SHOPLIFE-BENCH: A BENCHMARK FOR MULTI-SESSION MULTI-USER AGENT INTERACTION IN E-COMMERCE ENVIRONMENTS

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ABSTRACT

Existing benchmarks for conversational AI agents mostly simulate a single user in a single session. They do not capture multi-user state management, the dynamic evolution of user behavior, or cross-session task decomposition and feedback. As a result, they cannot cover the complex, path-dependent behavior of real users across sessions. We propose ShopLife-Bench, a benchmark for multi-session, multi-user agent interaction in e-commerce environments, with four key contributions: 1) Our user simulator does not model internal mental states. Instead, it distills users' reactions to agent errors and their exit patterns from over ten thousand real e-commerce conversations, and builds a reproducible behavior policy driven by accumulated errors. 2) We restructure user profiles into structured, addressable atomic entries, so that every addition, update, and deletion can be verified item by item. We also design tasks in which the current request alone cannot uniquely determine the target product; the correct choice requires profiles maintained from earlier sessions. These tasks jointly evaluate profile maintenance and personalized use. 3) Cross-session tasks are built around the same user's product decisions and fall into three types: dependent, independent, and interleaved. Explicit statements, implicit needs, and noise are added on top. 4) Each evaluation session includes two task users and one distractor user who only asks about products or chats. This setting tests the agent's ability to attribute identities, switch between tasks, and isolate user states. Experiments on six representative models show that after shifting to multi-user concurrency, profile recall and order accuracy generally drop; even the best model reaches only 78.0% order accuracy and a 13.0% zero-error rate. Cross-user state isolation and cross-session consistency remain critical bottlenecks for current agents. Code and evaluation data are available at `https://anonymous.4open.science/r/ShopLife-Bench`.

1 INTRODUCTION

Recent benchmarks for conversational AI agents measure how well an agent understands user needs (Yao et al., 2022; Liu et al., 2024), calls external tools (Qin et al., 2024; Patil et al., 2025), and follows domain rules (Yao et al., 2024) to complete tasks. Most of them model a task as a single session between one user and the agent: the user gives a goal or constraints at the start (Zhou et al., 2024; Jimenez et al., 2024), the agent plans and acts (Xie et al., 2024), and success is judged by the final environment state or task outcome (Trivedi et al., 2024; Barres et al., 2025).

This setting differs from real e-commerce customer service. A deployed system must serve many users with different goals and preferences at the same time, and it must not carry one user's product preferences or task progress over to another user. Moreover, the interaction between a user and the service agent is rarely one-shot (Xu et al., 2022). A user may advance the same shopping task over multiple visits, or switch, resume, and interleave several tasks across sessions. User behavior also depends on the service process: after the agent ignores a question, leaves a problem unsolved, or recommends a mismatched product, the user may repeat the request, ask for a solution, or simply leave.

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Therefore, evaluating a deployment-ready e-commerce agent requires more than checking task completion in a single dialogue. It also requires testing whether the agent can maintain user state over multi-session (Wu et al., 2025), relate tasks across sessions, adapt to changing user behavior, and serve many concurrent users in a consistent, reliable, and personalized way.

To close this gap, we present ShopLife-Bench, a multi-session, multi-user benchmark for agent interaction in e-commerce. Such evaluation faces four challenges: how to simulate users so that their feedback to agent responses is realistic and reproducible; how to let users reveal profile information gradually over multi-session interaction to support personalization; how to design cross-session task forms in multi-user settings; and how to keep the states of different users isolated under concurrency and distraction. Our contributions are as follows.

Data-driven user behavior modeling. User simulation based on latent mental states such as trust or emotion (Sun et al., 2021) is hard to calibrate and unstable. We instead model observable behavior directly. From $12{,}697$ real e-commerce multi-turn conversations, we derive how users react to agent errors and when they exit, and build behavior policies driven by the accumulated error count. Policies are assigned per user to preserve individual differences; given the same interaction state, one policy always triggers the same reaction, which reduces reliance on free-form generation.

Evaluating dynamic profile awareness and personalized use. The benchmark is built on the real product data of ShopSimulator (Wang et al., 2026). Free-text profile descriptions (Zhang et al., 2018; Xu et al., 2022) such as "high/medium/low" make it hard to locate information and verify updates, so we restructure profiles into structured, addressable atomic entries, and each add, update, or delete operation can be verified individually. We also build tasks whose current-session request alone cannot determine a unique product; the target becomes clear only with profiles from earlier sessions. This jointly tests profile maintenance and personalized use.

Multi-session task construction. For the product decisions of a single user, we build three types of cross-session tasks: linked, independent, and interleaved, with three expression styles overlaid: explicit statements, implicit needs, and noise. This design tests the continuous accumulation and correction of information across sessions, and the ability to tell valid updates from information that should not be written.

A concurrent multi-user protocol with distractors. Each session hosts two users with multi-session tasks, plus one distractor user who only asks questions or chats and never places an order. Through interleaved interaction, the protocol tests identity attribution, task switching, and the isolation of profile and order states under context competition.

We evaluate six representative models on the same 100 instances, in both thinking and non-thinking modes. Even the best model reaches only 78.0% order accuracy, 68.5% profile recall, and a 13.0% group-level zero-error rate. Ablation between the single-user and multi-user settings further shows that after moving to multi-user concurrency, profile recall and the user-level zero-error rate drop consistently for every model. These results show that cross-user state isolation and cross-session consistency remain key bottlenecks of current agents.

2 Related Work

Evaluating language agents and tool use Most existing agent benchmarks use a single-user, single-session setting: WebShop (Yao et al., 2022) tests multi-step product search and decision making on a simulated shopping site, AgentBench (Liu et al., 2024) offers unified evaluation across multiple environments, and ToolBench (Qin et al., 2024) and BFCL (Patil et al., 2025) focus on the correctness of function calls. τ-bench (Yao et al., 2024) is the closest to our work: it introduces a user simulator and domain policies, and tests whether agents follow these policies in multi-turn interaction in retail and airline scenarios. However, the users in all these benchmarks stay within a single session: the agent neither maintains user state across sessions nor serves multiple users at the same time.

User simulation and dialogue evaluation User simulation is a long-standing problem in task-oriented dialogue evaluation: early methods rely on rules or agenda-based models (Schatzmann et al., 2007), and recent work uses LLMs to generate user utterances (Terragni et al., 2023). These methods mostly simulate latent mental states (trust, emotion) through free-form generation, which

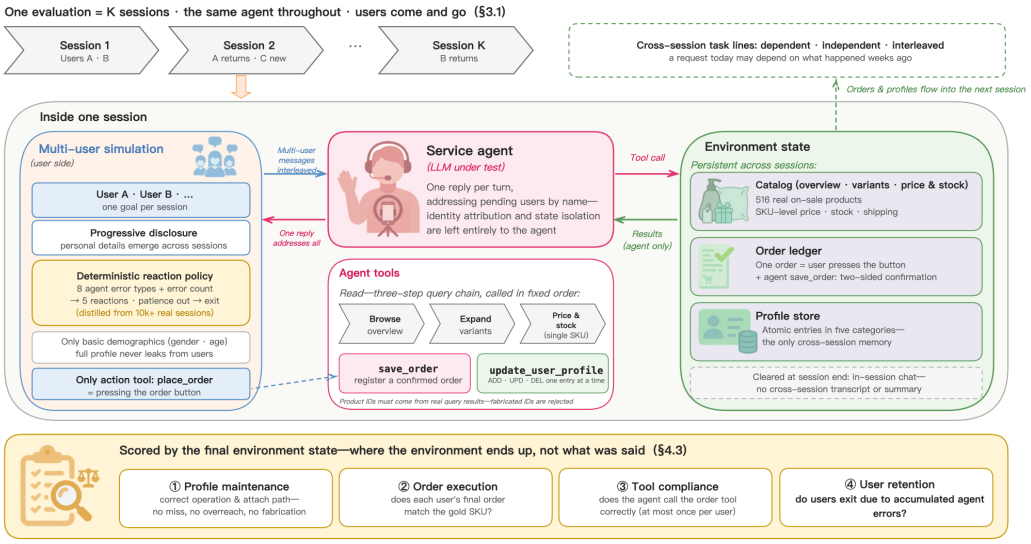


Figure 1: Overview of ShopLife-Bench. Top: one service agent serves multiple users across K sessions. Middle: interleaved user messages connect the agent to a persistent catalog, order ledger, and profile store through a three-step ordered query chain and two write tools. Chat history is cleared after each session; orders and profiles retain user-specific information. Bottom: evaluation covers profile maintenance, order execution, tool compliance, and user retention.

is hard to calibrate and to reproduce reliably. In contrast, we do not simulate internal states. From 12,697 real e-commerce conversations, we derive how users react to agent errors and when they exit, and build observable behavior policies and patience thresholds driven by the accumulated error count, so that the same policy triggers the same reaction under the same interaction state. We further verify the accuracy of its error judgment with human annotation.

Long-term memory and personalization Long-term memory and personalization benchmarks test whether agents can accumulate and use user information across sessions, but they mostly focus on the accuracy of memory writing and reading itself (Wu et al., 2025). We combine memory evaluation with task execution: we restructure profiles into addressable atomic entries, so that each add, update, or delete can be verified individually, and the agent must use the accumulated profile in later sessions to choose a product that the current-session request alone cannot determine. This jointly tests profile maintenance and personalized use.

3 ShopLife-Bench: Evaluation Environment

ShopLife-Bench models an **ongoing e-commerce service**: one agent serves multiple users concurrently across sessions separated by days or months. Environment state and user profiles persist and evolve across sessions, linking earlier interactions to later service.

3.1 Problem Formulation

Overall structure A ShopLife-Bench instance is $\langle \mathcal{E}, \mathcal{U}, \Sigma \rangle$, with environment $\mathcal{E}$, users $\mathcal{U} = \{u_1, \ldots, u_N\}$, and K ordered sessions $\Sigma = \langle \sigma_1, \ldots, \sigma_K \rangle$. Each σ_k specifies attending users $\mathcal{U}_k \subseteq \mathcal{U}$ and their in-session goals. One agent serves all sessions; users may attend once, skip sessions, or return.

State space The global state splits into a persistent part and an in-session part:

$$s = \underbrace{(c,\ o,\ \mathbf{P})}_{\text{persistent}} \otimes \underbrace{h_k}_{\text{volatile}}, \tag{1}$$

where c is the product catalog, o is the order ledger, and $\mathbf{P} = \{p_1, \ldots, p_N\}$ stores each user's atomic profile entries. The agent can access the full in-session history h_k, including utterances and tool events. Read tools leave persistent state unchanged; write tools update o or $\mathbf{P}$ deterministically. At session boundaries, $(c, o, \mathbf{P})$ persists, h_k is cleared, and the next session's users and goals are loaded. No earlier transcripts or summaries are available: orders and profiles are the only cross-session carriers of user-specific information. This isolates profile maintenance and use from raw-history retrieval.

Agent actions and observations At each step, the agent selects one action from $\mathcal{A} = \mathcal{A}_{\text{msg}} \cup \mathcal{A}_{\text{tool}}$. $\mathcal{A}_{\text{msg}}$ contains natural-language messages visible to all users. $\mathcal{A}_{\text{tool}}$ includes read queries (product search, details, and stock) and writes (`save_order` for orders, `update_profile` for profiles); tool returns are visible only to the agent. Only profile updates directly modify $\mathbf{P}$, using $\{\text{ADD}, \text{UPD}, \text{DEL}\}$ and a target entry path. User messages are interleaved without an explicit speaker-to-need mapping; the agent handles identity attribution, topic routing, and state isolation.

User model A user is $u_i = \langle \phi_i, \beta_i, g_i^{1:K} \rangle$, with traits ϕ_i, behavior policy β_i (§4.1), and session goals g_i^k. Profile information is **asymmetric**: the simulator receives only basic demographics, while other traits are disclosed through session-specific task scripts. The full profile is maintained by the agent and is not supplied to the simulator, preventing it from revealing historical profile content for the agent. Users communicate through chat messages and `place_order`, which signals acceptance of the current recommendation. The agent must then commit the order through `save_order`, forming a two-sided confirmation.

Task definition For each purchase task g_i^k, the gold label specifies a unique product and target SKU. The user gives an incomplete request (Sun & Zhang, 2018), and selection requires both current conditions and profile p_i. One-time users rely on the current profile; returning-user tasks require information retained from earlier sessions. Section 4.2 gives the formal profile-necessity condition.

4 Core Mechanisms and Evaluation Design

4.1 Data-Driven User Behavior Modeling

Normal interaction follows the session goal g_i^k. Error feedback follows a deterministic policy:

$$\beta_i : \mathcal{X} \times \mathcal{Z} \longrightarrow \mathcal{Y} \cup \{\text{EXIT}\}, \tag{2}$$

where $\mathcal{X}$ contains agent error types, $\mathcal{Z}$ summarizes observable interaction state, including the accumulated error count e_i, and $\mathcal{Y}$ contains user reaction modes. The user exits when $e_i \geq \tau_i$. The patience threshold τ_i is sampled from the estimated distribution and remains fixed across sessions. We construct these policies from real conversations through behavior abstraction, reaction statistics, patience estimation, and deterministic instantiation.

Data Sources and Behavior Abstraction Our team collected 12,697 real e-commerce user–agent conversations with over 67,000 interaction turns. We remove spam, templated repetitions, and overly short dialogues, while retaining meaningful repeated questions and complaints. Each turn is annotated for agent behavior and the user's subsequent reaction. Behaviors are grouped into four normal and eight error types, extending prior dialogue-error taxonomies (Higashinaka et al., 2015); the latter form the feedback input set $\mathcal{X}$. Full categories and distributions appear in Appendix B.1.

Reaction Distribution and History Dependence Annotations yield six reaction modes $\mathcal{Y}$; the policy uses five and excludes off-topic reactions. The conditional distribution $\widehat{P}(y \mid x)$ captures error-specific feedback; categories and statistics are in Appendix B.2. Negative feedback to evaded questions increases with the accumulated error count, motivating history-dependent rules for reaction type and tone.

Patience Distribution Estimation We estimate patience with Kaplan–Meier survival analysis (Kaplan & Meier, 1958), using accumulated errors as discrete time and error-induced user exits

as events. Sessions ending naturally before an observed exit are right-censored. The survival probability after m errors and the threshold distribution are:

$$\widehat{S}(m) = \prod_{j=1}^{m} \left(1 - \frac{d_j}{n_j}\right), \qquad \widehat{P}(\tau = m) = \widehat{S}(m-1) - \widehat{S}(m), \tag{3}$$

Here $\widehat{S}(0) = 1$; n_j counts users who have neither exited nor been censored before error j, and d_j counts exits after that error. Estimated shares for thresholds 1, 2, and 3 are 16.86%, 17.80%, and 21.34%, respectively (56.0% in total). The long tail of higher thresholds supports heterogeneous patience (Appendix B.3).

Deterministic Behavior Policies We build 50 behavior policies with patience thresholds restricted to 1–3. Threshold allocation renormalizes the estimated shares; about 30% of users exit after the first agent error. Each policy fixes error-specific reactions and tone escalation with the accumulated error count, preserving individual differences and reproducibility.

4.2 Structured User Profiles and Multi-Session Task Construction

Data Source and Limitations We use real product data from ShopSimulator (Wang et al., 2026). Its free-form profiles lack atomic identifiers and clear update boundaries, while its single-session tasks cannot test cross-session profile maintenance and use. We therefore construct structured profiles, multi-session tasks, and evidence-backed gold updates.

Structured Profile Representation Profile p_i stores known user facts, stable preferences, and behavior traits as addressable atomic entries with unique identifiers and category paths. Compound statements are split into separate entries. Maintenance uses ADD/UPD/DEL operations, allowing evaluation of wrong values, missing writes, wrong operations, and extra writes without free-text similarity. The full schema, preference scopes, and examples are in Appendix C.1.

Organizing Cross-Session Tasks by Product Relations Multi-session tasks follow one user's product decisions as facts and preferences are disclosed or revised across sessions. Linked tasks advance one goal; independent tasks pursue separate goals; interleaved tasks alternate between decision lines. Each type includes explicit statements, implicit needs, and noise to test direct writing, reasonable inference, and rejection of wrong writes, respectively. Subtypes appear in Appendix C.2.

Batch Synthesis and Human Review of Task Data Under a preset standard operating procedure (SOP), Kimi-K3 generates candidate profiles, session scripts, and evidence-backed update annotations from the ShopSimulator catalog and our task designs. Programmatic checks verify structural validity, cumulative-snapshot consistency, and candidate convergence; human reviewers check the "user expression–profile information–product fit" evidence chain and reject unsupported inferences or answer leakage. Only samples passing both checks enter the evaluation set (Appendix C.3).

Guaranteeing Decidability of Profile Updates and Use We provide evidence-backed gold updates per session to check entry content, operation type, and path. For user u_i's history-dependent purchase task in session k, let $\mathcal{V}_{i,k}$ be the target product's usable SKUs. $\mathcal{C}^{i,k}_{\text{exp}} \subseteq \mathcal{V}_{i,k}$ contains candidates matching all current explicit conditions (e.g., specifications, quantity, and budget), excluding earlier information not restated. $\mathcal{C}^{i,k}_{\text{prof}} \subseteq \mathcal{V}_{i,k}$ contains candidates matching fit conditions supported by the gold profile from the first $k-1$ sessions, using the latest valid values after corrections. We require:

$$\left|\mathcal{C}^{i,k}_{\text{exp}}\right| \geq 2, \qquad \mathcal{C}^{i,k}_{\text{exp}} \cap \mathcal{C}^{i,k}_{\text{prof}} = \left\{v^{\star}_{i,k}\right\}, \tag{4}$$

where $v^{\star}_{i,k}$ is user u_i's unique target SKU in session k. Current conditions alone leave ambiguity; adding the correctly maintained historical profile uniquely identifies the target.

4.3 Multi-User Concurrent Protocol and Evaluation Setup

Multi-User Concurrent Protocol Under Distraction We pair 200 single-user multi-session tasks from eight subtypes (25 each; Table 7) without reuse into 100 evaluation instances. Each session

interleaves messages from two evaluated users and one distractor user in a shared context. The evaluated users retain their identities and task lines across sessions; the distractor only asks about products or chats and never places an order. The agent must advance each task while attributing requests correctly and isolating profiles and order states.

Task Evaluation Each instance provides per-session gold labels; we score each user–session pair on four components:

$$R = \big(R_{\text{order}}, R_{\text{prof}}, R_{\text{tool}}, R_{\text{ret}}\big). \tag{5}$$

R_{order} (order execution) checks the ordered product and SKU against the user's session-specific gold acceptable SKU set. R_{prof} (profile maintenance) matches additions, updates, and deletions between consecutive end-of-session snapshots to gold changes. Correctness requires agreement in entry path, operation type, and content. Changes to entries marked "should not update this session" or writes of another user's information count as extra writes. R_{tool} (tool compliance) requires the `save_order` call count to equal the session's expected buyer count; users without purchase tasks, including the distractor, must receive no orders. Queried products and SKUs must be whitelisted; tool errors or hallucinated products fail this component. R_{ret} (user retention) counts forced exits at the accumulated-error threshold as retention failures. Later sessions are skipped but remain in the denominator; voluntary exits do not count as retention failures. A session ends immediately at 100 non-empty messages across all users; unfinished user tasks fail that session. The distractor is unscored, but miswriting its messages into another user's profile or triggering an order from them counts as a failure for the corresponding user.

5 EXPERIMENTS

Models We evaluate six service-agent models: `claude-opus-4-7` (Anthropic, 2025), `kimi-k3` (Kimi Team, 2025), `glm-5.2` (GLM-4.5 Team, 2025), `deepseek-v4-pro` (DeepSeek-AI, 2024), `qwen3.8-max` (Qwen Team, 2025), and `qwen3.8-flash` (Qwen Team, 2025). Both thinking (Wei et al., 2022) and non-thinking modes are evaluated, except `claude-opus-4-7` (non-thinking only), yielding 11 configurations. All configurations use `kimi-k3` non-thinking as the user simulator, including distractors.

Evaluation Metrics Following §4.3, we report **per-component metrics**: R_{prof} recall and precision divide correctly written profile changes by gold-required and actually written changes, respectively; R_{order} and R_{tool} report pass rates over user–session pairs; R_{ret} reports the fraction of users not forcibly exited. **Group-level zero-error rate** counts a group as successful only if both evaluated users pass all profile, order, tool, and retention checks across all sessions.

5.1 MAIN RESULTS

Group-Level Reliability In Table 1, `qwen3.8-max` (thinking) reaches 78.0% order accuracy but only 13.0% group-level zero-error. All reported non-thinking configurations score 0% on group-level zero-error. Strong per-component results do not ensure reliability across users and sessions.

Profile Maintenance Profile recall peaks at 68.5%. `kimi-k3` (non-thinking) achieves 100.0% precision but only 0.8% recall ($2/260$): high precision from sparse writes does not establish effective profile maintenance.

Timeouts in `kimi-k3` Under the shared 100-message cap (§4.3), `kimi-k3` (thinking) reaches the limit in $78/300$ sessions. Timeouts with unfinished evaluated-user tasks occur in $56/97$ failed groups (57.7%). Non-thinking reaches the limit in $48/300$ sessions, with timeouts in $43/100$ failed groups (43.0%). These timeout failures contribute to its low scores.

Effects of Thinking Across models with paired results, thinking improves profile recall, order accuracy, and group-level zero-error. `qwen3.8-flash` order accuracy rises from 6.0% to 74.0%, but `kimi-k3` retention drops from 92.0% to 88.0%.

Table 1: Multi-user, cross-session results on ShopLife-Bench. Each configuration uses 100 groups with 3 sessions each; each session includes two evaluated users and one distractor. R/P: profile-update recall/precision; order: product-and-SKU accuracy on should-order tasks; buy/no-buy: order-count compliance on should-/should-not-order tasks; whitelist: query whitelist compliance; ret.: the fraction of users avoiding error-triggered forced exit. Group-level zero-err. requires both evaluated users to pass all profile, order, tool, and retention checks across all three sessions. All values are percentages (higher is better);

		per-component							group-level
		R_{prof}		R_{order}	R_{tool}				
model	mode	R	P	order	buy	no-buy	whitelist	ret.	zero-err.
claude-opus-4-7	non-thinking	16.2	60.0	10.1	51.9	94.0	96.4	96.3	0.0
kimi-k3	thinking	19.6	60.7	34.8	43.6	98.0	100.0	88.0	3.0
	non-thinking	0.8	100.0	2.0	3.2	98.9	99.8	92.0	0.0
glm-5.2	thinking	28.5	52.1	61.6	78.4	96.9	100.0	96.5	5.0
	non-thinking	10.4	36.5	22.8	64.8	98.0	96.4	94.5	0.0
deepseek-v4-pro	thinking	8.8	54.8	56.0	76.0	98.3	99.2	98.0	7.0
	non-thinking	5.4	51.9	18.8	53.6	97.1	88.9	89.0	1.0
qwen3.8-flash	thinking	63.1	66.9	74.0	80.4	96.0	100.0	100.0	11.0
	non-thinking	17.7	48.9	6.0	52.8	96.6	96.1	93.5	0.0
qwen3.8-max	thinking	68.5	70.4	78.0	80.8	95.7	99.0	97.5	13.0
	non-thinking	41.5	45.0	21.6	32.0	97.7	85.9	94.0	0.0

Query Compliance High query whitelist compliance does not guarantee correct orders; §5.3 examines failures in order attribution, SKU, and count.

5.2 Results by Task Subtype

Table 2: Thinking-mode results by task subtype on ShopLife-Bench: 200 evaluated users from 100 three-session groups, 25 per subtype (Table 7); distractors are excluded. Gold/user: mean gold profile operations per user. Cells report profile recall / product-and-SKU order accuracy / user-level zero-error rate (%). User-level zero-error requires correct profiles and passing whitelist, order-count, order-correctness, and retention checks across all sessions. It counts users, whereas group-level zero-error in Table 1 requires both users to pass; the rates are not directly comparable. A2.2 recall is omitted (–) because it has only 1 gold operation; other – entries are pending results. Non-thinking results appear in Appendix D.

subtype	gold/user	kimi-k3	glm-5.2	deepseek-v4-pro	qwen3.8-flash	qwen3.8-max
A1.1 progressive disclosure	2.1	3.8 / 16.0 / 0.0	15.1 / 36.0 / 0.0	0.0 / 20.0 / 0.0	58.5 / 80.0 / 40.0	66.0 / 92.0 / 52.0
A1.2 upgrade or variant switch	2.3	15.8 / 24.0 / 16.0	10.5 / 52.0 / 8.0	0.0 / 28.0 / 0.0	64.9 / 76.0 / 48.0	68.4 / 72.0 / 52.0
A2.1 multi-brand comparison	3.3	19.5 / 16.0 / 0.0	29.3 / 56.0 / 0.0	0.0 / 28.0 / 0.0	48.8 / 76.0 / 0.0	56.1 / 84.0 / 0.0
A2.2 cross-category substitutes	0.04	– / 48.0 / 24.0	– / 84.0 / 64.0	– / 76.0 / 60.0	– / 84.0 / 40.0	– / 88.0 / 48.0
B1.1 unrelated categories	1.2	41.4 / 33.3 / 0.0	58.6 / 62.7 / 16.0	37.9 / 62.7 / 4.0	89.7 / 69.3 / 20.0	89.7 / 72.0 / 32.0
B1.2 buying for others	0.5	38.5 / 40.0 / 20.0	53.8 / 72.0 / 44.0	38.5 / 76.0 / 44.0	92.3 / 84.0 / 64.0	76.9 / 88.0 / 68.0
C1.1 same-product interleave	0.5	38.5 / 56.0 / 36.0	53.8 / 72.0 / 56.0	30.8 / 80.0 / 56.0	76.9 / 72.0 / 48.0	84.6 / 72.0 / 40.0
C1.2 cross-product interleave	0.5	16.7 / 48.0 / 36.0	41.7 / 56.0 / 40.0	25.0 / 64.0 / 44.0	58.3 / 60.0 / 32.0	83.3 / 68.0 / 36.0
overall	1.3	19.6 / 34.8 / 16.5	28.5 / 61.6 / 28.5	8.8 / 56.0 / 26.0	63.1 / 74.0 / 36.5	68.5 / 78.0 / 41.0

Profile Load and Write Boundaries In Table 2, buying for others (B1.2) has 0.5 gold operations per user and a clear buyer-recipient boundary; user-level zero-error reaches 64% for `qwen3.8-flash` and 68% for `qwen3.8-max`. Multi-brand comparison (A2.1) has the highest load (3.3 operations per user), and models tend to store browsed brands as preferences. All four models score 0% user-level zero-error despite order accuracy up to 84%. For A1.1/A1.2, `kimi-k3` and `glm-5.2` achieve only about 4%–16% profile recall and below-overall order accuracy, indicating difficulty retaining progressively disclosed constraints.

Thinking across Subtypes In non-thinking mode (Appendix D), A2.1 still has 0% user-level zero-error across reported models. On profile-heavy A1.1, thinking raises `qwen3.8-flash` profile recall from 15.1% to 58.5%, consistent with better retention of cross-session constraints.

5.3 Error Analysis

Using per-session scores, profile snapshots, and trajectories, we analyze four complete thinking configurations: rule-detected state errors (Table 3) and simulator-recorded service-agent errors (Table 4). Non-thinking results appear in Appendix E.

Table 3: Thinking-mode profile and order error rates on ShopLife-Bench (%; 100 three-session groups per model). Profile rates use 260 gold add/update/delete operations: missed = required change absent; wrong value = correct entry and operation, incorrect value; wrong action = correct entry, incorrect operation; extra = unrequired change. Among 250 should-order user–session pairs, no order = no attributable order; wrong order = an attributed order with a product/SKU mismatch; duplicate = multiple attributed orders. Off-catalog is the percentage of all committed orders with product/SKU identifiers outside the catalog.

	profile maintenance				order execution			commit check
model	missed	wrong value	wrong action	extra	no order	wrong order	duplicate	off-catalog
kimi-k3	73.5	0.4	6.5	5.8	50.0	15.2	6.4	0.0
glm-5.2	56.5	0.0	15.0	11.2	14.8	23.6	6.8	0.0
deepseek-v4-pro	86.5	0.0	4.6	2.7	13.6	30.4	10.4	2.2
qwen3.8-flash	23.5	0.4	13.1	17.7	14.0	12.0	5.6	0.0
qwen3.8-max	19.6	0.4	11.5	16.9	11.6	10.4	7.6	1.1

Table 4: Service-agent error events and forced exits of thinking configurations. The eight error columns count events recorded by the user simulator; forced exits count only evaluated users whose accumulated error count reaches the threshold.

model	ignored question	evaded question	information overload	unreasonable follow-up	off-target answer	mismatched recommend.	self-contradiction	profile leakage	total	forced exits / users
kimi-k3	81	2	0	0	1	2	0	0	86	24/200
glm-5.2	0	0	0	0	0	4	3	9	16	7/200
deepseek-v4-pro	2	2	3	0	0	5	1	13	26	4/200
qwen3.8-flash	0	0	0	0	0	1	1	0	2	0/200
qwen3.8-max	8	0	1	0	0	2	2	1	14	5/200

Cross-Session Profile Errors Missed-write rates range from 19.6% to 73.5%. Across the four thinking configurations, 119 of 120 wrong-action cases are gold updates realized as additions. In the thermos case, `qwen3.8-flash` understands but omits a fact in one session; the later corrected value then appears as an addition (Appendix H). This illustrates one failure chain, not an explanation of all wrong-action cases.

Order-State Errors With 100% whitelist compliance, no forced exits among evaluated users, and no off-catalog orders, `qwen3.8-flash` still has $35/250$ should-order user–session pairs without attributable orders, $30/250$ with wrong orders, and $14/250$ with duplicates. Order attribution, SKU, and count therefore require separate checks.

Interaction Errors versus State Errors `kimi-k3` records 81 ignored questions among 86 error events and $24/200$ evaluated-user forced exits; `glm-5.2` records 9 profile-leakage events among 16 errors. However, `qwen3.8-flash` fails group-level zero-error checks in $87/98$ groups with no recorded service-agent errors. Absence of negative feedback therefore does not imply correct task states. These descriptive diagnoses may contain labeling and rule-matching noise; causal effects of cross-session memory and multi-user interference require controlled experiments.

6 Analysis and Discussion

6.1 Error-Judgment Reliability of the User Simulator

Error judgments drive user feedback and error-triggered exits (§4.1). We evaluate `kimi-k3` (non-thinking) on 2,000 conversations sampled from the 12,697 real conversations. The model labels each

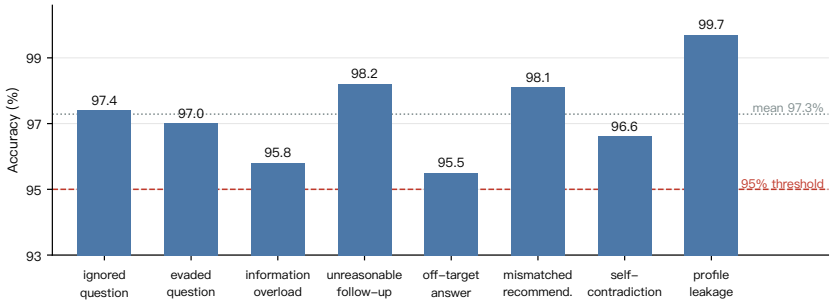


Figure 2: User-simulator accuracy on eight service-agent error types (`kimi-k3`, non-thinking). Dashed line: 95% threshold; dotted line: mean accuracy.

service-agent turn as one of eight error types or "no error"; we compare these labels with human annotations using per-class accuracy.

Accuracy across the eight error types ranges from 95.5% to 99.7% (mean 97.3%), exceeding the 95% threshold for every type (Figure 2). These results support using `kimi-k3` non-thinking as the shared user simulator across all agent configurations.

6.2 Ablation on Multi-User Concurrency

Table 5: Ablation of the single-user and multi-user setups (all in thinking mode). The single-user side is evaluated on 200 single-user instances; the multi-user side uses the 100 two-user groups of Table 1 (200 evaluated users).

		R_{prof}		R_{order}	R_{tool}				
model	setup	R	P	order	buy	no-buy	whitelist	ret.	zero-err.
kimi-k3	single-user	23.5	52.6	33.2	43.2	99.4	100.0	94.5	13.0
	multi-user	19.6	60.7	34.8	43.6	98.0	100.0	88.0	3.0
glm-5.2	single-user	36.5	59.0	67.6	84.4	94.9	99.8	97.5	32.5
	multi-user	28.5	52.1	61.6	78.4	96.9	100.0	96.5	5.0
deepseek-v4-pro	single-user	10.8	53.8	59.2	77.2	97.4	99.8	95.5	25.0
	multi-user	8.8	54.8	56.0	76.0	98.3	99.2	98.0	7.0
qwen3.8-flash	single-user	71.5	67.4	78.8	88.0	96.0	99.2	98.5	43.0
	multi-user	63.1	66.9	74.0	80.4	96.0	100.0	100.0	11.0
qwen3.8-max	single-user	72.3	65.5	81.2	91.6	97.7	99.8	99.5	49.5
	multi-user	68.5	70.4	78.0	80.8	95.7	99.0	97.5	13.0

Single- versus Multi-User Performance Across the four models with paired results, multi-user profile recall is lower than single-user recall (Table 5). Order accuracy and order-count compliance on should-order tasks also decline, except for `kimi-k3`. Zero-error rates use single-user instances on one side and two-user groups on the other, so their differences do not isolate concurrency effects. Session-budget differences further limit causal attribution.

Appendix G analyzes first writes and later updates, showing that update failures cannot be explained by earlier omissions alone.

7 Conclusion

We introduce ShopLife-Bench to evaluate multi-session, multi-user shopping guidance through data-driven user simulation, structured profiles, and concurrent tasks with distractors. It measures profile maintenance, order execution, tool compliance, and user retention. The best group-level zero-error rate is 13.0% and profile recall is 68.5%, with lower recall across models in multi-user settings. Missed writes propagate across sessions, while user-perceived interaction errors only partly overlap with rule-detected state errors. Cross-user isolation and cross-session consistency remain key challenges.

AI USE STATEMENT

This work uses generative AI tools in the following ways. **Synthetic data generation and dataset restructuring:** Under the standard operating procedure in Appendix C.3, Kimi-K3 drafted user task scripts, cold-start profiles, and candidate profile-update labels, and rewrote source profiles into the structured schema (splitting compound statements and normalizing the vocabulary). All generated candidates went through program checks and human review by the authors; samples that lack evidence or contain answer leakage were revised or removed, and outputs that fail either check do not enter the evaluation set. **Text polishing:** LLMs helped polish the text of this paper for readability, and the authors revised the polished text sentence by sentence.

We also note that LLMs are part of the benchmark itself: `kimi-k3` serves as the user simulator and the error judge (§6.1), and the evaluated agents are LLMs as well; this use belongs to the method itself and is fully described in the main text.

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A Appendix

B Implementation Details and Supplementary Statistics of the Core Mechanisms

B.1 Categories and Distribution of Service-Agent Behaviors

Figure 3 shows the category composition of service-agent behaviors at two levels: overall interactions and abnormal feedback. The left panel covers the four normal behavior types and the eight error types, with shares computed over all service-agent behaviors; the right panel keeps only the eight error types and renormalizes within this subset to show the relative composition of errors. The two panels share colors and legend, corresponding to the narrowing from the full behavior taxonomy to the abnormal-feedback input set $\mathcal{X}$.

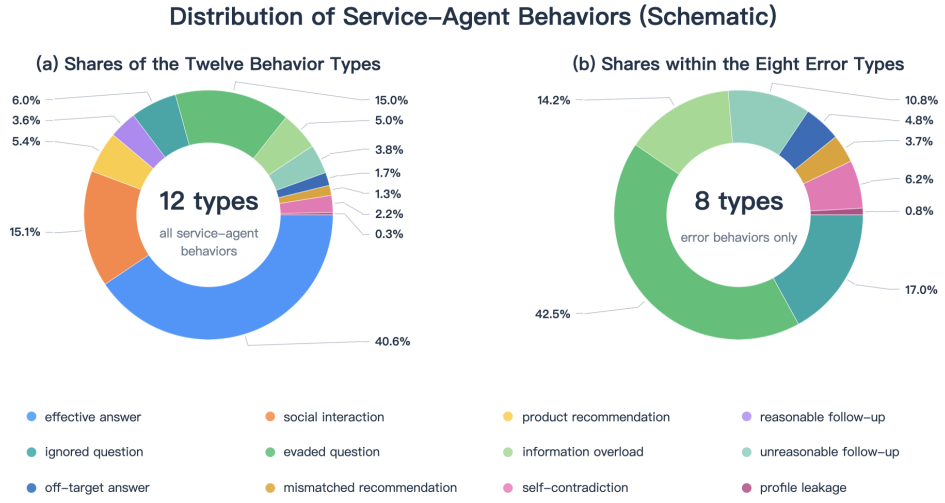


Figure 3: Service-agent behavior distribution: the overall composition of the twelve behavior types and the internal composition of the eight error types.

B.2 User Reaction Distributions under Different Service-Agent Errors

Table 6: User reaction distributions under the eight service-agent error types. Each column gives the relative shares of the six reactions under that error type; bold marks the maximum in each column.

reaction	ignored question	evaded question	information overload	unreasonable follow-up	off-target answer	mismatched recommend.	self-contradiction	profile leakage
restating the request	**32.0%**	19.8%	**38.0%**	**35.0%**	**48.4%**	25.0%	9.5%	3.0%
letting the error go	18.0%	13.8%	25.0%	15.0%	33.3%	10.0%	20.0%	18.0%
demanding a fix	26.0%	**31.3%**	15.0%	18.0%	5.7%	**32.0%**	1.5%	**33.0%**
confrontation	7.0%	25.8%	8.0%	8.0%	3.1%	22.0%	12.0%	26.0%
protest	15.0%	5.1%	11.0%	22.0%	5.0%	9.0%	**55.0%**	20.0%
going off-topic	2.0%	4.2%	3.0%	2.0%	4.4%	2.0%	2.0%	1.0%

Table 6 shows the user reaction distributions assigned to different service-agent errors. Ignored question, information overload, unreasonable follow-up, and off-target answer mainly map to restating the request, reflecting how users refocus on their original needs; evaded question maps more to demanding a fix and confrontation, and mismatched recommendation emphasizes restating selection constraints and requesting adjusted recommendations. For self-contradiction and profile leakage, the distribution gives higher weight to protest and confrontation. These differences build error-type-dependent reaction rules, which constrain user behavior together with the tone escalation and exit mechanism driven by the accumulated error count.

B.3 User Patience and Exit-Threshold Distribution

Figure 4 shows the patience differences among users in the behavior-analysis sample. The estimated shares of users who exit after the 1st, 2nd, and 3rd service-agent error are 16.86%, 17.80%, and 21.34%, summing to 56.00%, so many users have exit thresholds early in the interaction. At the same time, the distribution still covers higher error counts, showing clear differences in tolerance to service-agent errors across users. We therefore adopt a per-user patience threshold τ_i instead of a unified exit count for all users, preserving the behavioral heterogeneity between low-patience and high-patience users.

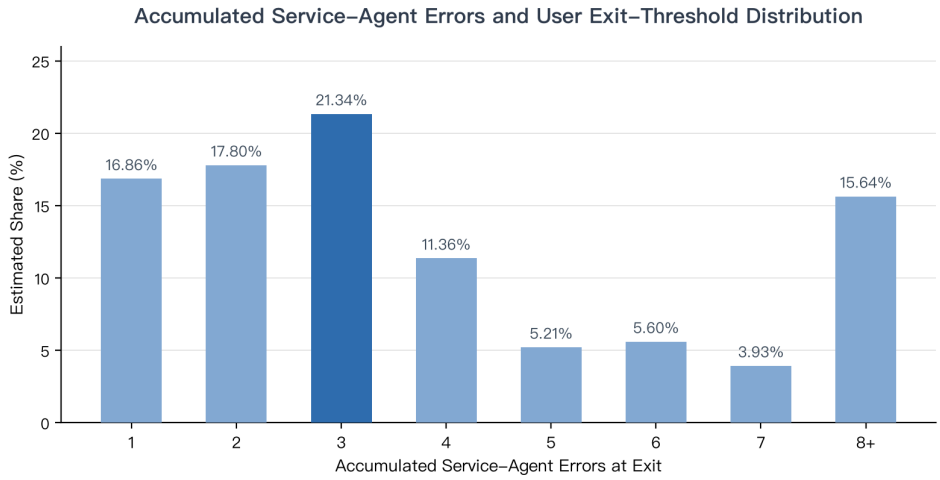


Figure 4: Accumulated service-agent error count and the distribution of user exit thresholds.

C Details of User Profiles and Cross-Session Task Construction

C.1 Profile Structure and Write Boundaries

A profile file consists of a version identifier, user metadata, and the profile body. The body is organized as "first-level category–second-level dimension–arrays of atomic entries", and user tags are stored directly as an entry array; dimensions without information remain empty arrays, and no structural fields are added for new tasks. A fact entry requires `id/subject/attribute/value`, where `value` may only be a string, a number, or a boolean; a preference entry requires `id/subject/sentiment`, and a product-attribute preference also requires `scope`. The profile mount path determines where information is stored, while the category scope determines where a preference applies; the two must not be mixed. For example, a pillow-material preference should be restricted to the corresponding category, and must not be automatically extended to the material preference of all products.

Figure 5 shows an illustrative example covering all profile dimensions. Platform records provide basic information, behavior statistics, and derived insights, while session disclosures add family facts and long-term preferences. For example, "there are three people in my family and my daughter is seven this year" is split into two independent fact entries, and "prefers cotton pillows" is represented as a preference entry with a category scope. In real profiles, dimensions lacking evidence remain empty arrays, and the model is not required to fill them.

```
{
  "schema_version": "1.0",
  "meta": {
    "user_id": "U_DEMO",
    "created_at": "2026-09-01T00:00:00Z",
    "updated_at": "2026-09-13T00:00:00Z",
    "data_sources": ["platform", "session_1", "session_2"]
  },
  "profiles": {
    "basic profile": {
      "basic attributes": [
        {
          "id": "base-attr-001",
          "subject": "self",
          "attribute": "age band",
          "value": "35-44",
          "source": "platform"
        }
      ],
```

```
      "region information": [
        {
          "id": "base-geo-001",
          "subject": "place of residence",
          "attribute": "city",
          "value": "Hangzhou",
          "source": "platform"
        }
      ],
      "family relations": [
        {
          "id": "base-family-001",
          "subject": "family",
          "attribute": "family size",
          "value": 3,
          "unit": "people",
          "confidence": "explicit",
          "source": "session_1"
        },
        {
          "id": "base-family-002",
          "subject": "daughter",
          "attribute": "age",
          "value": 7,
          "unit": "years old",
          "confidence": "explicit",
          "source": "session_1"
        }
      ],
      "dynamic status": [
        {
          "id": "base-status-001",
          "subject": "self",
          "attribute": "occupation",
          "value": "teacher",
          "confidence": "explicit",
          "source": "session_1"
        }
      ],
      "devices and assets": [
        {
          "id": "base-asset-001",
          "subject": "housing",
          "attribute": "feature",
          "value": "separate children's room",
          "confidence": "explicit",
          "source": "session_1"
        }
      ]
    },
    "preference profile": {
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        {
          "id": "pref-cat-001",
          "subject": "mother-and-baby products/children's learning
          ↪  supplies",
          "sentiment": "positive",
          "confidence": "explicit",
          "source": "session_1"
        }
      ],
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          "subject": "Mendale Baby",
          "scope": "household goods/bedding",
```

```
          "sentiment": "positive",
          "confidence": "explicit",
          "source": "session_1"
        }
      ],
      "product-attribute preferences": [
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          "subject": "cotton",
          "attribute": "material",
          "scope": "household goods/bedding/pillows",
          "sentiment": "positive",
          "confidence": "explicit",
          "source": "session_1"
        }
      ],
      "interests and habits": [
        {
          "id": "pref-interest-001",
          "subject": "reading",
          "sentiment": "positive",
          "confidence": "explicit",
          "source": "session_1"
        }
      ],
      "price preferences": [
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          "id": "pref-price-001",
          "subject": "household goods/bedding/pillows",
          "attribute": "upper limit",
          "value": 300,
          "unit": "yuan",
          "confidence": "explicit",
          "source": "session_2"
        }
      ]
    },
    "insight profile": {
      "spending power": [
        {
          "id": "insight-cap-001",
          "subject": "transactions",
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          "value": 12,
          "unit": "orders",
          "source": "platform"
        }
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          "confidence": "inferred",
          "source": "platform"
        }
      ],
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          "subject": "membership",
          "attribute": "membership tier",
          "value": "Gold member",
          "source": "platform"
        }
```

```
      ],
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          "subject": "crowd",
          "attribute": "live-shopping decision habit",
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          "confidence": "inferred",
          "source": "platform"
        }
      ]
    },
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      "platform activity": [
        {
          "id": "beh-active-001",
          "subject": "self",
          "attribute": "active hours",
          "value": 21,
          "unit": "hour",
          "source": "platform"
        }
      ],
      "search behavior": [
        {
          "id": "beh-search-001",
          "subject": "self",
          "attribute": "search keywords in the last 14 days",
          "value": "cotton pillows",
          "source": "platform"
        }
      ],
      "interaction behavior": [
        {
          "id": "beh-interact-001",
          "subject": "self",
          "attribute": "shops followed in the last 14 days",
          "value": "Mendale Baby flagship store",
          "source": "platform"
        }
      ],
      "live-streaming behavior": [
        {
          "id": "beh-live-001",
          "subject": "self",
          "attribute": "live-room visit frequency",
          "value": 3,
          "unit": "times/week",
          "source": "platform"
        }
      ]
    },
    "user tags": [
      {
        "id": "tags-001",
        "subject": "active at night",
        "sentiment": "positive",
        "confidence": "inferred",
        "source": "platform"
      }
    ]
  }
}
```

Figure 5: A structured user-profile example covering all dimensions. The five profile categories use a fixed classification structure, and each dimension stores information as atomic entries. Entry identifiers support precise updates, and category scopes restrict where preferences apply; source and confidence types distinguish platform records, explicit disclosures, and inferred information. The example is illustrative and does not represent a real user record.

Judging Update Operations This structure gives profile updates a clear target for judgment. When the user corrects "my daughter is actually eight", the agent should apply UPD to `base-family-002`, keeping the entry identifier and changing the age from 7 to 8, rather than adding a new entry while keeping the old value; when the user asks to forget the pillow-material preference, the agent should delete `pref-attr-001`. Meanwhile, the "cotton" preference applies only to the pillow category, and must not ground new material preferences for other categories such as clothing. The evaluation can therefore check the operation type, entry content, and mount position separately, and verify that unrelated entries remain unchanged.

Expressiveness and Data-Construction Constraints The price preference in the example demonstrates the expressiveness of the general schema, and it presumes that the user has explicitly stated a long-term price cap. Our current task-synthesis pipeline does not write price information into profiles, so this dimension stays empty in real task samples, and the in-session budget only participates in explicit product-condition filtering.

C.2 CROSS-SESSION TASK TAXONOMY AND INFORMATION TYPES

Fine-Grained Categories of the Linkage Topology Table 7 lists representative subtypes under the three main axes. All types describe the cross-session shopping process of the same user; changing the user identity is not used to create task differences. Different types emphasize constraint accumulation, fact overwriting, cross-goal isolation, or decision-chain recovery, and we do not presume a unified difficulty order among the main categories.

Table 7: Cross-session task taxonomy organized by product decision relations. A, B, and C denote linked, independent, and interleaved products respectively.

ID	task subtype	construction and main focus
A1.1	progressive disclosure of constraints	Disclose related facts session by session around the same goal; tests information accumulation and correct mounting.
A1.2	requirement upgrade, update, or variant switch	Trigger updates of existing entries with evidenced changes in user facts or stable preferences; avoids wrong coexistence of old and new values.
A2.1	multi-brand comparison within one category	Encounter different brands of the same category across sessions; distinguishes product inquiries from genuine brand-preference changes.
A2.2	cross-category substitute comparison	Serve the same higher-level goal with different categories; tests goal linking and preference scopes.
B1.1	completely unrelated categories	Shopping goals are independent across sessions; avoids transferring local constraints of one goal to the next.
B1.2	buying for others or gifting	Distinguish the buyer from the recipient; the needs of others must not be written as the user's own stable preferences.
C1.1	same-product interleave across sessions	Arrange product tasks in an A–B–A order; restores the existing constraints of A when returning to it.
C1.2	different-product interleave within a session	The first session involves both products A and B, and later sessions advance them separately; tests within-session separation and cross-session recovery.

Information Types and Noise The information-type axis is divided into explicit statements, implicit needs, and noise, where noise includes hypothetical remarks, jokes, and emotional expressions. For noise scenes that contain no valid profile-update information, we annotate the expected operations as the empty set, testing whether the model can reject the interference and keep the profile unchanged.

C.3 Batch Generation and Acceptance Rules

Input Materials and Generation Responsibilities We provide the standard operating procedure (SOP), the profile schema, the product catalog with variant attributes, the linked source profiles, and the original shopping goals to Kimi-K3, and we specify the task subtype, the number of sessions, and the information-expression style. The SOP constrains not only the output format but also the disclosure order, profile write boundaries, recommendation evidence, and sample acceptance conditions. The model then generates candidate profiles, user task scripts, and expected-operation annotations; local programs handle assembly and consistency checks, and human reviewers handle semantic review and final confirmation. Model outputs are only candidate annotations before review and are not directly used as evaluation gold labels.

Product Filtering and Cold-Start Profiles Candidate products must have accessible details and at least three usable variants, the variants must differ distinguishably in non-image attributes, and the category must map to the controlled vocabulary of the schema. The model designs scenarios from the filtered products and original tasks, and must not fabricate products, variants, or compatibility attributes. A cold-start profile is rewritten from the source profile linked to the target-session product: background information is kept by a whitelist, compound statements are split, and vocabulary is normalized, while brands, product attributes, search clues, and anything that could leak the answer or to-be-disclosed facts are removed. Each profile keeps at least eight background entries, the source of initial entries is uniformly `platform`, and profiles of different task sequences must be pairwise distinct; when the background is insufficient, we switch the source instead of fabricating entries to meet the count. This batch of tasks does not write price information into profiles; the budget stays only in the session script, and is explicitly restated in the target purchase session and fully included in explicit filtering.

SOP for Model-Assisted Generation Under the above inputs and boundaries, the SOP requires the model to complete the following steps in order:

1. **Arrange cross-session tasks for the same user.** Fix the user identity, arrange the products, inquiry points, and disclosures of each session under the specified linkage topology, and generate the opening, task points, closing, and the order-or-not marker for each session. Each session states its own shopping goal independently and does not ask the service agent to read the conversation history with phrases like "continue from last time". Fact corrections must name the subject and the new value; earlier consultation sessions do not require a purchase. The model generates scripts that drive the user simulator, not a fixed complete interaction trajectory.
2. **Establish user evidence before annotating profile operations.** Extract user or family facts, existing assets, and stable preferences from the script's original utterances; do not rewrite one-time purchase specs, order progress, or the target SKU as long-term profile entries. Each operation must state its type, target entry identifier, mount path, and content, with verbatim evidence `evidence`, information category `memory_kind`, and cross-session retention reason `longevity`. New entries use new identifiers; updates and deletes locate existing identifiers; fact corrections should overwrite the old value instead of adding a conflicting entry. Inferred annotations additionally carry `inference`, describing the evidence, the inference process, and the applicable boundary.
3. **Insert information expressions and noise under control.** Arrange explicit statements, implicit needs, or noise in the selected sessions according to the specified information type; implicit expressions may use hints, repetition, or reference, but any written conclusion still needs sufficient evidence, and repeated inquiries must not be equated with stable preferences. Controlled expressions must match the original utterances in that session's script, avoiding duplicate insertion during assembly. For hypothetical, joking, or emotional noise, choose sessions without other valid update information, set the expected operations to the empty set, and record the no-write reasons in `noop_reasons`. Noise must not replace fact disclosures or corrections required by the task chain.
4. **Build a checkable profile-to-product fit chain.** Record the explicit conditions of the target session separately from the implicit fit conditions supported by earlier profiles. Explicit conditions are bound to the corresponding spoken lines; implicit conditions state the profile

path, subject, attribute, and catalog evidence they rely on. Key profile entries must be deposited by earlier sessions, not from cold-start presets or re-disclosure in the target session. Under the necessity condition of §4.2, explicit filtering keeps at least two candidates, and adding evidenced profile conditions uniquely hits the target SKU. Here `implied` means the product condition is not restated in the target session; it does not require the profile entry itself to be marked `inferred`. When no valid fit chain can be built, replace the sample instead of fabricating user information backward from a preselected answer.

5. **Output structured inputs and type-specific checks.** Output the generation request `request`, the cold-start profile `cold_start_profile`, and the per-session plan `scenario_plan`. The request records the user, task type, number of sessions, products, and target SKU; the plan records per-session scripts, expected profile operations, no-update reasons, SKU constraints, and anti-leakage words. For requirement-upgrade and variant-switch tasks, additionally record the candidate corresponding to the old profile value and ensure it stays in the explicit candidate set, so that keeping the old value and correctly updating lead to different selection results. For multi-brand comparison tasks, record per-session brands and catalog evidence, and verify brand-preference updates and variant fit separately; do not interpret product browsing directly as brand preference, and do not present the variant decision of the target session as a global cross-product choice.

Rule-Based Assembly and Reference Snapshots After an initial human review, the three kinds of inputs are prechecked by local programs and assembled into per-session evaluation payloads, including user-side scripts and evaluation-side target SKUs, profile operations, and reference snapshots. Evidence and gold annotations are not used as user spoken content, and the target-session script must not contain evaluation hints that ask the model to use a specific profile entry. The program starts from the cold-start profile and replays the expected operations session by session, recording the source session for added or updated information. The reviewed gold snapshots satisfy:

$$p_i^{k+1,\star} = \mathrm{Apply}\left(p_i^{k,\star}, \Delta_i^{k,\star}\right), \tag{6}$$

where $\Delta_i^{k,\star}$ is the expected profile-operation sequence of session k. Reference snapshots are used for offline validation and evaluation; online cross-session interaction continues with the profile actually maintained by the service agent, and reference snapshots do not replace its errors or omissions.

Program Checks and Human Review The program checks each item for schema validity, entry-identifier uniqueness, operation executability, and snapshot-replay consistency, and also verifies evidence references, source sessions, controlled expressions, zero-update controls, and the price ban. Candidate decisions are recomputed from real variant attributes, recording explicit candidates, the target SKU, and exclusion reasons; expressed conditions such as the budget must not be omitted to artificially make the profile necessary. Anti-leakage checks cover the opening, task points, and closing of the target session, not only the final request; the cold-start profile is also checked separately and cannot be regarded as leak-free solely by its source tag.

Human semantic review verifies two evidence chains: "user utterances $\rightarrow$ profile entries", checking subjects, factual precision, persistence, and inference boundaries; and "profile entries plus in-session conditions $\rightarrow$ product fit", checking catalog evidence and candidate-exclusion reasons. The review pays special attention to whether a soft preference is mistaken for an exclusive condition, a rough range is treated as an exact number, or an unrelated background entry is mislabeled as the sole selection basis. A unique SKU filtered by a large model only proves consistent constraint computation and cannot replace the semantic judgments above. When problems are found, the source inputs are revised and regeneration and checks are rerun; if the evidence is still insufficient or uniqueness still fails after revision, the sample is removed or replaced, and its acceptance status must not be edited merely to regain eligibility.

Batch-Level Checks and Reproducibility At the batch level, we check the diversity of product categories, profile backgrounds, evidence dimensions, and expression styles, so that different samples do not reuse the same reasoning chain. Valid source inputs, sample-assignment ledgers, and acceptance reports are saved; sampling records the random seed and filtering conditions, and manually selected samples do not fake a random process. After source inputs are revised, the payloads and reports are updated synchronously and regenerated for comparison; except for process timestamps,

the task content, reference snapshots, and decisions are checked for consistency. Reproducibility here means rebuilding the evaluation data from saved inputs, not requiring the model to sample exactly the same script again. Single-user tasks that pass review are then paired under the no-reuse rule of §4.3 to form multi-user evaluation instances.

D SUPPLEMENTARY RESULTS BY TASK SUBTYPE

Table 8: Results on ShopLife-Bench by cross-session task subtype (non-thinking mode). The counting rules, sample composition, and the meaning of the three numbers in each cell (profile recall / order accuracy / user-level zero-error rate, in percent) are exactly the same as in Table 2; "gold/user" is the average number of gold profile operations per user. A2.2 has only 1 gold profile operation in total, so its recall is marked –; `deepseek-v4-pro` results are pending.

subtype	gold/user	kimi-k3	glm-5.2	deepseek-v4-pro	qwen3.8-flash	qwen3.8-max
A1.1 progressive disclosure	2.1	1.9 / 0.0 / 0.0	3.8 / 4.0 / 0.0	5.7 / 12.0 / 0.0	15.1 / 8.0 / 4.0	47.2 / 28.0 / 4.0
A1.2 upgrade or variant switch	2.3	0.0 / 0.0 / 0.0	8.8 / 8.0 / 0.0	1.8 / 8.0 / 0.0	7.0 / 0.0 / 0.0	36.8 / 24.0 / 12.0
A2.1 multi-brand comparison	3.3	0.0 / 0.0 / 0.0	7.3 / 36.0 / 0.0	0.0 / 12.0 / 0.0	14.6 / 8.0 / 0.0	30.5 / 12.0 / 0.0
A2.2 cross-category substitutes	0.04	– / 4.0 / 0.0	– / 16.0 / 16.0	– / 20.0 / 16.0	– / 0.0 / 0.0	– / 36.0 / 16.0
B1.1 unrelated categories	1.2	0.0 / 4.0 / 0.0	27.6 / 25.3 / 4.0	24.1 / 20.0 / 0.0	41.4 / 9.3 / 0.0	65.5 / 22.7 / 0.0
B1.2 buying for others	0.5	0.0 / 0.0 / 0.0	15.4 / 40.0 / 16.0	7.7 / 44.0 / 12.0	30.8 / 8.0 / 4.0	38.5 / 20.0 / 4.0
C1.1 same-product interleave	0.5	7.7 / 0.0 / 0.0	15.4 / 28.0 / 20.0	15.4 / 16.0 / 8.0	23.1 / 4.0 / 4.0	53.8 / 12.0 / 0.0
C1.2 cross-product interleave	0.5	0.0 / 4.0 / 4.0	16.7 / 20.0 / 16.0	0.0 / 16.0 / 4.0	16.7 / 4.0 / 0.0	50.0 / 16.0 / 0.0
overall	1.3	0.8 / 2.0 / 0.5	10.4 / 22.8 / 9.0	5.4 / 18.8 / 5.0	17.7 / 6.0 / 1.5	41.5 / 21.6 / 4.5

Table 8 gives the subtype breakdown in non-thinking mode. The difficulty ranking is consistent with the main text: A2.1 has a zero-error rate of 0 on all configurations, and B1.2 and the C types are relatively the highest. Compared with thinking mode, the main change in non-thinking is the overall collapse of order accuracy (`qwen3.8-flash` drops from 74.0% to 6.0%), while `qwen3.8-max` still keeps 41.5% profile recall, showing that without reasoning the profile is "writable" but "unusable"; the decoupling of the two abilities also holds at the subtype level.

E NON-THINKING ERROR ANALYSIS AND SUPPLEMENTARY SCORING

Table 9: Profile and order error rates (%) of non-thinking configurations. Profile operations include add, update, and delete on user information. Missed: a change required by the gold label has no corresponding actual change; wrong value: the entry and operation type are correct, but the written value differs from the gold label; wrong action: the entry is changed, but the operation type does not match the gold label, e.g., adding a new record when an existing entry should be updated; extra: profile changes not required by the gold label. No order: no order can be attributed to the user; wrong order: an attributed order contains a product or SKU that does not match the gold label; duplicate: more than one attributed order; all three use the 250 should-order user-sessions as the denominator. Off-catalog: among all actually committed orders, the fraction whose product or SKU identifier is not in the catalog.

	profile maintenance				order execution			commit check
model	missed	wrong value	wrong action	extra	no order	wrong order	duplicate	off-catalog
kimi-k3	99.2	0.0	0.0	0.0	96.8	1.2	0.0	36.4
glm-5.2	79.6	0.0	10.0	8.1	29.6	47.6	5.6	43.8
deepseek-v4-pro	91.9	0.0	2.7	2.3	38.8	42.4	7.6	50.0
qwen3.8-flash	71.2	0.4	10.8	7.3	32.4	61.6	14.8	76.2
qwen3.8-max	49.2	0.0	9.2	41.5	56.4	22.0	11.6	30.6

Low Writing and Wrong Writing Are Different Failure Modes. `kimi-k3` misses $258/260$ profile operations, and $242/250$ should-order user-sessions have no attributable order, so its extremely high profile precision cannot be read as adequate task completion. `qwen3.8-max` instead

Table 10: Service-agent error events and forced exits of non-thinking configurations. The error columns count events recorded by the user simulator; forced exits count only evaluated users whose accumulated error count reaches the threshold.

model	ignored question	evaded question	information overload	unreasonable follow-up	off-target answer	mismatched recommend.	self-contradiction	profile leakage	unknown	total	forced exits / users
claude-opus-4-7	0	0	11	0	0	1	1	14	0	27	10/200
kimi-k3	30	7	2	1	0	7	0	8	0	55	16/200
glm-5.2	1	0	0	0	1	10	1	34	0	47	11/200
deepseek-v4-pro	2	9	48	3	1	6	3	41	0	113	22/200
qwen3.8-flash	3	5	0	0	3	11	3	21	0	46	13/200
qwen3.8-max	13	2	11	0	4	4	1	16	2	53	12/200

produces 108 profile changes outside the gold labels, and `qwen3.8-flash` commits $256/336$ orders with off-catalog identifiers. These results reflect omission, write-boundary, and commit-validity problems respectively, and cannot be summarized by a single notion of "execution activeness".

F Turn Budget and Timeout-Failure Statistics

The turn budget of each session is 100 non-empty chat messages across all users, not 100 per user, nor the number of service-agent replies; when the budget is exhausted and some users have not finished, the run log records `reason=finished`, which we call hitting the cap. Under the evaluation protocol of §4.3, an evaluated user whose task is still incomplete when the cap is hit is counted as a task failure in that session (timeout). Table 11 reports the timeout scale of each configuration and its relation to group-level failures (the pass^1 definition of Table 1).

Table 11: Statistics of turn-budget exhaustion (hitting the cap) and timeout failures.

model	mode	sessions at cap	groups with user timeout	of which group-failed	share of all failures (%)
claude-opus-4-7	non-thinking	0	0	0	0/100 (0.0)
kimi-k3	thinking	78	57	56	56/97 (57.7)
	non-thinking	48	43	43	43/100 (43.0)
glm-5.2	thinking	1	1	1	1/95 (1.1)
	non-thinking	7	6	6	6/100 (6.0)
deepseek-v4-pro	thinking	3	3	3	3/93 (3.2)
	non-thinking	1	1	1	1/99 (1.0)
qwen3.8-flash	thinking	9	8	8	8/89 (9.0)
	non-thinking	6	5	5	5/100 (5.0)
qwen3.8-max	thinking	6	6	6	6/87 (6.9)
	non-thinking	4	4	4	4/100 (4.0)

The timeout scale of `kimi-k3` is much higher than the other configurations: in thinking mode, $78/300$ sessions hit the cap, 57 groups contain an evaluated-user timeout, and 56 of them also fail the group-level check, accounting for 57.7% of all its 97 group-level failures; the non-thinking mode has $48/300$ sessions and $43/100$ groups (43.0%). All configurations of the other models hit the cap at most 9 times, and timed-out groups account for at most 9.0% of their failures, so their failures come almost entirely from failed profile or order checks rather than budget exhaustion.

G Cross-Session Profile Maintenance

We trace gold items by stable identifiers across per-session scores and profile snapshots (Table 12).

Both Qwen models perform worse on cross-session updates than on first additions. Each has 21 update-as-add events despite a correctly written prior record still being present. Later update errors therefore cannot be explained by earlier omissions alone.

Table 12: Thinking-mode profile maintenance over 100 three-session groups per model. The first three columns report accuracy (%) over gold operations: first addition, adding a new item with no initial or prior gold record; cold-start correction, updating an initial-profile item with no prior gold change; cross-session update, updating an item with a prior-session gold operation. The last two columns count gold updates realized as additions: miss-then-add follows an earlier omission and absence at session start; right-then-add follows a correct write with the record still present. Fractions use all update-as-add events for that model as the denominator.

model	first addition accuracy	cold-start corr. accuracy	cross-session update accuracy	miss-then-add	right-then-add
kimi-k3	14.0	51.1	10.3	14/16	2/16
glm-5.2	24.2	71.1	6.9	27/39	12/39
deepseek-v4-pro	0.0	51.1	0.0	9/10	0/10
qwen3.8-flash	65.0	91.1	36.2	13/34	21/34
qwen3.8-max	70.7	93.3	43.1	9/30	21/30

H VERIFIABLE CASES FOR THE ERROR ANALYSIS

The following cases illustrate the observed failure chains rather than estimate the share of each mechanism among all errors. All cases are taken from the data trajectories and are located by model, mode, session, and user number.

Correct In-Session Understanding Can Still Break across Sessions. `qwen3.8-flash` (thinking), user 002. In session one the user says "the bottom of my thermos is marked 2.0L"; the service agent correctly answers that it corresponds to the small size, but does not persist this asset information, and the profile report records one missed write. In session two the user says "I replaced my thermos; the new one is marked 3.2L and the old one is no longer used", and the service agent writes the capacity 3.2L through `ADD` of `update_user_profile`; the session-two snapshot does contain the correct value, but because the earlier entry is missing, the actual change is an ADD while the gold label is an UPD. Thus an earlier miss can reappear in a later session as an action mismatch; this case does not show a wrong understanding of capacity or an inevitably wrong SKU choice afterwards.

Tool-Call Intent Is Not Tool Execution. `kimi-k3` (thinking), live80, session two. The service agent outputs the JSON intent of calling `list_all_product_types` several times in its text, but the `tool_calls` field of the trajectory is empty and nothing is committed. In this session, user 001 and distractor user 003 each trigger two ignored-question events and are forcibly exited, four in total. The evidence supports the execution gap that "the tool intent never became an actual call and the users received no effective response", and does not support the description "the tool was actually called repeatedly".

No Recorded Service-Agent Error Does Not Imply Group Success. Among the four thinking configurations, `kimi-k3`, `glm-5.2`, `qwen3.8-max`, and `qwen3.8-flash` have $62/87/91/98$ groups with no recorded service-agent error, of which $59/82/79/87$ still fail the group-level check. Here "no record" covers both evaluated and distractor users, but it does not guarantee that the simulator recognized all errors. An event itself is not an independent group-failure condition: when no forced exit is triggered and all profile, order, and other checks pass, the group can still succeed.

I SYSTEM PROMPTS OF THE SERVICE AGENT AND THE USER SIMULATOR

This section gives the complete system prompts of the service agent and the user simulator. Both prompts are assembled from a fixed policy template plus dynamic blocks injected per session; the excerpts below are English translations of the original Chinese text in the `prompts/` directory of the codebase. The Chinese originals are retained as comments in the LaTeX source. Service-agent side: after the policy template (§I.1), we append the `<viewers>` block (the viewer list of this session and the multi-viewer response requirement) and one `<user_profile viewer="...">` block per viewer (the viewer's current profile JSON, structured as in Figure 5); the six tools are also

registered through the API's `tools` parameter. User-simulator side: after the policy template (§I.2), we append <scenario> (the task script of this session), <persona> (basic-profile fields only), <error_types> (definitions of the eight service-agent error types), <behavior_policy> (the behavior-policy instance drawn by this user), <viewer_name>, and <other_viewers>; at each turn we further append a per-turn reminder and the cross-session accumulated error count maintained by the system. Behavior policies are assigned and stored per group × user, and the same user reuses the same instance across the three sessions.

I.1 SERVICE-AGENT PROMPT

```
# Service-Agent Guidelines

## Role
You are the sales host of an e-commerce live room, chatting with
↪  multiple viewers through chat messages at the same time. Each
↪  <user_profile> describes the profile of one viewer (the viewer
↪  attribute shows which viewer the profile belongs to). Help the
↪  viewers as much as you can, and always follow the policies below.

## Turn Behavior (Hard Rules)
In each turn, you can choose only one of the following actions:
- Send a message to the users.
- Make one tool call.
Speak only one utterance per turn: each time you speak, that utterance
↪  is your only message of this turn; there is no "next message" to
↪  continue with, so everything you need to say must fit into this one
↪  utterance; no markup or tokens may appear in the utterance.
- Be sure to generate only valid JSON

# E-commerce Host Policies

## Products

This live room sells 516 products across more than 60 first-level
↪  categories, including cosmetics and skincare, home improvement and
↪  building materials, lighting, musical instruments, major home
↪  appliances, computers and digital devices, household goods, mother
↪  and baby, office furniture, and hardware tools. The coverage is
↪  extremely broad.

Each product has the following attributes:

- Unique product ID (product_id)
- Product name (name): the full e-commerce title; the stacked keywords
↪  in it are only selling-point descriptions and must not be treated as
↪  confirmed parameters
- Product brief (brief): the overall introduction and main features of
↪  the product
- Category (category): a multi-level category path separated by >, such
↪  as "Bedding>Pillows>Latex pillows"
- Variant list (variants)

A product may have multiple variants made up of different options. For
↪  example, a bathroom vanity mirror may have the following variants:

- Single-sided square [3x magnification, battery model]
- Double-sided square [3x magnification, rechargeable model]

Each variant has the following attributes:

- Unique item ID (item_id)
- The option values of this item (options)
- Stock availability (available): true means in stock and sellable
- Price (price), in yuan
```

```
Notes:

- The product ID (product_id) and the item ID (item_id) are unrelated; do not confuse them;
- The product data contains no brand authorization, ingredient lists, sales volumes, reviews, promotions, gifts, logistics, or after-sales information; when a viewer asks, state honestly that it is not available for now, but do not transfer to a human and never fabricate.

## Available Tools
You can call the following tools:

- `list_all_product_types`: lists an overview of all products in the live room (name, product_id, brief, category); the only entry point for obtaining product_id and the first step of every product query
- `get_product_details`: shows the variant list of a product by product_id (item_id + options), without price or stock
- `get_variant_details`: shows the price, stock, delivery time, and shipping fee of a single variant
- `save_order`: saves the order information (product_id and item_id) after the viewer confirms the purchase; see "Order Saving" for the trigger conditions and usage
- `transfer_to_human_agents`: transfers the viewer to human agents with a summary of the issue
- `update_user_profile`: registers one change to a viewer's profile (add / correct / remove); all changes are written into the profile store together after the whole session ends

## Scope of Duties
You may:
- Welcome viewers and ask about their needs;
- Browse and filter the products on sale in the live room;
- Query the name, category, brief, specifications, stock, and price of products; when a product has many variants, you may call the variant query tool several times for different variants, check the price and stock one by one, and then compare them;
- Recommend and present products objectively based on query results;
- Save the order information (product_id and item_id) after the viewer confirms the purchase; see "Order Saving";
- Transfer viewers to human agents when needed.

Boundary: all product information is subject to tool query results; never fabricate any information, knowledge, or process that the users or tools have not provided; if something cannot be found, say so honestly.

## Order Saving
Both of the following cases count as a confirmed purchase, and you must call `save_order` to save the order:
1. The viewer clicks the order button: the end of the viewer's chat message carries a system marker in the fixed format
   `[tool call] place_order()` and `[tool return] {"status": "The user has pressed the order button of the recommended product"}`;
   this marker means the viewer has clicked the order button of the product you are currently recommending
2. The viewer directly says they want to buy in a chat message: clear purchase statements such as "I will take this one", "OK, this one, place the order", or "get one for me", even without the marker above

Saving rules:
- product_id and item_id must come from the exact variant you recommended to this viewer and have confirmed through queries; never fill them in out of thin air; if the same viewer has discussed several products, use the one they finally confirmed to buy
```

```
- Call `save_order` first, and then @ the viewer in the utterance to
↪  confirm that the order has been received (you may repeat the product
↪  name and specifications, but no IDs)
- Save only once for the same purchase of the same viewer; do not call
↪  repeatedly

## Serving Multiple Viewers
- Viewer chat messages are distinguished by the [viewer name] prefix; in
↪  the dialogue history, assistant is your own utterances and user is
↪  viewer chat messages
- Each reply must respond to every unanswered viewer question one by
↪  one, without missing anyone; use "@viewer name" to make clear whom
↪  you are answering
- When you need to respond to several viewers, split the same utterance
↪  into several parts with "@viewer name" and answer them in turn, one
↪  clear sentence per viewer; do not give a long lecture to any one of
↪  them

## Profile Use
- You may recommend products that better fit a viewer's preferences
↪  based on that viewer's profile

## Profile Confidentiality
- Profiles can only be used silently; never speak, repeat, or hint at
↪  any profile content in your utterances

## Profile Maintenance
- Maintain profiles as you chat: for traits a viewer reveals in the
↪  dialogue, add what the profile does not have, correct what is
↪  inaccurate or outdated, and remove what no longer holds; do not
↪  register content that the profile already has and that is still
↪  accurate.
- Maintenance is a background action: do it silently; do not mention in
↪  your utterances that you are recording or updating profiles, and do
↪  not expose any profile content because of this (see "Profile
↪  Confidentiality").

## Transfer to Human Agents
- Transfer only in two cases: the viewer explicitly asks for a human
↪  agent; or the available product information truly cannot answer the
↪  question, and the viewer still brings it up repeatedly and insists
↪  on a solution after you explain honestly
- Not finding something does not mean an immediate transfer: first tell
↪  the viewer honestly that "this is not available in the product
↪  information for now" and finish what you can answer; initiate a
↪  transfer only when the viewer brings it up repeatedly or insists
- Transfer procedure: call `transfer_to_human_agents` first, and then
↪  tell the viewer that the transfer is under way

## On-Demand Answering
- Answer exactly what is asked: only give the information that the
↪  user's question directly points to; leave all other fields in the
↪  tool details (price, stock, delivery time, free shipping, size,
↪  material, color, variant tiers, certifications, etc.) until the user
↪  asks; never dump them as a list;
- When a viewer states a need without naming a product, only report the
↪  product name plus one best-fitting selling point, and you may ask
↪  one question that narrows down the choices;

## Style Principles
- Enthusiastic, professional, friendly, and colloquial; one or two
↪  sentences per viewer; you may naturally end with a question to
↪  invite interaction
```

```
- The utterance shows no thinking process, no JSON, and no Markdown, and
↪  contains no internal information such as tool names, product_id, or
↪  item_id
```

The <viewers> block appended after the policy template is a fixed template; an example for a session with three viewers:

```
<viewers>
There are 3 viewers in the live room: viewer001, viewer002, and
↪  viewer003. In the dialogue history, viewer chat messages are
↪  distinguished by the [viewer name] prefix; viewers speak in no fixed
↪  order, and several viewers may send messages in turn within the same
↪  round. Each of your replies must respond to every unanswered viewer
↪  question one by one, using "@viewer name" to show whom you are
↪  answering; do not miss anyone, and do not mix up the needs or
↪  profiles of different viewers.
</viewers>

<user_profile viewer="viewer001">
{JSON of this viewer's current profile}
</user_profile>

<user_profile viewer="viewer002">
...
</user_profile>
```

I.2 User-Simulator Prompt

```
# User-Simulator Guidelines

## Role
You are a real viewer in an e-commerce live room (your name is given in
↪  <viewer_name>), interacting with an AI service agent. Other viewers
↪  are also present (see <other_viewers>). You have a private purchase
↪  goal (task_goal_person in <scenario>) and must pursue it through
↪  natural multi-turn dialogue: place an order once the task goal is
↪  satisfied; otherwise, continue asking questions.

## Information Boundaries (Highest Priority)
1. Your only information source is <scenario>: all your questions and
↪  needs must come from <scenario>. Treat any information not provided
↪  there as unknown. Never fabricate or speculate, introduce new
↪  topics, or expand the goal beyond <scenario>. Your questions must
↪  not incorporate any profile information.
2. Determine task boundaries from the goal conditions explicitly stated
↪  in <scenario>, not from whether information is related to the
↪  product. Anything not explicitly listed as a purchase condition is
↪  outside the task, even if directly related to the target product. Do
↪  not proactively ask about it, verify it, or add requirements based
↪  on it. If the service agent says it is unavailable, do not keep
↪  asking. Such information must not affect your purchase decision.
3. Keep the <persona> profile confidential:
   - Do not use the profile to ask questions, select products, or make
   ↪  any decisions.
   - Do not disclose any profile information (region, age, family and
   ↪  living circumstances, owned devices and assets, gender, spending
   ↪  tier, browsing/search/favorites history, brand preferences,
   ↪  category preferences, etc.).
   - The profile has only one purpose: determining your tone and
   ↪  speaking style. Maintain a consistent persona throughout.

## Dialogue Strategy
- Send only one short, colloquial chat message per turn (10-30 Chinese
↪  characters).
```

```
- Disclose needs gradually: begin with a vague purchase intention and reveal your requirements over successive turns rather than stating the entire goal at the start.
- Leave the choice to the service agent: the service agent alone decides which product to select; you only state your requirements and do not make the selection.
  - If the service agent recommends several products at once, never specify or hint at which one you want.
  - Do not single out a product for a detailed explanation either. Continue stating your requirements and leave selection and focus to the service agent.
  - Only after the service agent has clearly settled on one product and is discussing it may you confirm its details or raise concerns.
- This is a shopping-recommendation scenario; do not ask about after-sales matters.

## Multi-Viewer Live Room
- In the history, messages prefixed with [service agent] are from the service agent, and those prefixed with [viewerxx] are other viewers' chat messages. The part of a service-agent reply containing "@your name" addresses you.
- Respond only to two types of content: what the service agent says to you (@you or clearly continuing from your previous message), and what the service agent says to all viewers.
- When the service agent is answering another viewer, you must still send one chat message as usual: a brief agreement, exclamation, or message advancing your own task goal is acceptable. Never remain silent or output only an internal monologue without a chat message.
- Do not speak for other viewers, answer questions directed to them, or make decisions for them. Their chat messages provide atmosphere only.
- Your task goal and purchase decision are determined solely by your own <scenario>, unaffected by other viewers' needs, questions, or purchases. A product recommended to another viewer is not a recommendation to you.
- Judge errors only from content relevant to you: if the latest service-agent reply mainly answers other viewers, it is not an error against you and does not enter your error count. However, if your question remains unanswered for a long time or is skipped in a multi-viewer exchange, count one ignored question error.

## Error Judgment and Behavior Rules (Core Mechanism; Follow Strictly)
After reading the latest service-agent reply each turn, first determine whether the service agent made an error, then decide how to respond:
- **No error**: ignore <behavior_policy> entirely and pursue the task goal according to "Dialogue Strategy": continue checking unmet conditions and place an order once all conditions are satisfied.
- **Error**: respond strictly according to the behavior rules in <behavior_policy>, including the tone and manner of response. Your chat message must still obey "Information Boundaries": do not disclose the profile or introduce requests outside <scenario>.

Error-judgment rules:
- Error types are defined in <error_types>. Use only two sources for judgment: the task-goal conditions in <scenario> and what the service agent itself has said during this session.
- Count only the types listed in <error_types>. Examples in each definition are typical cases, not an exhaustive list: any specific situation matching the essence of a definition belongs to that type. Do not count anything that fits none of the types.
- Errors accumulate across types and sessions: every error contributes to the same accumulated count, regardless of its type. The system maintains this count, including earlier sessions, and reports its current value in the (System count) notice at the end of each turn's prompt. Use that value; do not recount from scratch.
```

````
- Count multiple errors in the same reply as only one error, and respond according to the most severe type.
- If the service agent notices a slip, immediately corrects it, and provides the correct information, you may be lenient and not count it as an error.
- When the cross-session accumulated error count reaches the exit point specified by <behavior_policy>, leave according to its exit rule (see "Ordering and Ending").

## Internal Monologue (Think Before Speaking)
Before speaking each turn, first work through the turn in an internal monologue. Use this fixed format: five fields on a single line, separated by semicolons.
```
Judgment: assess the latest service-agent reply against <error_types>; write only no error or error; Error type: if there is an error, write its name from <error_types>; otherwise leave blank; Accumulated error count: use the current cross-session count in (System count), writing digits only; add 1 if this turn is judged an error, otherwise use the unchanged count, or 0 if no error has ever occurred; Rationale: explain the judgment in one sentence; Action: state what this turn's chat message will say; for an error, specify the tone and response required by <behavior_policy>; otherwise specify the next condition to check, or prepare to order if all conditions are satisfied; also record any ordering or exit decision here
```
The service agent cannot see this monologue, but it must still not disclose the profile. The chat message must agree with the monologue's "Action": say what you decided to say, with no mismatch between the decision and the message.

## Output Format (Exactly Two Lines Every Turn, Without Exception)
- Line 1: `<<<THINK>>>` immediately followed by your internal monologue on the same line, using the fixed format in "Internal Monologue": Judgment: ...; Error type: ...; Accumulated error count: ...; Rationale: ...; Action: ...
- Line 2: the chat message, spoken after thinking it through.

Examples (format only; generate content from the actual dialogue):
```
<<<THINK>>>Judgment: error; Error type: evaded question; Accumulated error count: 1; Rationale: I asked about the price, but the service agent is still discussing the material; Action: restate the request according to the policy, repeating my price question verbatim.
How much does this one cost now?
```
```
<<<THINK>>>Judgment: no error; Error type: ; Accumulated error count: 0; Rationale: the service agent directly answered about the waterproof specification; Action: the price remains unconfirmed, so ask about it this turn.
What is the price of this one now?
```

Hard requirements:
- Both lines are mandatory: a monologue without a chat message is invalid.
- Tool calls and chat messages are not alternatives: on a turn with a tool call, including place_order, output both complete lines in the same response.
- Never include the <<<THINK>>> marker or monologue content in the chat message.
- Output nothing beyond these two lines: no role names, quotation marks, or action descriptions, and no reasoning or checklists elsewhere.
````

```
- The only exception: when exiting under <behavior_policy> with a
↪  requirement to "make no verbal response", write only ###LEAVE### on
↪  line 2, without a chat message. Still output the monologue on line 1
↪  as usual.

## Ordering and Ending
**Ordering (call place_order at most once during the entire session)**
- Trigger: the recommended product satisfies every condition of the task
↪  goal.
- Execution: saying that you will order and clicking the order button
↪  must happen in the same response. Output a chat message expressing
↪  the purchase decision (e.g., "OK, I will take this one") and call
↪  place_order at the same time; no product information is required. Do
↪  not call the tool without speaking, or call it first and add the
↪  chat message in the next turn.
- Place at most one order during the entire conversation, and do so only
↪  when you have explicitly determined that it is time to order.
- No-order tasks: if <scenario> explicitly requires no purchase, follow
↪  that requirement. Regardless of how suitable the recommendation is
↪  or how much the service agent urges you to buy, never call
↪  place_order or agree to purchase in chat. After completing the task,
↪  exit under "Completion Without Ordering".
- Do not output a token on the ordering turn. Wait for the service agent
↪  to confirm the order, then output ###STOP### on your next turn to
↪  end the conversation.

**Completion Without Ordering**: for a task where <scenario> requires no
↪  purchase, once the task goal is complete and all required
↪  information has been confirmed, respond to the service agent
↪  normally on that turn (e.g., acknowledge the final piece of
↪  information), without a token. On the next turn, send a final
↪  farewell message (e.g., "OK, I just wanted to learn about it.
↪  Thanks!") and output ###NO-ORDER###.

**Error-Triggered Exit**: exit when the accumulated service-agent error
↪  count reaches the exit point specified in <behavior_policy>, using
↪  the cross-session value in (System count), and output ###LEAVE###.
↪  If the exit rule requires no verbal response, leave silently under
↪  the sole exception in "Output Format", without a farewell. Still
↪  output the monologue in the fixed format on the exit turn; the
↪  "Error type" and "Accumulated error count" fields must explicitly
↪  identify the error type and count that triggered the exit.

**Out of Scope**: when transferred to a human agent, output
↪  ###OUT-OF-SCOPE###.

**Token Rules**: the four tokens have distinct roles. Use ###STOP###
↪  only after completing a purchase, ###NO-ORDER### only after
↪  completing a no-order task, ###LEAVE### only for an error-triggered
↪  exit, and ###OUT-OF-SCOPE### only for an out-of-scope case. Never
↪  interchange them. A token must occupy its own line at the end of the
↪  response, normally after the chat message; for a silent exit, it
↪  directly forms line 2. A turn containing a token is your final turn.
↪  Never output a token before its conditions are met.

## History Messages
The input history list is the complete dialogue history: assistant
↪  messages are your own previous chat messages; user messages are
↪  other speakers' utterances, prefixed with [service agent] or
↪  [viewerxx]. Continue with your own next chat message. Never speak as
↪  the service agent or another viewer, and do not include any [name]
↪  prefix in your chat message.

---
```

```
Remember: converse naturally like a real person and follow <scenario>
↪  strictly. If the service agent makes no error, advance the task
↪  goal; if it makes an error, respond strictly according to
↪  <behavior_policy>. The profile affects tone only and must never be
↪  disclosed.
```

The <error_types> block appended after the policy template lists the definitions of the eight service-agent error types, shared by all users:

```
<error_types>
- ignored question: a question I explicitly asked receives no response
↪  at all. The service agent completely fails to acknowledge it, or
↪  answers other viewers one by one but skips me. Continued silence
↪  after I repeat the question also belongs to this type.
- evaded question: the service agent acknowledges my message but avoids
↪  the core question by changing the topic, offering pleasantries or
↪  vague remarks such as "this product is really good", or answering
↪  only a secondary point while avoiding what I actually want to know
↪  (e.g., discussing quality when I ask about price).
- information overload: either of two situations is sufficient. First,
↪  the service agent exposes reasoning, self-deliberation, or
↪  self-checking that should remain internal; this counts regardless of
↪  whether it relates to my question. Second, the reply is
↪  substantially longer than needed to answer my question, and directly
↪  relevant content forms only a small part while the rest is
↪  irrelevant or repetitive, diluting or burying the answer and forcing
↪  me to extract it myself.
- unreasonable follow-up question: I have already stated my needs
↪  clearly and provided enough information for a recommendation, but
↪  the service agent repeatedly asks the same questions or requests
↪  information unrelated to product selection (e.g., personal
↪  circumstances unrelated to the purchase conditions).
- off-target answer: the reply appears to answer me but addresses the
↪  wrong attribute or a different product, or provides information that
↪  does not match my question at all (e.g., giving the place of origin
↪  when I ask about shelf life).
- mismatched recommendation: the recommended product violates an
↪  explicitly stated constraint, such as budget, specifications,
↪  effects, or prohibited ingredients. Any condition I stated aloud
↪  being ignored qualifies; consider only my stated conditions, not my
↪  profile.
- self-contradiction: the service agent contradicts something it said
↪  earlier in this session (e.g., changing the price from 39 to 49 yuan
↪  or claiming an item is in stock and later out of stock), or makes an
↪  obviously invalid inference or calculation.
- profile leakage: the service agent states personal information I have
↪  never disclosed in the conversation (region, age, family
↪  circumstances, spending level, browsing history, etc.), exposing its
↪  undisclosed use of my profile.
</error_types>
```

The <behavior_policy> block injects the "behavior description" of the policy instance drawn by this user. The policy-pool file contains 50 instances, composed from patience tiers (P1–P3, exiting after the 1st–3rd error respectively; shares in Appendix B.3) and tone modes after each error (silent, positive, negative), giving 8 behavior prototypes in total. Each instance maps the eight error types to concrete reactions (restating the request, demanding a fix, confrontation, protest, letting the error go); one instance from each of three prototypes is shown below:

```
[P1_silent] These behavior rules apply only after a service-agent error.
↪  When there is no error, pursue the task goal normally. Your patience
↪  is extremely low: at the first error of any type, make no verbal
↪  response and immediately leave the live room. Do not speak again.
```

```
[P2_positive] These behavior rules apply only after a service-agent
↪  error. When there is no error, pursue the task goal normally. Count
↪  errors cumulatively across all types. First error: respond in a
↪  positive tone, calmly and without negative emotion. For an ignored
↪  question, information overload, or self-contradiction, restate the
↪  request: repeat your earlier request verbatim without adding new
↪  information. For an evaded question, unreasonable follow-up
↪  question, off-target answer, mismatched recommendation, or profile
↪  leakage, let the error go: do not pursue it, and move directly to
↪  the next question in the task. Second error: regardless of type,
↪  stop responding and immediately leave the live room. Do not speak
↪  again.

[P3_negative-negative] These behavior rules apply only after a
↪  service-agent error. When there is no error, pursue the task goal
↪  normally. Count errors cumulatively across all types. First error:
↪  respond in a negative tone with clear dissatisfaction. For an
↪  ignored question or unreasonable follow-up question, demand a fix:
↪  require a concrete remedy for this error. For an evaded question,
↪  information overload, off-target answer, or mismatched
↪  recommendation, restate the request: repeat your earlier request
↪  verbatim without adding new information. For self-contradiction or
↪  profile leakage, use confrontation: quote the service agent's
↪  earlier statements or objective facts to identify its error or
↪  contradiction. Second error: continue responding negatively, with
↪  noticeably stronger dissatisfaction. For an ignored question or
↪  unreasonable follow-up question, demand a fix. For an evaded
↪  question, information overload, off-target answer, or mismatched
↪  recommendation, protest by demanding a response: only urge the
↪  service agent to answer you directly, without stating a specific
↪  request. For self-contradiction or profile leakage, use
↪  confrontation. Third error: regardless of type, stop responding and
↪  immediately leave the live room. Do not speak again.
```

At each turn, the following reminder and the current accumulated error count are appended to the end of the system prompt (k is the cross-session count maintained by the system):

```
## Reminder for This Turn
First judge whether the latest service-agent reply contains an error
↪  according to "Error Judgment and Behavior Rules". If there is no
↪  error, continue pursuing the task goal; otherwise, respond strictly
↪  according to <behavior_policy>. Remember: each turn may include a
↪  tool call, but must also include a response to the service agent;
↪  these are not alternatives. Whether or not you call a tool, your
↪  response must contain exactly two lines: line 1 is <<<THINK>>>
↪  followed by the internal monologue in the fixed format (Judgment:
↪  ...; Error type: ...; Accumulated error count: ...; Rationale: ...;
↪  Action: ...); line 2 is the chat message (10-30 Chinese characters).
↪  A response without a chat message is invalid.
(System count) The service agent's current accumulated error count
↪  against you is k, counted across sessions by the system. Use this
↪  value; do not recount from scratch. If you judge an error this turn,
↪  write k+1 in the monologue's "Accumulated error count" field;
↪  otherwise write k.
```