a single tap will not lead to irreversible consequences. The accessibility of rural digital public services therefore cannot be measured solely by platform launch, device ownership, or network access; it further requires examining whether users can complete real tasks and obtain benefits in knowledge acquisition, everyday problem handling, social connection, and public services.

1.1 The Digital Inequality Context and the Definition of Core Concepts

Analyzing the interaction costs of rural digital public reading services first requires specifying the digital inequality context in which the research population is situated. Digital divide research has expanded from a binary distinction of whether one owns devices or network access to multi-layered inequalities spanning quality of material access, operational and information skills, patterns of use, available support, and outcomes of digital participation [1, 2, 3, 4, 5]. Drawing on prior research on digital inequality and digital vulnerability [4, 10, 14, 15, 16] and on measurement frameworks for digital capital [17, 18], this study defines digitally disadvantaged users as people who, in a specific digital public service context, find it difficult—owing to the accumulation of disadvantages in age, educational attainment, occupational type, and device conditions—to accomplish meaningful digital participation in an independent, stable, and low-burden manner and to obtain benefits comparable to those of other users. This concept is situational and relational, defined by the accumulation of multiple disadvantages rather than by any single demographic label; the term "digitally disadvantaged users" is used consistently below to refer to the target population of this study.

Within this context, Cognitive Load Theory (CLT) and Perceived Risk theory provide complementary conceptual bases for defining the two types of interaction costs. CLT holds that, because working memory capacity is limited, task complexity, information organization, and interface presentation directly affect users' allocation of processing resources [19, 20, 21, 22, 23, 24]; HCI research further treats text density, visual decoding, and memory steps as core interface factors shaping user experience [25, 26, 27]. Perceived risk theory, by contrast, focuses on the potential losses that service adoption may entail and their influence on users' adoption decisions [28]. Building on these two theoretical traditions, this study distinguishes two components of interaction cost in digital public reading services: cognitive load, defined as the information-processing demands arising from tasks such as reading, input, navigation, comprehension, and memory; and cognitive friction, defined as the interaction resistance users experience—owing to a lack of perceived control over consequences—when facing system consequences that are opaque, unpredictable, uncontrollable, or difficult to recover from. This distinction provides the conceptual basis for analyzing five types of practical problems and their relationships with continuous use intention.

1.2 Practical Problems: Five Intertwined Interaction Barriers

The practical difficulties currently faced by rural digital public services have moved beyond any single infrastructure shortage and evolved into multidimensional, compound barriers that digitally disadvantaged users encounter in actual interaction. These barriers run through five key stages—basic interaction between users and the interface, expectation formation regarding service value, cognitive processing for task completion, risk assessment of system consequences, and behavioral decision-making about long-term use—and manifest sequentially as five intertwined problems: interaction constraints, destabilized utility expectations, excessive cognitive load, cognitive friction, and declining continuous use intention.

First, interaction constraints refer to the contraction of interaction opportunities caused by the interweaving of objective condition limits and subjective skill gaps. In rural digital public services, digitally disadvantaged users struggle to smoothly complete basic interaction tasks such as entering, recognizing, inputting, navigating, and handling errors. This barrier stems not only from experiential deficits such as low literacy and difficulties with pinyin or Mandarin recognition, but also from objective software, hardware, and environmental constraints—for example, using outdated phones left idle at home, relying on unstable mobile data connections, and operating the system in fragmented time interleaved with farm and housework. After repeated setbacks in concrete service activities such as reading and searching, users are often forced to turn to compensatory modes of use that depend on family members or acquaintance networks. Interaction constraints are therefore not an abstract skill deficit but a deprivation of interaction opportunities caused by the mismatch between concrete task requirements and realistically available resources; this foundational barrier directly interferes with users' subsequent judgments of service value.

Second, destabilized utility expectations refer to the supply–demand mismatch between abundant service resources and the value users actually perceive. Although rural digital reading platforms offer rich resources covering agricultural techniques, policy information, and healthy living, digitally disadvantaged users often find it difficult to rapidly anchor content that matches their own needs within a cluttered interface. Because retrieval goals are vague, evaluation criteria are lacking, and service entry points are hidden—compounded by difficulties at the input and comprehension levels—users easily lose their way in the platform and cannot form clear and stable utility expectations. This uncertainty of utility expectations prevents the objective richness of platform resources from being effectively converted into users' subjective perceived value, thereby weakening their intrinsic motivation to invest further time, cognitive effort, and operational cost.

Third, excessive cognitive load refers to the information-processing pressure that exceeds users' capacity when digitally disadvantaged users handle service tasks. When completing system tasks such as reading, input, navigation, and memory, high-density text, complex hierarchical structures, and obscure visual symbols all substantially raise the processing threshold of tasks; constrained by users' literacy level, pinyin ability, and fragmented attention, and further amplified by device performance and network latency, this information-processing burden is magnified. When task processing difficulty exceeds the cognitive threshold, users often need to read repeatedly, memorize operation steps by rote,

or rely heavily on others' explanations, and may even give up before completing the task. However, cognitive load only reveals the difficulty of task information-processing demands; it cannot fully explain why users refuse to operate out of fear of unknown consequences, which inevitably leads to another dimension of interaction resistance.

Fourth, cognitive friction refers to the interaction impedance users experience because they find it difficult to predict, confirm, or control system feedback. In actual operation, digitally disadvantaged users commonly harbor deep concerns about potential risks such as accidental charges from mis-taps, privacy leakage, malicious pop-ups, and device damage. When the consequences of tapping on system interfaces are opaque, feedback on operation status is delayed, or error recovery paths are invisible, users cannot accurately judge whether an operation has taken effect or whether a loss can be recovered. Compared with the cognitive load brought by dense text, this cognitive friction—arising from a lack of perceived control over system consequences—constitutes a more hidden psychological barrier and directly transmits the panic experienced at the level of concrete operations to users' rejection of subsequent overall use.

Fifth, declining continuous use intention is the ultimate behavioral reflection of the combined effects of the interaction constraints, destabilized utility expectations, cognitive load, and cognitive friction described above. When digitally disadvantaged users repeatedly experience operational setbacks, value disorientation, energy depletion, and loss of risk control during short-term use, their continuous use intention—to proactively revisit, explore functions, and retain the service over the long term—is severely eroded, and they exhibit hesitation, repeated help-seeking, habitual avoidance, and even complete withdrawal during use. Although withdrawal in short-term tasks is not fully equivalent to long-term abandonment, these negative micro-level experiences precipitate into systematic resistance to subsequent use. This indicates that continuous use intention depends not only on users' rational evaluation of service value but is also profoundly constrained by cognitive processing costs and the experienced risk of system consequences.

Taken together, the core practical dilemma of rural digital public services is essentially a compound, systemic barrier that digitally disadvantaged users encounter across the entire chain of service use. These five sequentially progressive yet intertwined problems can neither be masked by single indicators such as device access rates or overall ease of use, nor simply attributed to deficiencies in the personal digital capabilities of disadvantaged groups. The relational structure of "interaction constraints–utility expectations–cognitive load–cognitive friction–continuous use intention" and its concrete manifestations in digital public reading services provide the practical foundation for systematically reviewing the existing literature and defining the research gaps.

1.3 Research Status: Three Streams and Their Explanatory Limitations

Around the practical problems described above, existing research has mainly formed three interrelated streams—digital library service research, research on digitally disadvantaged groups, and human-

computer interaction (HCI) research—which provide theoretical accumulation from the perspectives of service evaluation, social divide, and situational shaping, respectively, but have not yet adequately explained how the five types of practical problems interweave and co-construct one another in specific micro-level interaction processes.

First, digital library service research has constructed an explanatory framework of user behavior centered on service quality and technology acceptance. Prior studies have shown that system quality, information quality, service quality, interface characteristics, and individual differences jointly influence users' system evaluations [29, 30, 31, 32, 33, 34]. On this basis, the Technology Acceptance Model (TAM) treats perceived usefulness and perceived ease of use as key antecedents of usage intention [35]; the Unified Theory of Acceptance and Use of Technology (UTAUT) further incorporates performance expectancy, effort expectancy, social influence, and facilitating conditions [36]. In addition, the Expectation-Confirmation Model (ECM) and the Information Systems Success Model (ISSM) have demonstrated the influence of pre-use expectations, post-use confirmation, and satisfaction on continuous use intention [37, 38, 39]. Research on technology use has also found that experiential factors such as cognitive absorption can jointly influence technology-use-related judgments together with instrumental beliefs [40]. However, this stream generally subsumes the operational difficulties users face under overall ease of use or effort expectancy, and rarely distinguishes at the micro level between the information-processing demands arising from tasks such as reading, input, and memory, and the difficulties in controlling consequences arising from system events such as hidden charges, privacy violations, and irreversible errors.

Second, research on digitally disadvantaged groups has expanded digital inequality from a binary difference in access to a complex process involving multi-level differences in participation. van Dijk [1] reconstructed digital inequality as a stepwise process of motivation, material access, skills, and use; Warschauer [2] emphasized that technology access must be embedded in human and social capital to achieve social inclusion; and Selwyn [3] criticized the tendency to reduce the digital divide to device ownership rates. A recent review likewise shows that the digital divide is a multi-layered inequality interweaving access, skills, use, and social outcomes [5]. Related empirical studies have examined differences in material access such as device quality and maintenance costs [41], as well as differences in online skills such as navigation, information search, and evaluation [42, 43], and have noted that digital inequality mutually reinforces existing social vulnerabilities [4, 6, 7, 8, 9, 10, 14, 15, 16, 44]. However, this stream focuses mainly on macro- or meso-level sociological analysis and rarely extends its lens into concrete micro-level interaction events; it lacks an independent examination of specific technical obstacles such as opaque consequences and uncontrollable operations, and it has not clearly explained how digitally disadvantaged groups form utility expectations and sustain continuous use intention in concrete public services.

Third, rural HCI research has further revealed how local contexts reshape the ways digital technologies are used. Rural areas are not merely regions with relatively underdeveloped infrastructure; their spatial distribution, labor rhythms, family structures, and local industries endow technologies with differentiated

meanings and pathways of use [45]. Studies have found that rural digitally disadvantaged users often overcome text and input limitations through compensatory behaviors such as voice retrieval, acquaintance-mediated use, or shared family reading; that digital library users differ significantly across groups in retrieval goals, evaluation criteria, and path preferences [11, 12]; and that, for low-literacy and novice users, images, voice, and task-oriented entry points are crucial for completing mobile interactions [13]. However, this stream has not yet formed sufficient theoretical crossover with the two preceding streams and lacks a unified account of task-processing demands and consequence-control experience; the internal mechanism by which rural-specific situations such as fragmented time, shared devices, and acquaintance support systematically shape interaction tasks, induce cognitive load and cognitive friction, and ultimately alter continuous use intention remains insufficiently explained.

It is worth noting that cognitive load theory and perceived risk theory—often introduced to compensate for the explanatory deficiencies described above—are typically applied in isolation from one another in the existing literature. CLT research emphasizes the influence of task complexity and information organization on the allocation of processing resources, but rarely ties information-processing difficulties to concrete system-consequence events; perceived risk research generally evaluates risk as an overall potential loss of service adoption, without grounding it in micro-level interaction events such as pop-ups, verification codes, charges, and permission requests. The separation of the two theories prevents existing research from precisely answering: within the same rural digital public service scenario, how should cognitive load arising from information-processing demands and cognitive friction arising from difficulties in controlling consequences be defined and distinguished; how do the two jointly relate to and influence users' continuous use intention; and how do the compensatory use behaviors users develop reflect this distinction?

In summary, the limitations of existing research concentrate on three levels: first, research on digital library user acceptance lacks a clear distinction between cognitive load and cognitive friction; second, digital disadvantage research lacks a fine-grained examination of interaction events, compensatory behaviors, and difficulties in controlling system consequences in concrete rural service contexts; and third, existing research has not established a continuous theoretical linkage running through "interaction constraints–utility expectations–cognitive load–cognitive friction–continuous use intention."

1.4 Research Gaps and Research Questions

A clear explanatory gap remains between the progress of existing research and the practical problems of rural digital public services. Actual use processes show that digitally disadvantaged users face not a single access barrier but the superposition of five types of interaction problems, whereas existing theoretical and empirical research tends to discuss service quality, digital access, digital skills, overall ease of use, or overall risk separately. The absence of a unified and clear conceptual organization of the five types of practical problems makes it difficult to accurately describe the actual difficulties of digitally disadvantaged users and to further explain the inclusiveness problems of digital public services. This gap manifests concretely as three research gaps.

The first research gap is the unclear conceptual boundary of interaction costs. Existing digital library and technology acceptance research can explain why users consider a system useful, easy to use, or worth continuing to use, but rarely clarifies whether user difficulties originate from information-processing demands—such as text decoding, information comprehension, input and navigation, and memory burden—or from difficulties in controlling consequences, such as opaque operation outcomes, unpredictable risks, uncontrollable operations, and irreversible errors. If cognitive load and cognitive friction continue to be merged into overall ease of use or overall frustration, the sources and consequences of problems in concrete interaction events will be obscured.

The second research gap is the insufficient situational explanation of digital disadvantage. Existing research on digital disadvantage has moved beyond the binary division of device ownership and network access, yet demographic attributes such as age, education, occupation, and devices are still readily treated as proxy explanations of digital capability. Labor rhythms, fragmented time, shared devices, family support, acquaintance networks, literacy conditions, dialect input, and risk judgment in rural digital public services may jointly alter users' interaction opportunities and service use outcomes; without interaction analysis in concrete service contexts, users' voice use, reliance on recommendations, preference for short audiovisual content, family sharing, and acquaintance help-seeking may be misread as personal capability deficits rather than conditional modes of digital participation.

The third research gap is the insufficient explanation of the linkage between practical problems and continuous use intention. Existing continuance research emphasizes the importance of perceived usefulness, confirmation, satisfaction, and trust, but rarely places utility expectations together with cognitive load and cognitive friction within the same analytical framework, and rarely explains why users hesitate, seek help, avoid, withdraw, or become unwilling to use again after encountering interaction constraints and difficulties in controlling system consequences. Short-term behavioral performance cannot be directly equated with long-term retention, but neither can continuous use intention be discussed in the abstract, detached from concrete task experience and consequence-control experience.

These three gaps require systematically distinguishing the two types of interaction costs within a single analytical framework and examining them in connection with utility expectations and continuous use intention. Taking rural digital public reading services as the concrete observational context, this study adopts an exploratory sequential mixed-methods design [46, 47, 48]. The focus is neither on the visual redesign of a particular local application nor on reducing digitally disadvantaged users to a demographic label, but on explaining how digitally disadvantaged users face five interrelated problems in actual service use. Accordingly, this paper answers three progressive research questions in turn:

1. **What interaction barriers do digitally disadvantaged users encounter in rural digital public reading services, and into which thematic dimensions can these barriers be grouped?** Analytically, this study expects that the interaction barriers reported by users can be grouped into five thematic dimensions—interaction constraints, utility expectations, cognitive load, cognitive friction, and

continuous use intention—and that task information-processing demands and difficulties in controlling system consequences manifest as two distinguishable types of interaction experience.
2. **What are the path relationships among interaction constraints, utility expectations, cognitive load, cognitive friction, and continuous use intention?** Analytically, this study expects that cognitive load and cognitive friction are two mutually independent constructs and that utility expectations indirectly influence continuous use intention via a chain path through cognitive load and cognitive friction.
3. **Can an interface optimization scheme derived from the significant paths improve the usage performance of digitally disadvantaged users?** Analytically, this study expects that interface interventions corresponding to the significant paths can reduce task information-processing demands and enhance the certainty of system consequences, thereby improving the usage performance of digitally disadvantaged users on both objective behavioral indicators and subjective perception indicators.

The three questions above define the object boundaries, conceptual boundaries, and evidence boundaries that the subsequent theoretical framework and research hypotheses need to address.

2 Methods

This chapter reports the materials, procedures, and analysis methods of four research phases in the order of "qualitative exploration–quantitative verification–statistical testing–experimental evaluation." The four phases constitute an exploratory sequential mixed-methods design [46, 47]: the qualitative phase (2.1) extracts barrier constructs from authentic usage corpora; the quantitative phase (2.2) converts the constructs into a measurement instrument and collects large-sample data; the statistical testing phase (2.3) tests the path relationships among constructs using confirmatory factor analysis and structural equation modeling; and the experimental evaluation phase (2.4) derives an interface optimization scheme from the testing results and verifies its effectiveness through a within-subject A/B test. The output of each phase serves in turn as the input of the next, and the results correspond to Sections 3.1–3.5 of Chap. 3, respectively. A sequential design also emphasizes data connection and result integration between adjacent phases [49]. Figure 1 illustrates the overall research process.

2.1 Qualitative Exploration: Text Analysis and Construct Development

2.1.1 Corpus Sources and Participants

The qualitative corpus comprised two types of text: on-site records from four brainstorming sessions held at rural digital reading rooms (12 records in total), and verbatim transcripts of semi-structured interviews with target users. Interview participants were selected through maximum variation purposive sampling along the dimensions of age, educational attainment, occupational type, and terminal device conditions, so as to ensure that the sample covered variation on these dimensions; this sampling

strategy of deliberately widening differences in key attributes conforms to the principle of purposive sampling in qualitative research [50]. The final interview sample consisted of 24 participants, aged *M* = 54.2 years (*SD* = 10.3, range 41–76 years); educational attainment was junior high school or below for 15 participants, senior high school/secondary vocational school for 7, and junior college or above for 2. The interview sample was independent of the questionnaire sample in Section 2.2. Each interview lasted 35–50 minutes (*M* ≈ 42 minutes), yielding transcripts totaling approximately 184,000 Chinese characters. The interview outline comprised three modules—system function experience, operational difficulties, and usage needs (see SI A). All texts were de-identified before analysis.

2.1.2 Coding Procedure and Construct Extraction

Coding proceeded in four steps: "semantic segmentation–initial coding–concept merging–theme clustering" [51, 52, 53]. In the first step, the transcripts were segmented into minimal semantic events, each containing all four elements of "user condition–interaction behavior–immediate experience–behavioral feedback," which served as the coding units. In the second step, each semantic event was assigned a descriptive label close to the original wording. In the third step, labels with the same underlying mechanism were merged into concepts. In the fourth step, concepts were aggregated into themes. Taking one piece of raw corpus as an example: the interviewee's statement "I don't know how to type in pinyin, so I can only rely on my child to help with searching" was segmented into one semantic event, assigned the initial label "difficulty with pinyin input," merged into the concept "text input skill constraints," and finally aggregated into the theme "interaction constraints."

Coding was conducted independently by two coders with backgrounds in HCI and cognitive psychology. Inter-coder agreement was assessed with Cohen's κ, and items of disagreement were resolved through item-by-item discussion until consensus; the κ coefficient quantifies the degree of agreement in categorical coding [54]. Theoretical saturation was judged to be reached when consecutively added texts no longer produced new themes. The coding process was managed with NVivo 12, and memos were used to document the basis for theme merging.

2.2 Quantitative Verification: Questionnaire Design and Data Collection

2.2.1 Measurement Instrument

The main body of the questionnaire was converted from the five thematic dimensions extracted in the qualitative phase, comprising 20 measurement items with 4 items per construct (see Table 2 − 1; the source themes, source sub-themes, and representative interview quotes for each item are provided in SI C). All items were scored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Demographic and device information (age, education, occupation, device) was used only for sample screening and descriptive statistics and did not enter the structural model.

Table 2

− *1.* Measurement constructs, items, and scoring direction

Construct	Item	Item content	Scoring direction
Interaction Constraints (IC)	IC1	I often find it difficult to use the app due to many unrecognized characters or incomprehensible meanings	Original scoring (higher = stronger constraints)
	IC2	I cannot use Pinyin input, or frequently make errors and encounter inconveniences when searching via Pinyin or voice input	Original scoring (higher = stronger constraints)
	IC3	My current mobile phone is old or low-configured, and often freezes or responds slowly when opening apps	Original scoring (higher = stronger constraints)
	IC4	I am not able to download apps or register accounts by myself, and usually need others to help set it up	Original scoring (higher = stronger constraints)
Utility Expectations (UE)	UE1	I can find useful knowledge such as agricultural planting, breeding techniques or pest control	Positive (higher = stronger expectations)
	UE2	I can keep abreast of rural policies and anti-fraud knowledge in a timely manner	Positive (higher = stronger expectations)
	UE3	It provides content on health preservation, disease prevention or daily life tips that I care about	Positive (higher = stronger expectations)
	UE4	The content is practically helpful for daily life and farm work	Positive (higher = stronger expectations)
Cognitive Load (CL)	CL1	The font size is too small or the layout is too dense, making it tiring and strenuous to read	Positive (higher = higher load)
	CL2	There are too many and too miscellaneous categories, and I often cannot find the content I want	Positive (higher = higher load)
	CL3	It takes a lot of mental effort and energy to understand an article or video	Positive (higher = higher load)
	CL4	There is too much information, and I often cannot remember it or keep up with it	Positive (higher = higher load)
Cognitive Friction (CF)	CF1	After clicking a button, link or pop-up, I cannot judge what will happen next	Positive (higher = higher friction)
	CF2	I worry that one accidental touch will bring irreversible consequences, such as deductions, information loss or exiting the current task	Positive (higher = higher friction)

Construct	Item	Item content	Scoring direction
	CF3	The system does not clearly indicate whether the current operation has taken effect, and I need to confirm repeatedly before proceeding	Positive (higher = higher friction)
	CF4	When something goes wrong, I do not know how to undo, return or restore to the previous state	Positive (higher = higher friction)
Continuous Use Intention (CUI)	CUI1	I am willing to actively open and view the content in my spare time	Positive (higher = stronger intention)
	CUI2	When encountering problems, I am willing to look for answers in this app first	Positive (higher = stronger intention)
	CUI3	I am willing to try and learn when new functions or content are launched	Positive (higher = stronger intention)
	CUI4	I will keep the app and use it frequently for a long time in the future	Positive (higher = stronger intention)

The questionnaire underwent three rounds of calibration before finalization. Scale development followed a procedure combining construct definition, item generation, expert evaluation, and empirical testing [55]. In the first round, six experts (three in HCI, two in psychometrics, and one in rural informatization practice) reviewed the content validity of the items. In the second round, eight target users completed cognitive interviews, reporting their comprehension of item semantics, on the basis of which expressions beyond the target group's linguistic habits were revised. In the third round, a pilot test with 52 respondents yielded Cronbach's α values between 0.79 and 0.86 for all constructs, and no item was deleted for low corrected item-total correlation. Pilot reliability is part of the scale development procedure and is therefore reported here.

2.2.2 Data Collection and Quality Control

The formal survey was conducted from October to December 2025 through on-site distribution at county-level public cultural institutions, on-site distribution at grassroots training activities, and targeted online invitations; participants could choose to respond independently online or with assistance. A total of 562 records were collected, and four categories of invalid records were removed in sequence according to preset rules: duplicate devices or contact information, completion time below one third of the sample median (approximately 4 minutes), long strings of identical responses, and failure on attention-check items; 516 records remained for sample screening.

Sample screening applied dual criteria of "usage experience + disadvantage indicators." Usage experience meant that the participant had actually used digital information services in the past year (e.g., digital reading, news and information, government affairs, or agricultural information platforms; yes/no); all 516 baseline-qualified samples met this condition. On this basis, further screening was conducted using cumulative disadvantage indicators. Referring to the digital capital measurement framework [17], the digital disadvantage assessment index was defined as:

$$D = I_1 + I_2 + I_3 + I_4$$

The four indicators were each dichotomously coded according to preset thresholds: I_1 for age (scored 1 if ≥ 41 years), I_2 for educational attainment (scored 1 if senior high school or below), I_3 for occupational type (scored 1 if primarily engaged in agricultural labor or part-time farming), and I_4 for device conditions (scored 1 if using a phone three to four years old or a feature phone). Participants with $D \geq 3$ were classified as digitally disadvantaged users.

The final main-analysis sample consisted of 234 cases, with no missing values on core items. Sample composition: 128 women (54.7%) and 106 men; age *M* = 52.8 years (*SD* = 11.4, range 41–78 years); educational attainment of junior high school or below for 68.4%, senior high school/secondary vocational school for 26.5%, and junior college or above for 5.1%; occupation primarily agricultural labor for 71.8% and part-time farming for 28.2%; daily device a three- to four-year-old phone for 76.9% and a feature phone for 23.1%.

2.3 Statistical Analysis and Model Testing Methods

2.3.1 Measurement Model (CFA)

The measurement model was tested with confirmatory factor analysis using R 4.3.2 (lavaan 0.6–17). The primary estimation method was robust maximum likelihood (MLR), with diagonally weighted least squares (DWLS, WLSMV specification) as a robustness check for ordinal categorical data [56]. The measurement equation is:

$$\backslash\mathrm{varvec}x = \Lambda\,\eta\, + \epsilon$$

where $\backslash\mathrm{varvec}x$ is the vector of observed variables, η is the vector of latent variables, Λ is the factor loading matrix, and ϵ is the vector of measurement errors. Model identification used the marker-variable method, fixing the factor loading of each construct's first item to 1.

Model evaluation adopted the following a priori criteria [57, 58, 59, 60, 61]: goodness of fit $\chi^2/df < 3$, CFI ≥ 0.95, TLI ≥ 0.95, RMSEA ≤ 0.06, SRMR ≤ 0.08; standardized factor loadings ≥ 0.70; Cronbach's α and composite reliability (CR) ≥ 0.70 [62, 63]; average variance extracted (AVE) ≥ 0.50; and discriminant validity HTMT < 0.85 [63, 64]. The measurement architecture was established through a competing-model comparison strategy: the theoretical five-factor model was compared one by one with alternative models, including a four-factor model merging CL and CF, and the optimal structure was determined by differences in goodness of fit. The significance level for all tests was α = .05.

2.3.2 Structural Model (SEM)

The variable roles of the structural model were set according to theoretical deduction: interaction constraints (IC) and utility expectations (UE), reflecting users' background conditions and initial expectations, were specified as exogenous latent variables; cognitive load (CL), cognitive friction (CF),

and continuous use intention (CUI), reflecting interaction process experience and behavioral tendency, were specified as endogenous latent variables. The structural equation is:

$$\eta = B\eta + \Gamma \xi + \zeta$$

where η is the vector of endogenous latent variables, ξ is the vector of exogenous latent variables, B is the matrix of path coefficients among endogenous latent variables, Γ is the matrix of effects of exogenous latent variables on endogenous latent variables, and ζ is the vector of structural residuals. The structural part estimated eight directed paths and the covariance between the exogenous latent variables IC and UE; no correlations were specified among the residuals of endogenous latent variables, and the model degrees of freedom were accordingly 161. The relationship between sample size and model fit should also be considered in conjunction with model complexity and power analysis [65]. The standardized path coefficients and their significance were used to answer the mechanism question of "how background and expectations influence continuous use intention through cognitive experience."

2.3.3 Mediation Testing (Bootstrap)

The indirect effect of the chain mediation was tested with the percentile bootstrap method, so as to avoid inferential bias caused by the non-normal sampling distribution of indirect effects. The indirect effect estimator is the product of the segment standardized coefficients:

$$\widehat{\theta} = \widehat{a} \times \hat{b} \times \hat{c}$$

Based on 5,000 case-level resamples with replacement, the 95% confidence interval is:

$$CI_{95\%} = [\widehat{\theta}^{*}_{0.025B},\ \widehat{\theta}^{*}_{0.975B}]$$

An indirect effect was judged significant when the confidence interval did not contain 0 [66, 67, 68]. The significant paths identified by the tests in this section constitute the empirical basis for the interface design interventions in Section 2.4.

2.4 Experimental Evaluation: Interface Design Translation and Usability Testing

2.4.1 Interface Prototypes (Materials)

The interface optimization scheme was derived from the SEM results according to the mapping rule of "construct–user problem–design goal–interface strategy" (see SI D). The optimized interface (Version B) and the current digital public reading service interface (baseline Version A) were equivalent in content and functional tasks, differing only in the mode of interaction presentation. Version B contained three categories of design interventions, each corresponding to one of the three significant paths:

1. a. **Front-loading of core utility** (corresponding to UE → CL): core functional entry points such as agricultural technology and policy/anti-fraud information were placed at the first visual hierarchy of

the first screen, shortening the navigation depth to core content; this strategy is consistent with the ideas of exploratory search and information foraging research regarding reducing information discovery costs and increasing cue returns [69, 70].

2. b. **Cognitive filtering and multimodal compensation** (corresponding to CL → CF): body text adopted information chunking and large-text prompt cards, and the search and input steps provided global voice/pinyin input; the goal was to reduce divided attention, redundant decoding, and interface learning costs [26, 71, 72].
3. c. **State certainty and recoverability design** (corresponding to CF → CUI): immediate state feedback was displayed after operations, pages were marked with safety commitments such as "completely free to use," and all settings pages provided reversible return and undo paths. Such state-transparency, risk-reduction, and recoverability designs draw theoretical support from research on online trust, risk, and privacy [73, 74, 75, 76, 77].

The item-by-item differences between the two interface versions and their comparative screenshots are provided in Figure S1 of the Supplementary Information (SI E). The prototypes were produced in Figma as high-fidelity interactive versions and deployed on a unified test device (see Section 2.4.2).

2.4.2 Experimental Design and Participants

The experiment adopted a within-subject A/B comparison design to control for the interference of individual differences in digital skills on the version comparison. The order of interface use was counterbalanced across participants: nine participants were tested in the A→B order and nine in the B→A order, and order effects were examined at the analysis stage.

Participants were 18 digitally disadvantaged users meeting the D ≥ 3 criterion, recruited through two county-level public cultural service stations, none of whom had participated in the questionnaire survey in Section 2.2. Sample composition: 10 women and 8 men; age *M* = 55.3 years (*SD* = 9.7, range 43–72 years); 14 participants with junior high school education or below; all occupations primarily agricultural labor or part-time farming; daily devices were old phones for 13 participants and feature phones for 5. Compensation was 50 yuan per person.

Each participant completed six tasks on each of the two interface versions, yielding 216 trials in total (18 participants × 2 versions × 6 tasks). The task set covered three categories of high-frequency scenarios—reading assistance, information retrieval, and settings modification and return—with a time limit of 180 seconds per task (see Table <link rid="tb2">2</link>–2). The experiment was conducted in a quiet laboratory environment using a unified Redmi Note 9 (6.53-inch screen, Android 12), with screen brightness and network conditions held constant across trials.

Table 2
2. Experimental task list

Task ID	Task name	Task instruction
T1	Adjust reading assistance	In "Me–Settings," set the body font size to the maximum level and enable the read-aloud function
T2	Identify reading help	Find and open the "Usage Help" entry, and state one piece of help content from it
T3	Confirm settings and return	Modify one message notification setting, confirm that it takes effect, and then return to the home page
T4	Find planting materials	Retrieve and open an article about wheat pest and disease control
T5	Find the voice entry	Complete one content search using voice input
T6	Adjust settings and return	Consecutively modify two display settings, and return step by step to the home page

2.4.3 Measures

a. **Objective behavioral indicators** were automatically recorded at the trial level by backend logs, comprising three items:

- Task completion status: a binary variable, scored 1 if the task was completed independently within 180 seconds, and 0 for timeout, failure, or help-seeking;
- Operation time: the duration (in seconds) from task presentation to successful completion, defined only for successfully completed trials;
- Number of misoperations: the number of non-target taps and return operations deviating from the shortest operation path of the task, automatically counted from the event log; the shortest operation path of each task was independently annotated in advance by two researchers according to the task goal, and disagreements were resolved through discussion.

b. **Subjective perception indicators** were administered immediately after the tasks on each interface version, comprising three items:

- System Usability Scale [78]: 10 items, converted to a 100-point scale; empirical research on the SUS further demonstrates its stable measurement performance and interpretability [79].
- Post-Study System Usability Questionnaire [80]: 16 items on a 7-point scale, with lower scores indicating better experience;
- Immediate construct short scales: two items each for immediate cognitive load (CL), immediate cognitive friction (CF), immediate value perception (VP), and immediate continuous use intention (CUI), selected from the formal items of the corresponding constructs in Table 2 − 1 (CL: CL1, CL3; CF: CF1, CF3; VP: UE1, UE4; CUI: CUI1, CUI4), with the stems rewritten to the immediate context of

"during the use just now…", scored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

2.4.4 Experimental Procedure

Each session followed a fixed sequence: (1) informed consent and background information registration, approximately 8 minutes; (2) use of the two interface versions in the counterbalanced order, completing six tasks on each version, with the within-version task order counterbalanced across participants via a Latin square; (3) immediately after the tasks on each version, completion of the SUS, PSSUQ, and immediate construct short scales; (4) the whole session lasted approximately 50 minutes. The experimenter intervened only when a participant explicitly asked for help, and that trial was recorded as incomplete.

2.4.5 Statistical Analysis

Behavioral indicators were analyzed with mixed-effects models; all three models included a random intercept for each participant to separate individual baseline differences [81]:

a. Task completion status (binary variable) was modeled with a binomial logistic mixed model:

$$\operatorname{logit}\left(\Pr\left(Y_{ij}=1\right)\right)=\beta_0+\beta_1\cdot\ \mathrm{Version}_{ij}+u_i,\ u_i\sim\ N(0,\sigma_u^2)$$

b. Operation time (continuous variable) was modeled with a linear mixed model. Because this indicator is defined only for successfully completed trials, the model was fitted on 165 successful trials, with denominator degrees of freedom computed using the Satterthwaite approximation:

$$T_{ij}=\beta_0+\beta_1\cdot\ \mathrm{Version}_{ij}+u_i+\epsilon_{ij}$$

c. Number of misoperations (count variable) was modeled with a Poisson generalized linear mixed model:

$$\log\left(E\left(N_{ij}\right)\right)=\beta_0+\beta_1\cdot\ \mathrm{Version}_{ij}+u_i$$

where i indexes participants, j indexes trials, $\mathrm{Version}_{ij}$ denotes the interface version (A = 0, B = 1), and u_i is the individual random intercept. Subjective scale scores were compared with paired-samples t tests, reporting mean differences and 95% confidence intervals, with Bonferroni–Holm correction applied to the comparisons of the six subjective indicators. Models were fitted in R 4.3.2 (lme4 1.1–35), with a test level of α = .05.

2.5 Research Ethics and Data Management

The research protocol was approved by the social science research ethics committee of the authors' institution (institution name and approval number anonymized for peer review). Before the interviews, questionnaire, and experiment began, participants were presented with an informed consent form explaining the research purpose, data usage, and the right to withdraw at any time, and data collection

began only after written consent was obtained. Interview transcripts, questionnaire logs, and experimental behavioral data were all de-identified and labeled only with anonymous codes; the identity mapping table was stored separately from the analysis datasets.

3 Results

This chapter reports the empirical results in the order of "qualitative coding results–data screening and sample–measurement model testing–structural model and mediation effects–experimental verification." The statistical analyses followed the scheme preset in Chap. 2: confirmatory factor analysis (CFA) and structural equation modeling (SEM) used robust maximum likelihood estimation (MLR) with weighted least squares mean- and variance-adjusted estimation (WLSMV) as a robustness check; indirect effects were estimated based on 5,000 percentile bootstrap samples; behavioral indicators in the experiment were fitted with mixed-effects models, subjective indicators were compared with paired-samples t tests, and multiple comparisons were corrected with the Bonferroni–Holm method.

Statistical assumption checks were conducted before the formal analyses. The Mardia multivariate kurtosis coefficient of the questionnaire data was 18.42 ($p < .001$), deviating from multivariate normality; robust estimators (MLR/WLSMV) were therefore used to control for the influence of non-normality. For the six subjective indicators in the experiment, Shapiro–Wilk tests on the within-subject difference scores were all non-significant ($W = 0.943–0.972$, all $p > .05$), satisfying the normality assumption of paired-samples t tests. Unless otherwise specified, the test level was set at $\alpha = .05$. Descriptive statistics, factor loadings, model fit indices, and effect decomposition beyond the main-text tables are reported in Tables S1–S4 (SI F).

3.1 Qualitative Coding Results

Coding of the 24 interview transcripts and 12 brainstorming records yielded 486 semantic events. Initial coding produced 137 descriptive labels, which were merged level by level into 36 concepts and finally aggregated into five thematic dimensions: interaction constraints (8 concepts), utility expectations (6 concepts), cognitive load (7 concepts), cognitive friction (9 concepts), and continuous use intention (6 concepts) (the initial coding dimensions, sub-themes, and corresponding initial concepts underlying these thematic dimensions are provided in SI B). Inter-coder agreement was Cohen's $\kappa = 0.82$. No new themes emerged starting from the 21st interview, indicating that coding had reached theoretical saturation.

The conversion of the five thematic dimensions into measurement constructs followed the principles of conceptual stability and quantifiability [82, 83]. The dimension characterizing prior digital literacy was converted into "interaction constraints (IC)"; the dimension characterizing intrinsic value-driven motivation was converted into "utility expectations (UE)"; the dimension characterizing cognitive constraints was split, according to processing demands versus perceived consequence control, into the two constructs "cognitive load (CL)" and "cognitive friction (CF)"; and the dimension characterizing long-

term behavior and value feedback formed "continuous use intention (CUI)" [32, 36]. Demographic and geographic characteristics such as age, occupation, and device conditions are situational boundary conditions under which digital disadvantage arises rather than psychological states in the interaction process [1, 84], and were therefore set as control variables outside the model rather than entering the latent variable structure [14].

3.2 Data Screening and Sample Characteristics

The quality control and sample screening procedure for the questionnaire data is shown in Table 3 − 1. Of the 562 collected records, 516 were retained after four rounds of quality screening; a further 282 records were removed by the cumulative disadvantage indicator screening (D ≥ 3), leaving a final main-analysis sample of 234 cases with no missing values on core items (demographic composition reported in Section 2.2).

Table 3
− *1.* Quality control and sample screening procedure for the questionnaire data

Screening stage	**Sample size (n)**	**Processing note**
Initially collected records	562	Entered data quality checks
Excluded: duplicate device or contact information	6	Removed duplicate responses
Excluded: abnormally short completion time	12	Removed speeders
Excluded: long strings of identical responses	18	Removed cases with abnormal response patterns
Excluded: failed attention checks	10	Removed invalid responses
Baseline quality-qualified sample	516	Entered disadvantage indicator screening
Excluded: did not meet cumulative disadvantage criterion (D < 3)	282	Did not match the target population definition
Final main-analysis sample	234	Entered CFA/SEM analysis

3.3 Measurement Model Testing (CFA)

The five-factor measurement model met the preset fit criteria: $\chi^2(160) = 229.62$, $\chi^2/df = 1.44$, CFI = 0.980, TLI = 0.977, RMSEA = 0.043, SRMR = 0.041. The WLSMV robustness check yielded consistent fit results: $\chi^2(160) = 236.42$, CFI = 0.979, TLI = 0.976, RMSEA = 0.045. The standardized factor loadings of all 20 items ranged from 0.817 to 0.899, all above the threshold of 0.70.

The reliability and convergent validity of each construct are shown in Table 3 − 2. Cronbach's α and composite reliability (CR) were all greater than 0.90, and average variance extracted (AVE) was greater than 0.70 for all constructs, meeting the preset criteria. Regarding discriminant validity, HTMT values

ranged from 0.187 to 0.408, with the maximum occurring between cognitive load and continuous use intention (HTMT = 0.408), below the judgment ceiling of 0.85 [58].

Table 3
− *2.* Reliability and convergent validity of the five-factor measurement model

Construct	Cronbach's α	Composite reliability (CR)	Average variance extracted (AVE)
Interaction Constraints (IC)	0.912	0.916	0.733
Utility Expectations (UE)	0.931	0.934	0.780
Cognitive Load (CL)	0.914	0.918	0.738
Cognitive Friction (CF)	0.903	0.907	0.709
Continuous Use Intention (CUI)	0.915	0.918	0.737

Competing-model comparisons further supported the five-factor structure. The four-factor model merging cognitive load and cognitive friction showed significantly worse fit (CFI = 0.837, RMSEA = 0.123; $\Delta\chi^2(4) = 512.45$, $p < .001$), and the one-factor model showed the worst fit (CFI = 0.612, RMSEA = 0.187). These results indicate that cognitive load and cognitive friction are two distinguishable, independent constructs and that the five-factor measurement model can serve as the basis for structural model analysis. No other measurement issues requiring attention were identified.

3.4 Structural Model and Mediation Effects (SEM)

The overall fit of the structural model was: $\chi^2(161) = 246.33$, $\chi^2/df = 1.53$, CFI = 0.976, TLI = 0.972, RMSEA = 0.048, SRMR = 0.045. The proportions of variance explained in the three endogenous latent variables were R^2*CL = 0.158,* R^2CF = 0.226, and R^2_CUI = 0.274, respectively. The standardized path coefficients are visualized in Fig. 2.

The path coefficient estimates are shown in Table <link rid="tb7">3</link>–3. Utility expectations significantly and negatively predicted cognitive load (β = -0.246, $p < .001$), and cognitive load significantly and positively predicted cognitive friction (β = 0.315, $p < .001$). For the outcome variable, utility expectations positively predicted continuous use intention (β = 0.219, $p = .002$), while cognitive load (β = -0.257, $p < .001$) and cognitive friction (β = -0.164, $p = .024$) both showed significant negative prediction. Two exploratory paths reached significance: interaction constraints negatively predicted cognitive load (β = -0.201, $p = .006$) and cognitive friction (β = -0.154, $p = .031$). The direct path from utility expectations to cognitive friction was not significant (β = -0.136, $p = .057$), and this marginal result was retained in the model as observed.

Table 3
3. Structural model path coefficients and parameter estimates

Path	Standardized coefficient (β)	Standard error (SE)	Z value	p value	Conclusion
UE → CL	-0.246	0.068	-3.424	< .001	Significant
CL → CF	0.315	0.067	4.375	< .001	Significant
UE → CUI	0.219	0.063	3.124	.002	Significant
CL → CUI	-0.257	0.071	-3.502	< .001	Significant
CF → CUI	-0.164	0.075	-2.253	.024	Significant
IC → CL	-0.201	0.075	-2.774	.006	Significant (exploratory)
IC → CF	-0.154	0.069	-2.162	.031	Significant (exploratory)
UE → CF	-0.136	0.062	-1.900	.057	Not significant

Bootstrap tests of indirect effects showed that the indirect effect of the UE → CL → CF → CUI chain path was 0.012 (95% CI [0.001, 0.026], not containing 0). All other segment indirect effects were also significant: UE → CL → CUI was 0.063 (95% CI [0.024, 0.117]), UE → CL → CF was − 0.078 (95% CI [-0.132, -0.036]), CL → CF → CUI was − 0.052 (95% CI [-0.098, -0.017]), IC → CL → CUI was 0.052 (95% CI [0.014, 0.103]), IC → CL → CF was − 0.063 (95% CI [-0.118, -0.019]), and IC → CF → CUI was 0.025 (95% CI [0.004, 0.058]). The direct path UE → CF was not significant while the indirect path UE → CL → CF was significant, statistically supporting the complete mediating role of cognitive load between utility expectations and cognitive friction. Beyond the paths listed in Table <link rid="tb7">3</link>–3, no other significant paths were identified.

3.5 Experimental Results (A/B Test)

Tests of order effects showed that the main effect of interface use order was not significant for any indicator (e.g., SUS score: $t(16) = 0.87$, $p = .397$); trials from the two orders were therefore pooled in subsequent analyses. The 18 participants produced 216 valid trials in total.

3.5.1 Objective Behavioral Indicators

Mixed-effects model results showed significant effects of version on all three behavioral indicators. For task completion status, the odds of completion were significantly higher for Version B trials than for Version A trials (β = 1.52, $SE = 0.31$, $z = 4.90$, $p < .001$, OR = 4.57, 95% CI [2.49, 8.38]). For operation time,

the linear mixed model based on 165 successful trials showed that Version B was on average 30.81 seconds faster than Version A (β = -30.81, *SE* = 3.92, *t*(150) = -7.86, *p* < .001, 95% CI [-38.56, -23.06]). For the number of misoperations, Version B was significantly lower than Version A (β = -1.01, *SE* = 0.11, *z* = -9.18, *p* < .001, IRR = 0.36, 95% CI [0.29, 0.45]).

Descriptive comparisons by task are shown in Table 3–4. The overall mean completion rate of Version B was 88.9% (Version A: 63.9%), the mean time per successful task was 48.5 seconds (Version A: 79.3 seconds), and the mean number of misoperations was 0.59 (Version A: 1.62). All six tasks showed differences in the same direction as the overall pattern.

Table 3
4. Comparison of behavioral results across the six tasks

Task	Version A completion rate	Version B completion rate	Version A time (s)	Version B time (s)	Version A misoperations	Version B misoperations
T1 Adjust reading assistance	72.2%	94.4%	58.4	31.7	1.28	0.39
T2 Identify reading help	61.1%	88.9%	74.6	43.2	1.67	0.56
T3 Confirm settings and return	66.7%	94.4%	63.8	36.5	1.44	0.33
T4 Find planting materials	77.8%	94.4%	82.1	55.8	1.11	0.50
T5 Find the voice entry	55.6%	83.3%	88.7	52.6	1.94	0.72
T6 Adjust settings and return	50.0%	77.8%	108.3	71.4	2.28	1.06
Overall mean	63.9%	88.9%	79.3	48.5	1.62	0.59

3.5.2 Subjective Perception Indicators

Paired-samples t test results (see Table 3–5) showed that Version B was significantly superior to Version A on all six subjective indicators, with Cohen's d ranging from 0.86 to 1.19, all large effects. After Bonferroni–Holm correction, all six comparisons remained significant: the p value of each comparison was below its corresponding corrected threshold (the largest p = .002, corresponding to a corrected threshold of α = .050; the smallest *p* < .001, corresponding to a corrected threshold of α = .008). Specifically, the SUS score increased from 61.4 to 78.6 (*t*(17) = 5.06, *p* < .001, *d* = 1.19), and the PSSUQ score decreased from 3.42 to 2.18 (*t*(17) = 4.42, *p* < .001, *d* = 1.04). Immediate measures corresponding

to the theoretical constructs showed that immediate cognitive load and immediate cognitive friction were significantly lower for Version B, while immediate value perception and immediate continuous use intention were significantly higher. No other significant version effects were identified.

Table 3
5. Comparison of system usability and subjective evaluation indicators

Indicator	Version A M (SD)	Version B M (SD)	Mean difference [95% CI]	t (17)	p	d
SUS (higher is better)	61.4 (12.8)	78.6 (11.6)	17.20 [10.03, 24.37]	5.06	< .001	1.19
PSSUQ (lower is better)	3.42 (0.82)	2.18 (0.71)	1.24 [0.65, 1.83]	4.42	< .001	1.04
Immediate CL (lower is better)	3.71 (0.95)	2.36 (0.90)	1.35 [0.75, 1.95]	4.73	< .001	1.12
Immediate CF (lower is better)	3.48 (1.00)	2.07 (0.95)	1.41 [0.72, 2.10]	4.31	< .001	1.02
Immediate VP (higher is better)	3.16 (0.85)	4.21 (0.78)	1.05 [0.51, 1.59]	4.08	< .001	0.96
Immediate CUI (higher is better)	3.02 (0.92)	4.08 (0.86)	1.06 [0.45, 1.67]	3.64	.002	0.86

4 Discussion

The four phases of this study constitute a sequentially connected chain of evidence: the qualitative phase extracted five thematic dimensions from authentic usage corpora, the quantitative phase converted them into a measurement instrument and completed large-sample testing, the statistical testing phase verified the construct structure and path relationships, and the experimental phase tested the interface interventions derived from the significant paths. Among these, the reliability, validity, and model fit results only establish that the prerequisites for measurement and inference hold and do not directly answer the research questions; the answers to the three research questions depend on the distinguishability of cognitive load and cognitive friction, the structure and direction of the paths among the constructs, and the effects of the interface interventions on behavioral and perceptual indicators.

4.1 The Distinguishability of the Two Types of Interaction Costs

Consistent with the expectation of the first research question, the confirmatory factor analysis results supported the five-factor measurement model: the four-factor model merging cognitive load and cognitive friction showed significantly worse fit ($\Delta\chi^2(4) = 512.45$, $p < .001$, below the test level of $\alpha = .05$), and the maximum value of the discriminant validity indicator HTMT was 0.408, below the judgment ceiling of 0.85. At the measurement level, this result confirms that, in the usage experience of digitally

disadvantaged users, the information-processing demands arising from reading, input, navigation, and memory tasks and the interaction resistance arising from opaque, unpredictable, and irrecoverable consequences are two distinguishable components. The two also aggregated into independent themes in the qualitative corpus; the theoretical possibility that the two types of experience are accompanied by different coping strategies is consistent with reports in research on users with low digital literacy that processing difficulties and consequence concerns trigger different avoidance strategies [13, 15]. Cognitive load research itself also cautions that intrinsic load, extraneous load, and measurement approaches need to be carefully distinguished [85, 86, 87].

This finding contrasts with the conventional treatment in digital library and technology acceptance research. Existing frameworks generally subsume the operational difficulties users encounter under overall ease of use or effort expectancy [32, 35, 36], whereas the present results indicate that, in two situations with similar overall ease-of-use evaluations, the source of difficulty may lie in processing demands or in consequence control, respectively, and the corresponding design interventions are not the same. This distinction also provides a micro-level interaction juncture between cognitive load theory and perceived risk research: the problem of processing resource allocation described by cognitive load theory [19, 20] and the problem of potential loss evaluation described by perceived risk research [28] manifest, in the concrete interaction events of digital public reading services, as two sequentially occurring types of experience rather than two names for the same evaluation.

4.2 The Path Structure of Utility Expectations, the Two Interaction Costs, and Continuous Use Intention

Consistent with the research expectation, utility expectations significantly and negatively predicted cognitive load ($\beta = -0.246$, $p < .001$, $\alpha = .05$). The direction of this path is consistent with the logic of the expectation-confirmation model, but the locus of action differs: the expectation-confirmation model focuses on the influence of pre-use expectations and post-use confirmation on satisfaction [37, 39], whereas the present results indicate that, within the usage process itself, clear and stable value expectations may be associated with lower consumption of processing resources—when users can anticipate what to look for, where, and for what use, the processing demands of navigation and discrimination tasks decline accordingly. This logic is also consistent with the association among usefulness, system characteristics, and usage intention in technology acceptance research [88, 89, 90, 91, 92]. Prior observations of low-literacy and low-digital-literacy users likewise show that when navigation and discrimination costs are too high, users tend to abandon their intended retrieval goals and terminate use [11, 13], a behavioral pattern consistent with the direction of the statistical association in this study.

If value expectations are associated with task-processing demands, how is this effect transmitted to users' sense of control over system consequences? The structural model results provide an answer: cognitive load significantly and positively predicted cognitive friction ($\beta = 0.315$, $p < .001$, $\alpha = .05$), the direct path from utility expectations to cognitive friction was not significant ($\beta = -0.136$, $p = .057$, $\alpha = .05$),

while the indirect path via cognitive load was significant (indirect effect − 0.078, 95% CI [-0.132, -0.036]). This pattern of "non-significant direct path, significant indirect path" statistically supports the complete mediating role of cognitive load between utility expectations and cognitive friction: value expectations do not directly change users' sense of control over system consequences, but are first associated with task-processing demands and then transmitted to consequence evaluation through processing experience. One possible explanation for this pattern is that working memory capacity is limited [21, 24, 25, 93]; when processing resources are heavily occupied by text decoding, hierarchical navigation, and memory steps, the cognitive margin available for anticipating and verifying operation consequences decreases accordingly, and the uncertainty of consequences is thereby amplified into friction experience. This explanation is consistent with the mechanism described in perceived risk research whereby insufficient understanding amplifies loss expectations and thereby inhibits interaction attempts [28, 74, 75, 94, 95, 96], but it remains a post hoc explanation whose causal ordering needs to be verified through experimental manipulation.

For the outcome variable, utility expectations positively predicted continuous use intention (β = 0.219, p = .002, α = .05), cognitive load (β = -0.257, p < .001, α = .05) and cognitive friction (β = -0.164, p = .024, α = .05) both showed significant negative prediction, and the indirect effect of the UE → CL → CF → CUI chain mediation path was significant (0.012, 95% CI [0.001, 0.026]). This result complements the emphasis on confirmation, satisfaction, and trust in continuance research [34, 37, 38, 97, 98, 99]: for digitally disadvantaged users, processing costs and consequence-control experience at the micro-interaction level may constitute antecedent constraints on intention formation. The analysis of usage-level inequality in digital divide research [42, 43] also thereby gains a mechanism-level supplement: skill differences affect not only whether tasks can be completed but, possibly through the continuous accumulation of load and friction, whether users are willing to use the service again.

The directions of the two exploratory paths run counter to intuition: interaction constraints significantly and negatively predicted cognitive load (β = -0.201, p = .006, α = .05) and cognitive friction (β = -0.154, p = .031, α = .05)—that is, users reporting stronger constraints reported lower load and friction. For this unexpected result, this study proposes three testable candidate explanations. The first is insufficient exposure: users with the strongest constraints may complete only shallow, brief use, rarely touching tasks with high processing demands and high consequence risk, so their self-reported load is correspondingly lower. The second is compensatory use: prior research shows that digitally disadvantaged users often complete interactions through substitute channels such as acquaintance assistance and voice, transferring processing demands to others or to substitute channels [11, 13, 15]; if high-constraint users rely more on such support, the load and friction they themselves bear decline accordingly, and the negative paths would reflect burden shifting rather than burden elimination. The third is sample self-selection: users with the strongest constraints who cannot obtain compensatory support may have already withdrawn from use entirely and thus did not meet the usage-experience criterion for inclusion, so the association between constraints and load in the retained sample is systematically attenuated. Cross-sectional self-report data cannot distinguish among these three mechanisms. Given their exploratory nature, these two paths were not used as a design basis; the

interface interventions were derived only from the three a priori significant paths UE → CL, CL → CF, and CF → CUI.

4.3 Experimental Verification of the Design Translation Path

Consistent with the expectation of the third research question, the experimental results supported the interface optimization scheme derived from the significant paths. The task completion rate of Version B increased from 63.9% to 88.9%, with completion odds about 4.57 times those of Version A (OR = 4.57, $p < .001$, $\alpha = .05$); the mean time of successful trials was shortened by 30.81 seconds ($p < .001$, $\alpha = .05$); and the misoperation rate was about 0.36 times that of Version A (IRR = 0.36, $p < .001$, $\alpha = .05$). For the subjective indicators, all six comparisons remained significant after Bonferroni–Holm correction (the p value of each comparison was below its corresponding corrected threshold), immediate cognitive load and immediate cognitive friction were significantly lower, and immediate value perception and immediate continuous use intention were significantly higher, with all effect sizes being large ($d = 0.86–1.19$).

The three categories of interventions correspond one-to-one to the three target paths: front-loading of core utility corresponds to UE → CL, cognitive filtering and multimodal compensation corresponds to CL → CF, and state certainty and recoverability design corresponds to CF → CUI. Among these, the decrease in immediate cognitive friction occurred in tandem with the reduction in the number of misoperations, consistent with the design hypothesis that "when consequences are predictable and errors are recoverable, friction declines"; this also accords with classic usability principles of reducing users' operational uncertainty through state visibility, feedback, and recoverability [71, 72, 100]. The gains on the voice input task (T5 completion rate increased from 55.6% to 83.3%) are consistent with findings from multimodal interaction research on low-literacy and novice users [13]; at the same time, it should be noted that adding guidance does not mean that more information is always better, as excessive guidance can itself increase extraneous processing burden [101]. It should be pointed out that what the experiment verified is the overall effectiveness of the "construct–user problem–design goal–interface strategy" translation path in this context, not the independent contribution of each of the three intervention categories: the three categories were presented simultaneously as a combination, and the net effect of a single intervention needs to be isolated through a factorial design. In addition, the improvement in behavioral indicators and the improvement in immediate construct evaluations were consistent in direction, providing cross-method corroboration for the path directions established in the questionnaire phase, but the increase in immediate intention cannot be directly equated with long-term use retention.

4.4 Integrated Answers to the Research Questions

Integrating the evidence from the four phases, this study answers the three research questions as follows.

1. Consistent with the expectation of the first research question, the interaction barriers that digitally disadvantaged users encounter in rural digital public reading services can be grouped into five thematic dimensions—interaction constraints, utility expectations, cognitive load, cognitive friction, and continuous use intention (486 semantic events, Cohen's $\kappa = 0.82$)—and task information-processing demands and difficulties in controlling system consequences manifest as two distinguishable types of interaction experience at both the corpus coding and measurement testing levels.

2. Consistent with the expectation of the second research question, utility expectations negatively predicted cognitive load, cognitive load positively predicted cognitive friction, utility expectations, cognitive load, and cognitive friction predicted continuous use intention in the positive, negative, and negative directions, respectively, the UE → CL → CF → CUI chain mediation was significant, and cognitive load played a complete mediating role between utility expectations and cognitive friction. Contrary to expectation, the two interaction-constraint paths showed exploratory significant negative associations, whose direction and mechanism await further testing.

3. Consistent with the expectation of the third research question, the interface optimization scheme derived from the three significant paths significantly improved the usage performance of digitally disadvantaged users: the task completion rate increased by 25.0 percentage points, the mean time per successful task was shortened by 30.81 seconds, the misoperation rate declined markedly, and all six subjective indicators were significantly superior to the baseline version after multiple-comparison correction, supporting the design translation path at both the objective behavioral and subjective perception levels.

4.5 Limitations

It should be emphasized that the above results were obtained for a single service type in a specific region, with cross-sectional self-report data and a short-duration controlled experiment; different effects may emerge in other contexts and over longer use periods. Subject to this premise, the following limitations should also be considered when interpreting the above results.

First, the path relationships are based on cross-sectional self-report data, and the model directions were set by theoretical deduction; statistical testing itself cannot confirm causal ordering, and reverse or bidirectional relationships (e.g., users with lower continuous use intention reporting higher load) cannot be ruled out. The directional consistency between the questionnaire and the experiment within the same construct framework provides preliminary cross-method corroboration, but stricter causal tests need to be conducted in longitudinal tracking or in research designs that experimentally manipulate cognitive load and cognitive friction.

Second, all constructs were measured with self-report scales of four items per construct. The measurement instrument underwent three rounds of calibration—expert review, cognitive interviews, and a pilot test—with reliability and validity indicators meeting the preset criteria, and the experimental phase cross-validated with behavioral logs; nevertheless, self-report data may still be affected by social

desirability and retrospective reconstruction, and each construct was operationalized as a single dimension, failing to distinguish subcomponents such as intrinsic and extraneous load. Future research could combine task performance, eye tracking, or secondary-task paradigms as objective load indicators to measure the two types of interaction costs multimodally [93, 102].

Third, the sample and context have boundaries. The questionnaire sample came from users of rural digital public reading services in a specific region, and digital disadvantage status was operationally defined by the cumulative indicator $D \geq 3$, a threshold setting that is context-specific; the construct structure and path strengths may differ under different thresholds, different regions, and different service types (e.g., government affairs or medical information services). In addition, inclusion required participants to have used digital information services in the past year, so high-constraint users who had completely withdrawn from use did not enter the sample, and path estimates may therefore be conservative. Replication across regions and service types, as well as retrospective research on users who have withdrawn, are necessary steps for testing the extrapolation boundaries of the conclusions.

Fourth, the experimental sample size was small ($N = 18$), the tasks were controlled tasks with a 180-second time limit, and subjective measurement was conducted immediately after use. The within-subject design and order counterbalancing controlled for individual differences in digital skills and order effects, and short controlled tasks helped isolate version effects; however, improvement in immediate intention cannot be equated with long-term use retention, and combined interventions cannot isolate the net effect of a single design. Future research should conduct larger-sample, longer-period field experiments in real deployment environments and use factorial designs to test the independent contributions and interactions of the three intervention categories.

The above limitations must be considered together with the mechanistic explanations in this chapter: until causal ordering, multimodal measurement, and long-term retention receive stricter testing, the psychological explanations proposed for the chain path should be understood as candidate explanations compatible with the existing evidence, rather than as confirmed conclusions.

5 Conclusion

Taking rural digital public reading services as the observational context, this study distinguished two constructs of interaction cost in the experience of digitally disadvantaged users: cognitive load, constituted by information-processing demands, and cognitive friction, constituted by a lack of perceived control over system consequences. Qualitative coding, large-sample measurement testing, and the structural model jointly showed that the two are distinguishable, independent constructs; utility expectations indirectly acted on continuous use intention via a chain path through cognitive load and then cognitive friction, with cognitive load playing a complete mediating role between value expectations and consequence-control experience; and the interface optimization scheme translated from the significant paths significantly improved the usage performance of digitally disadvantaged users at both the objective behavioral and subjective perception levels.

One possible explanation for the chain path is the sequential occupation of processing resources. Cognitive load theory holds that working memory capacity is limited and that task-processing demands directly consume available cognitive resources [19, 21]; perceived risk research shows that insufficient understanding amplifies users' expectations of potential losses [28, 94]. The two perspectives can be connected within the same micro-level process: when clear value expectations reduce the processing demands of navigation and discrimination, the cognitive margin users retain allows them to anticipate and verify operation consequences, the uncertainty of consequences declines accordingly, and the intention to continue using is maintained; conversely, when processing resources are heavily occupied by high-density text and complex hierarchies, consequence evaluation is squeezed out, and a single tap with unpredictable consequences may turn into avoidance of overall use. This explanation remains a post hoc inference whose causal ordering awaits testing in manipulative studies.

At the methodological level, the results of this study support the "construct–user problem–design goal–interface strategy" translation path as an operational bridge from statistical evidence to interface intervention: significant paths specify intervention targets, qualitative corpora provide problem representations, and experimental evaluation verifies intervention effects. This path does not depend on a specific platform or a concrete visual scheme and can serve as a reference for the design of other inclusive digital public services for digitally disadvantaged groups.

It should be reiterated that the above conclusions come from controlled use of a specific service type in a specific region over a short period. The construct relationships under different labor rhythms, device conditions, and service contents, as well as the long-term maintenance of intervention effects, still need to be verified over longer use periods and in more diverse public service contexts; retrospective research on high-constraint users who have withdrawn from use will help fully characterize the whole process from interaction constraints to usage withdrawal.

Declarations

Funding.

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Author Contribution

Hanlei Zeng conducted the experiments and wrote the manuscript. Ziyuan Meng supervised the study, guided the experiments, and reviewed the manuscript.

Use of Artificial Intelligence. AI tools were used solely for AI-assisted copy editing (language polishing and grammar checking); no generative content was created with AI tools.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

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Figures

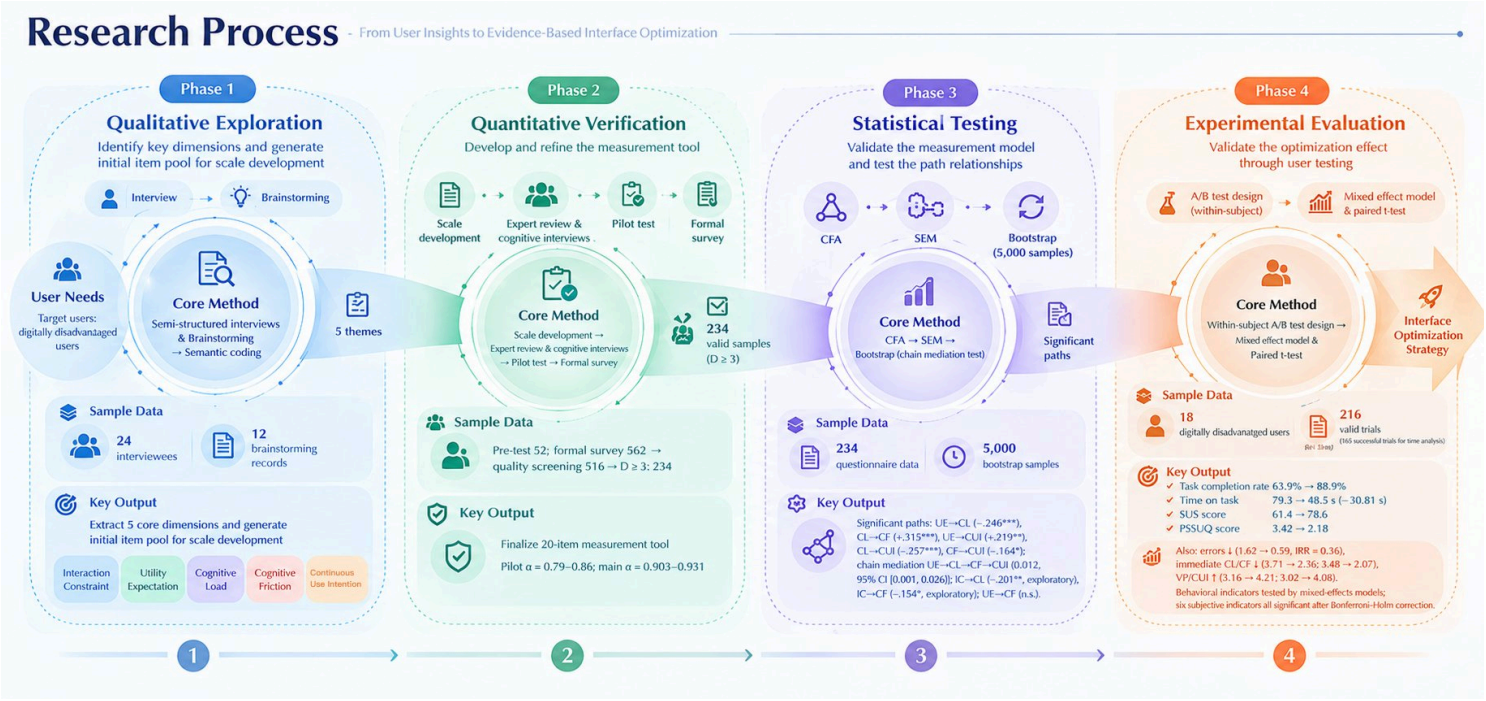

Figure 1

Research process: from user insights to evidence-based interface optimization.

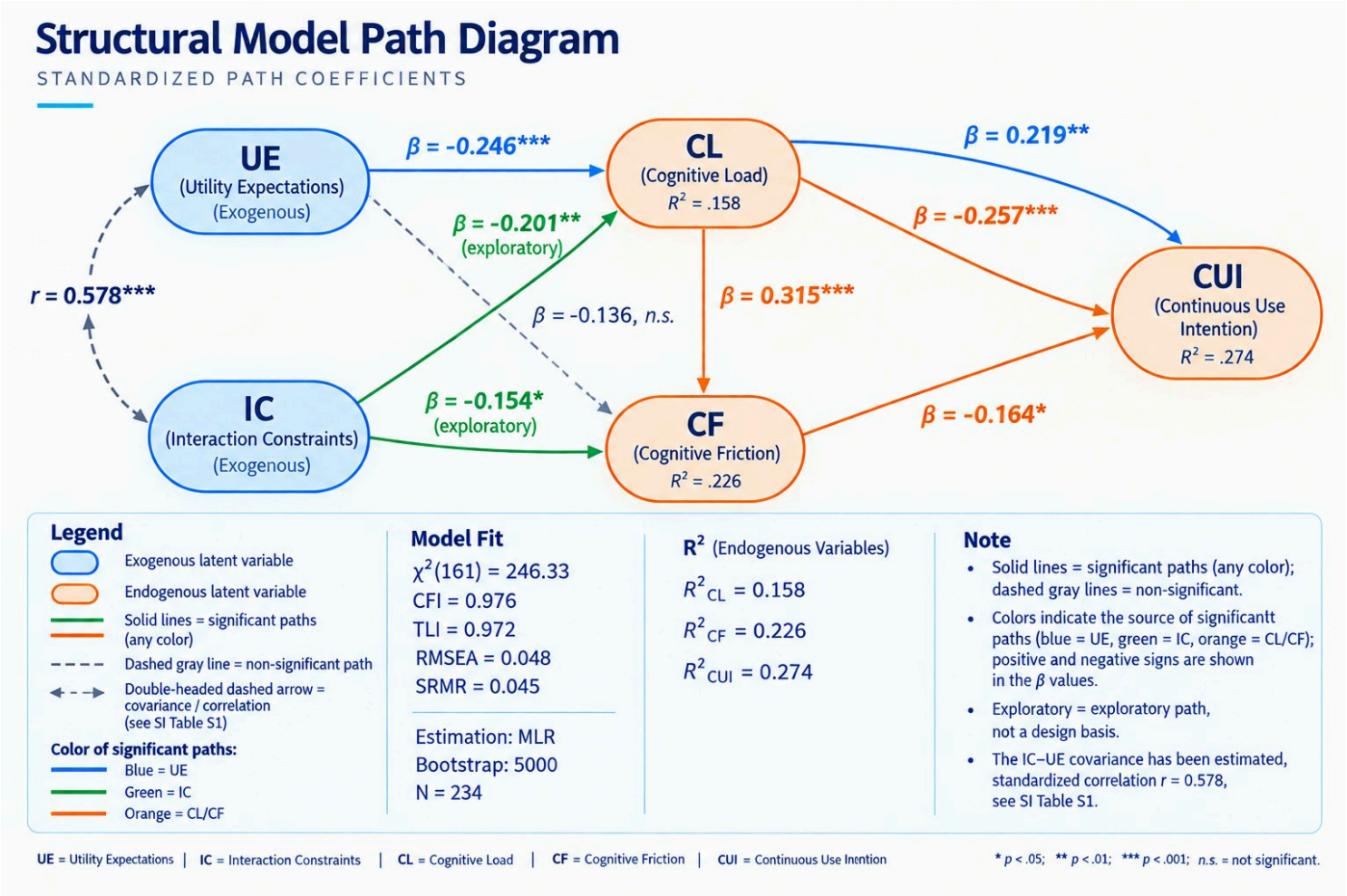

Figure 2

Structural model path diagram with standardized path coefficients. Solid lines indicate significant paths; dashed gray lines indicate non-significant paths. *p < .05, **p < .01, ***p< .001; n.s. = not significant.

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