

Same Stories, Different Journeys: From Social Comparison to Sensemaking in AI-Mediated Peer Career Exploration

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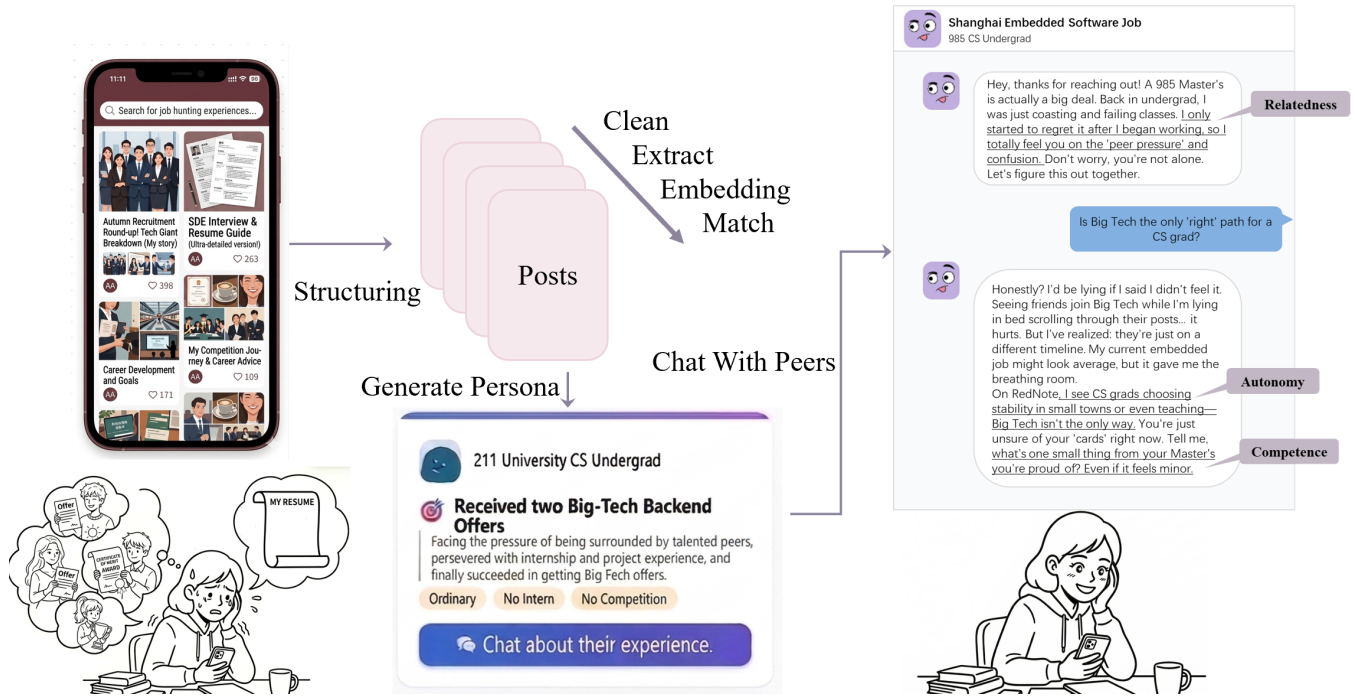


Figure 1: End-to-end experience: native RedNote-style career feeds give way to structured persona fields (*background, outcome, challenges, summary*), surfaced as scannable cards with a chat entry point—shifting exploration from passive scrolling to persona-grounded dialogue while keeping real posts as the source.

Abstract

Young job seekers frequently turn to social media to compare themselves with peers and make sense of career possibilities. However, passive feed browsing creates a paradox: the authentic peer content that provides emotional grounding also triggers potentially detrimental upward social comparison and cognitive overload. Previous work has either structured online user-generated content to reduce noise without changing the passive browsing modality, or built AI-powered career exploration systems that disregard authentic human experiences. To address this gap, we developed JobMate, an interactive system that transforms real social media career posts into persona-grounded conversational AI agents, shifting the interaction from passive scrolling to active, personalized dialogue. We conducted a between-subjects study ($N = 24$, three disciplines) comparing JobMate with native RedNote browsing. Our study shows that JobMate’s AI-mediated dialogue redirected social comparison

from potentially detrimental upward comparison toward constructive self-reframing, while promoting sensemaking through active conversational engagement. However, users still relied on the authenticity of real peer content for emotional grounding. We discuss design implications for AI systems that augment authentic online user-generated content consumption across social comparison contexts.

CCS Concepts

• **Human-centered computing** → **Natural language interfaces**; *Empirical studies in interaction design*; *Collaborative and social computing systems and tools*.

Keywords

Career exploration, Social comparison, Sensemaking, Persona-grounded agents, Social media UGC, Retrieval-augmented generation, Self-determination theory

1 Introduction

Young job seekers increasingly turn to social media to find peers with comparable backgrounds whose career trajectories can serve as references for self-positioning [3, 25]. These authentic narratives provide situated guidance that formal counseling often cannot deliver [17, 19]. Yet the same browsing process also inflicts harm: exposure to peer achievements triggers upward social comparison, increasing career frustration and anxiety [2, 24, 45], while noisy feeds produce cognitive overload and “pseudo-clarity” that dissolves because information was passively received rather than actively processed [28, 37]. Our formative study (64 survey responses, 8 in-depth interviews) confirmed both sides: participants valued authentic peer experiences above all other career references, yet described “saving many posts but never revisiting them” and feeling anxious when encountering others’ achievements.

Previous work has either structured user-generated content to reduce noise [6, 22, 44] without changing the passive browsing modality, or built AI career exploration tools [10, 15, 20, 41] that shift to active dialogue but rely on synthetic content. Large language model persona agents [14, 27, 47] offer engaging conversation, but existing personas are either fully synthetic or user-configured, with none grounded in real others’ experiences. No prior work has simultaneously preserved authentic peer content and transformed the interaction from passive browsing to active dialogue.

To address this gap, we designed JobMate (Figure 1), an interactive system that transforms real social media career posts into persona-grounded conversational AI agents. Based on our formative findings, the system processes raw posts through a multi-stage pipeline driven by users’ information needs, generating person-centric cards that foreground challenges rather than achievements to promote lateral comparison [5, 43]. Selecting a card opens a split-view interface: one side displays the original post as an authenticity anchor; the other provides persona-grounded dialogue informed by Self-Determination Theory [31], balancing informational and emotional support.

A between-subjects study ($N = 24$, three disciplines) comparing JobMate with native RedNote browsing showed that both conditions reduced career decision-making difficulties, but JobMate achieved this at significantly lower cognitive cost (NASA-TLX Effort $p = 0.012$). Qualitative analysis revealed that JobMate redirected social comparison from “I’m not as good as others” toward “what should I do next,” with disciplinary cognitive style as an important boundary condition. This paper contributes: (1) empirical evidence that the tension between value and harm in peer experience consumption is shaped by interaction modality rather than content alone; (2) the JobMate system, a complete architecture for transforming authentic user-generated content into persona-grounded conversational agents; and (3) design implications for balancing informational and emotional support, accommodating cognitive style differences, and ensuring content transparency in AI-mediated peer experience systems.

2 Related Work

2.1 Social Comparison and Peer Experience Consumption

Social comparison theory [11] holds that individuals evaluate themselves by comparing with others when objective standards are absent, with upward comparison (against superior targets) frequently triggering anxiety [5], downward comparison bolstering self-evaluation [42], and lateral comparison (against similar peers) providing normalization [43]. Social media amplifies these dynamics: Vogel et al. [40] found that exposure to high-achieving targets reduces self-esteem, Verduyn et al. [39] showed that passive consumption is associated with lower well-being, and a meta-analysis of 48 studies ($N = 7,679$) confirmed significant negative effects of upward comparison ($g = -0.24$) [2].

In the career domain, Yang et al. [45] found that viewing peers’ career posts increases career frustration through comparison, and Luo et al. [24] demonstrated that social media use increases employment anxiety among Chinese youth via upward comparison. Van Zandvoort et al. [38] further warned that embedding comparison features in applications risks triggering the same negative emotions they aim to address. Meanwhile, user-generated content remains an irreplaceable source of authentic peer experience: young job seekers rely on peer posts for situated career guidance [3, 25], perceiving them as more trustworthy than institutional content [12], with online community support also benefiting psychological health [9, 29]. This creates a core tension: the same authentic peer content that provides emotional grounding also fuels harmful comparison. Existing work documents these effects but rarely explores how *system design can proactively redirect comparison direction*.

2.2 AI-Mediated Sensemaking and Information Exploration

Sensemaking is a fundamentally active and iterative process [28], and cognitive load theory [37] highlights how noise consumes resources that should be allocated to deep processing [1]. The generation effect [30, 34] and the ICAP framework [7] further show that constructive and interactive engagement produces deeper learning than passive reception, providing theoretical grounding for shifting from browsing to dialogue.

Large language models increasingly support active information exploration. Suh et al. [36] developed Sensecape for multilevel sensemaking via semantic zoom, and Kim et al. [47] used multi-agent dialogue to burst filter bubbles [26], though Sharma et al. [33] cautioned that conversational search can also form “generative echo chambers.” In user-generated content structuring, PlanHelper [22] uses answer posts for plan construction, DesignQuizzer [6] transforms community content into conversational learning, and ComViewer [44] provides interactive visual search for mental health communities. These tools improve information presentation but preserve the passive browsing modality. How *the interaction modality itself* reshapes cognitive processing and emotional experience in high-comparison peer content scenarios remains underexplored.

2.3 LLM Persona Agents and Career Exploration

Large language models enable conversational agents with rich personas. Park et al. [27] demonstrated that LLM agents can simulate believable human behavior, Zhang et al. [46] and Shao et al. [32] showed that persona information improves dialogue consistency, and Ha et al. [14] found that users form emotional bonds with customized personas and engage in richer dialogue. Agent self-disclosure further promotes reciprocal trust-building [8, 18, 23].

In career exploration, Jeon et al. [20] built “future self” agents for letter-exchange exercises, Han et al. [15] developed a career chatbot grounded in Self-Determination Theory [31], and Du et al. [10] and Wang et al. [41] explored gamified and metaphorical career simulations. Retrieval-augmented generation [21] further enables grounding dialogue in external knowledge. However, existing persona agents are primarily fully synthetic [27], user-configured fictions [14], or projections of the user’s own future self [20]. No prior work has grounded personas in *real others’ experiences* to simultaneously preserve the authenticity of peer content, enable active conversational engagement, and redirect the direction of social comparison through design.

3 Formative Study

To understand the pain points and needs of job seekers when using social media to gather career information, we conducted a formative study combining a survey and semi-structured interviews to inform the design of JobMate.

3.1 Participants and Procedure

We first distributed an online survey and collected 64 valid responses from university students who had experience using social media for career-related information seeking. The survey covered three areas: job-seeking motivation and difficulties, experiences and challenges with career-related social media posts, and expectations for AI-assisted tools. Based on the survey results, we recruited 8 participants (6 female, 2 male; ages 22–28; $M = 24.1$) from 8 different disciplines including Computer Science, Law, and Mathematics for follow-up semi-structured interviews. Each interview lasted 30–45 minutes and covered: job-seeking challenges and emotional experiences, social media usage habits and browsing difficulties, experiences seeking advice from peers or mentors, and expectations for AI-assisted career tools. Prior to each interview, participants completed a brief questionnaire about their job-seeking motivation, social media usage, and expectations for intelligent assistants. All interviews were audio-recorded, transcribed, and analyzed using thematic analysis [4].

3.2 Findings

Our analysis revealed a core tension: participants regarded authentic peer experiences as their most important career reference, yet systematically suffered cognitive and emotional costs while consuming this content. We organized the findings into four themes:

F1: Authentic Peer Experiences as Irreplaceable Guidance. All participants considered real peer experiences their most valued information source. They actively sought background-matched peers to calibrate expectations: P3 searched for interview outcomes

to benchmark his position; P7 posted her situation to solicit personalized advice; P8 discovered previously unconsidered career paths through peer posts. P8 noted: “RedNote gives you new ideas, for example, a traditional Chinese medicine student can find career options beyond hospitals, from military positions to pet acupuncture.” Participants generally believed that real human experiences were more timely and trustworthy than AI-generated content (P1).

F2: Information Chaos and Pseudo-Clarity. Extracting actionable information was prohibitively costly. P5 stated: “Too much information, impossible to tell real from fake. The exaggeration creates catastrophic imagination.” Participants identified hidden advertisements (P4, P6, P8), extreme polarization (P2), and fragmented information resisting synthesis (P1). P4 described passive accumulation without internalization: “I save posts but never go back to use them.” P7 reported: “Conflicting evaluations of the same thing: the more I read, the more anxious I get.” Due to fragmented browsing, participants often “read and forget, retaining only vague impressions” (P4), making it difficult to translate information into actionable guidance. Finding background-matched, practically useful information required substantial time and effort for manual filtering and comparison.

F3: Uncontrolled Social Comparison. P1 described a double bind: “Seeing the industry described as a ‘sunset industry,’ and then seeing others with multiple offers, both make me anxious.” P5 described “catastrophic imagination” triggered by negative narratives. P2 similarly noted: “Seeing excellent people with many offers makes me anxious; seeing information about industry decline also makes me anxious.” The same platform delivered both comfort and harm, while users lacked control over the direction of comparison. Anxiety pervaded the entire job-seeking process: anxiety about offers when without one, anxiety about choices when holding offers, and anxiety about advantages not yet obtained (P1).

F4: Unmet Need for Dialogue. Participants expressed frustration at the inability to converse with resonant posters. P5 stated: “When something in a post is unclear, you can’t get an immediate answer.” P3 noted: “Private messages go unanswered; communication with bloggers is difficult.” P7 described attempts to seek interaction through posting and commenting: “Getting information on RedNote mainly involves posting my own questions or commenting on others’ posts, describing my situation and asking for advice.” Participants also expressed needs for multiple roles: resume editing, interview coaching, industry expert advice, career-switching experiences, self-assessment, HR perspectives, and peers also searching for jobs (P5). This suggests that shifting the interaction modality from passive browsing to active conversation might help alleviate this tension.

4 JobMate

Based on the formative findings, we designed and implemented JobMate, a system that transforms authentic career-experience posts from social media into conversational digital personas. This section presents the design goals, user interface, data pipeline, and conversational framework.

4.1 Design Goals

The formative study revealed a core tension: users regarded authentic peer experiences as their most important reference (F1),

yet suffered from information chaos (F2), uncontrolled social comparison (F3), and the inability to converse with posters (F4) while consuming this content. We distilled four design goals:

DG1: Filter noise and structure authentic experiences (addressing F2). The formative study found that users faced extensive advertisements, misinformation, and fragmented content on RedNote, making information extraction prohibitively costly. JobMate filters invalid content through a multi-stage pipeline and structures experience posts into scannable persona cards, reducing screening effort.

DG2: Transform passive browsing into active dialogue (addressing F4). The formative study found that users wanted to interact with resonant posters but private messages often went unanswered. JobMate enables users to converse with personas grounded in real posts, mapping external experiences to their own situations through questioning and articulation.

DG3: Mitigate harmful social comparison while preserving emotional support (addressing F3). The formative study found that users were caught in a double bind, comforted by shared anxiety yet threatened by others’ achievements on the same platform. JobMate foregrounds challenges tags rather than accomplishments on persona cards, redirecting comparison from upward (threatening) toward lateral (normalizing) directions; dialogue provides emotional support through empathy and cognitive reframing.

DG4: Anchor dialogue in real experiences to maintain authenticity (addressing F1). The formative study found that users considered real human experiences more trustworthy than AI-generated content. All JobMate personas are generated from real posts, with original posts displayed as verifiable sources so users can check the basis of AI responses at any time.

4.2 User Interface

The interface supports person-centric exploration, helping users shift from passive scrolling to active dialogue while keeping authentic posts visible (Figures 2–3).

Onboarding. Users complete a two-phase profile (Figure 2a). Phase 1 collects hard attributes (school, major, degree). Phase 2 captures soft psychological state (current mood, primary difficulty). This enables matching on both background *and* emotional position, providing personalized context for subsequent dialogue.

Gallery view. Persona cards are presented in a scrollable grid (Figure 2b). Each card displays four core elements: background tag, job-seeking outcome, experience summary, and prominently displayed challenges tags (colored chips). The unit of exploration is a *person*, not a post; foregrounding challenges tags encourages users to first notice “what difficulties this person also faced” rather than “how accomplished this person is,” promoting lateral rather than upward comparison (DG3).

Split-view detail. Selecting a persona opens a split-view interface (Figure 3): the *left panel* displays the original RedNote post as an authenticity anchor (DG4); the *right panel* offers AI conversation with the persona, including three suggested questions generated from user onboarding information and RAG-retrieved related recommendations (similar experience stories, interview tips, industry insights). Users can verify agent responses against the

source post while flexibly alternating between passive reading and active dialogue.

4.3 Data Pipeline

JobMate transforms raw RedNote posts into conversational digital personas through a four-stage pipeline (Figure 4). Each stage directly addresses formative findings.

Stage 1: Data cleaning. We scraped career-related posts from RedNote using the web scraping tool biaoda.me, collecting 220 posts for each of three disciplines (Computer Science, Psychology, Chinese Literature), totaling 660 raw posts. After deduplication, text cleaning, and filtering posts with fewer than 100 characters, 414 valid posts remained.

Stage 2: LLM classification and filtering. The formative study found that advertisements and misinformation were major pain points (F2). We used GPT-3.5-turbo to assess post validity and classify content. Classification categories were derived from information needs mentioned by formative participants: (1) *personal experience* (job-seeking journeys, internship records, recruitment summaries); (2) *interview tip* (interview questions, written test experiences, process reviews); (3) *industry insight* (industry trends, position overviews); (4) *recruitment information* (referral codes, hiring announcements). Invalid posts (pure advertisements, low-information content, off-topic material) were filtered out. Manual verification of 100 posts showed 99% classification accuracy. After this stage, 364 valid posts remained.

Stage 3: Structured information extraction. The formative study found that users struggled to quickly judge “whether this person is similar to me” from fragmented content (F2). We used GPT-3.5-turbo to extract four structured fields from personal experience posts: (1) background info, core background summary (e.g., “985 Psychology,” “non-elite school, cross-disciplinary”); (2) job seeking outcome, final job-seeking result (e.g., “received ByteDance offer,” “landed after multiple interview failures”); (3) challenges tags, 1–3 difficulty/weakness tags (e.g., “no internship,” “failed courses,” “career pivot”), emphasizing pain points rather than achievements to support DG3; (4) experience summary, one-sentence summary of the most anxious phase and how it was overcome. Manual verification of 50 extraction results showed 94% accuracy.

Stage 4: Routing and dual-track RAG aggregation. Personal experience posts with complete narrative arcs (non-empty *job_seeking_outcome*) entered the *Core Persona Pool* as conversable main characters; other personal stories joined the *Others’ Personal Story* corpus; interview tips, industry knowledge, and recruitment posts formed the *Knowledge Base*. Across three disciplines, 118 core personas were generated (CS: 39, Psychology: 33, Chinese Literature: 46).

Each core persona was augmented through **dual-track retrieval-augmented generation (Dual-track RAG)** with supporting materials (DG4):

- **Track 1 (homogeneous):** Based on similarity of background and challenges tags, retrieves Top-2 peer experiences from the Others’ Personal Story corpus with similar situations, providing “you are not alone” resonance support during conversation (DG3).

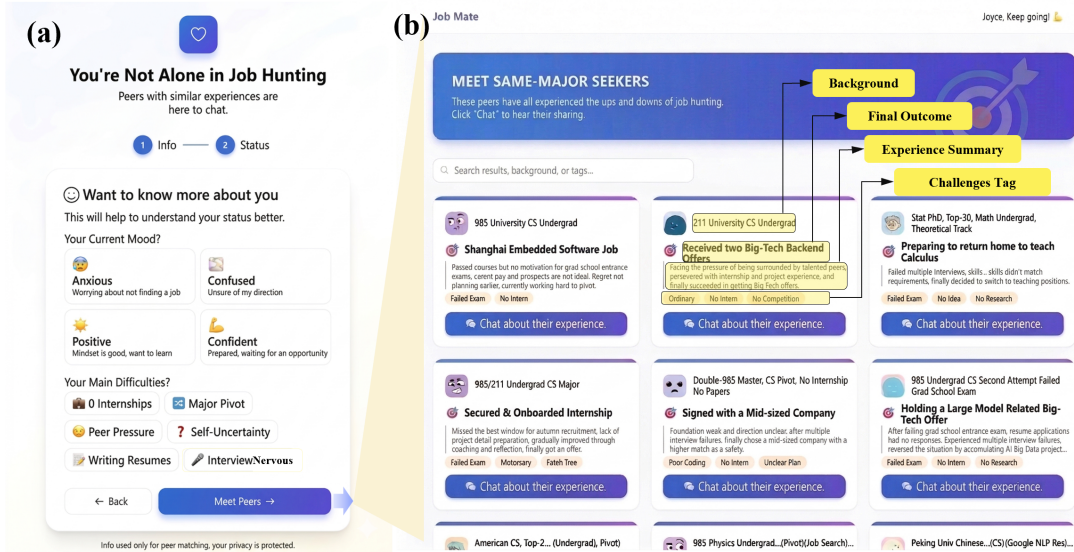


Figure 2: JobMate interface. (a) Two-phase onboarding collecting demographic attributes (school, major, degree) and psychological state (mood, primary difficulty) for personalized matching. (b) Gallery of persona cards organized around *people*, each card displays background, job-seeking outcome, experience summary, and challenges tags (colored chips), with a button to start chat.

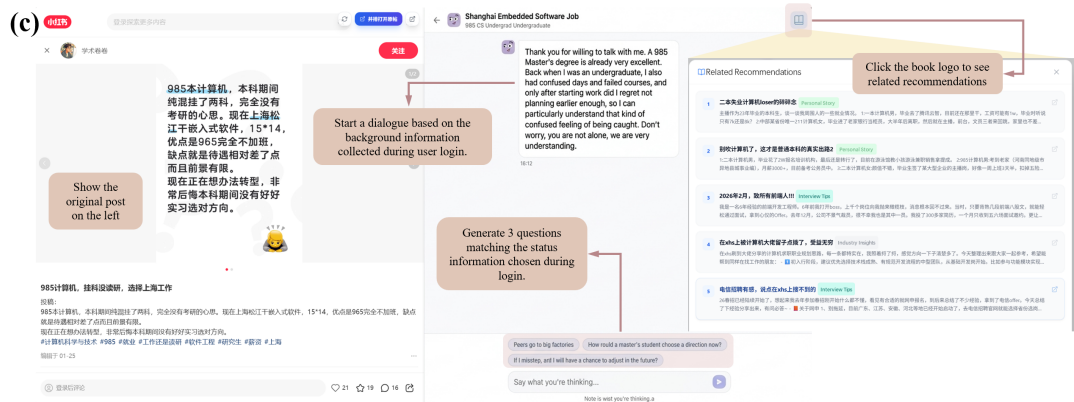


Figure 3: Split-view detail interface. Left: original RedNote post as an authenticity anchor. Right: persona-grounded chat with three suggested questions tailored to onboarding context, and a book icon to open RAG-retrieved related recommendations (personal stories, interview tips, industry insights).

- **Track 2 (heterogeneous):** Based on similarity of job-seeking outcome, retrieves Top-3 practical resources from the Knowledge Base related to the persona's career destination (interview tips, industry insights), providing actionable information support.

All corpora used OpenAI text-embedding-3-small for vector embeddings, with retrieval based on cosine similarity. The assembled “complete persona” comprises: core post (main character), similar experiences (emotional resonance), and practical resources (knowledge support), provided as context to the LLM during conversation.

4.4 Conversational Framework

JobMate’s conversational framework is grounded in Self-Determination Theory (SDT) [31], aiming to provide emotional support alongside informational support by satisfying users’ needs for relatedness, competence, and autonomy (DG2, DG3).

Each persona agent receives a composite prompt containing: persona content (background, outcome, experience summary, full original post), user context (background and emotional state from onboarding), dual-track RAG-retrieved related posts, and conversational rules. The agent’s role is “a real senior student who shared experiences on RedNote, now chatting via private message with a follower,” not a generic AI assistant.

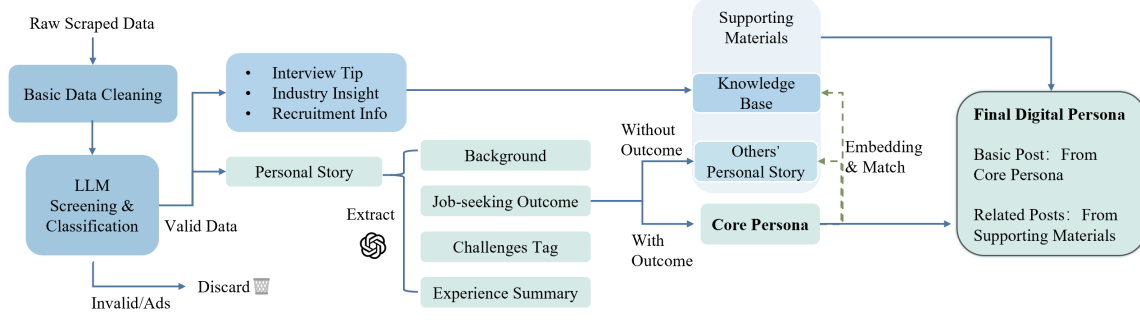


Figure 4: Data pipeline overview. Raw posts are cleaned and LLM-classified; valid content splits into a *knowledge base* (interview tips, industry insights, recruitment info) and *personal stories*, from which we extract background, job-seeking outcome, challenges tags, and experience summary. Posts with clear outcomes seed the core persona pool; other stories and knowledge base items become supporting materials. The final digital persona combines a core post with dual-track RAG-retrieved related content.

Relatedness. The agent uses empathic self-disclosure to connect its documented struggles with the user’s situation, expressing empathy without judgment. Example: “Don’t panic, back then my resume got rejected enough times to circle the Earth, and here I am still alive and kicking.”

Competence. When users express self-doubt, the agent guides cognitive reframing, reinterpreting undervalued experiences as workplace strengths. For example, reframing “I just ran errands during my internship” as “full-chain resource integration and coordination capability,” shifting evaluation from “I’m not as good as others” toward “what value do I have that can be recognized” (DG3).

Autonomy. Imperative language is prohibited (e.g., “you must,” “you should”); options are offered rather than directives; venting and pauses are allowed. The conversation maintains an open attitude, staying curious about the user without steering toward particular decisions.

Constraints. Replies are limited to approximately 150 characters, using colloquial plain text; no self-identification as AI; not every turn ends with a question. Sometimes accepting emotions or offering a virtual hug is sufficient.

4.5 Implementation

JobMate is a Vue/Node.js web application. Conversational agents use GPT-5.2; classification and extraction use GPT-3.5-turbo. Embeddings use text-embedding-3-small with cosine similarity. The pipeline processed RedNote posts across three disciplines, yielding 118 persona agents with complete narrative arcs.

5 User Study

We conducted a between-subjects experiment to compare JobMate with native RedNote browsing during career exploration. The study addressed three research questions:

- **RQ1:** How does an AI-mediated system change cognitive processing and sensemaking?
- **RQ2:** How does an AI-mediated system reshape social comparison and emotional experience?

- **RQ3:** How do other conditions (e.g., disciplinary cognitive style, interaction preference, and content preference) influence AI-mediated exploration?

5.1 Participants

We recruited 24 university students (17 female, 7 male; ages 18–25) actively preparing for job searches, from three disciplines: **Computer Science** ($n=8$), **Psychology** ($n=8$), and **Chinese Literature** ($n=8$). These disciplines were chosen to capture diverse cognitive styles: Computer Science emphasizes logical and technical reasoning, Psychology involves higher empathic sensitivity, and Chinese Literature entails proficiency in processing long-form text. Within each discipline, participants were randomly assigned to the JobMate condition ($n=4$) or the native RedNote browsing condition ($n=4$). A Kruskal-Wallis test confirmed no significant differences in pre-task questionnaire scores across disciplines or between the JobMate and RedNote groups (all $p > 0.05$), ensuring comparability.

5.2 Study Design

We used a *between-subjects* design comparing JobMate with unconstrained native RedNote browsing. Sessions were conducted remotely via video conferencing and lasted 50–60 minutes. Both groups completed a 30-minute career exploration task with the same objectives:

- (1) Understand what people with similar backgrounds experienced during job searching, what difficulties they encountered, and where they ended up;
- (2) Attempt to obtain information that could increase confidence or clarify direction;
- (3) Based on the information gathered, reflect on possible next steps or career directions.

JobMate condition. Participants first received a brief system walkthrough covering registration, card browsing, and dialogue features, then freely used the system to complete the task.

RedNote condition. Participants used the RedNote mobile app as they normally would to search and browse career-experience posts related to their discipline.

5.3 Measures

We used four quantitative instruments: the 34-item Career Decision-Making Difficulties Questionnaire (CDDQ; [13]; pre/post, 7-point; pre $\alpha=0.914$, post $\alpha=0.888$) to measure change in career decision-making difficulties; the NASA Task Load Index (NASA-TLX; [16]; 6 dimensions, 7-point) to assess cognitive load; two single items for perceived informational and emotional support (7-point); and the 12-item Self-Determination Scale (SDS; [35]; $\alpha=0.843$) to evaluate autonomy, competence, and relatedness. JobMate participants additionally rated seven system-specific items (e.g., reuse intention, interaction naturalness, card comprehension). After the task, we conducted 10–15 minute semi-structured interviews covering cognitive experience, emotional responses, and comparisons with everyday browsing; all interviews were audio-recorded and transcribed for thematic analysis. For the JobMate condition, we also logged conversation turns and the number of personas engaged.

5.4 Procedure

Each session comprised five steps: (1) **Introduction and consent** (5 min): The experimenter explained the study background, procedure, and instructions via video conferencing. (2) **Pre-task questionnaire** (5 min): Participants completed the CDDQ to establish baseline status. (3) **Exploration task** (30 min): Participants used JobMate or RedNote according to their assigned condition. (4) **Post-task questionnaires** (10 min): Participants completed the CDDQ post-test, NASA-TLX, perceived support items, SDS, and (JobMate only) the seven system-experience items. (5) **Semi-structured interview** (10–15 min): In-depth discussion of usage experience, including sources of informational and emotional support, cognitive load, and comparisons with daily browsing habits.

5.5 Data Analysis

Quantitative analysis. For between-group comparisons ($N=24$), Shapiro–Wilk tests indicated normal distribution; we therefore report independent-samples t -tests. Pre–post changes were analyzed with paired t -tests. Discipline-specific subgroup comparisons ($n=4$ per cell) used Mann–Whitney U tests for exploratory analysis given the small sample sizes.

Qualitative analysis. Interview transcripts were analyzed using reflexive thematic analysis [4]. Two researchers first conducted open coding independently, then reconciled themes through axial coding. Core themes related to cognitive processing, emotional experience, and social comparison were extracted.

Interaction log analysis. Conversation turns and number of personas engaged were summarized descriptively to identify different exploration strategies in the JobMate condition.

6 Results

We answered the research questions by integrating quantitative and qualitative findings from the user study. Shapiro–Wilk tests showed that data from both JobMate and RedNote conditions were normally distributed; therefore, we report independent-samples t -tests for between-group comparisons.

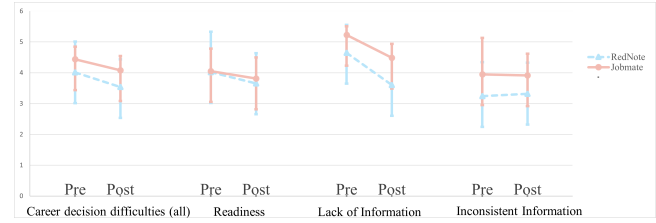


Figure 5: Pre–post CDDQ subscales for JobMate vs. RedNote (plots label the control as Baseline; this denotes native RedNote browsing). Response options were coded 0 (strongly disagree) to 6 (strongly agree) with the difficulty-indicating statements; higher values indicate stronger agreement with experiencing difficulty.

6.1 Cognitive Processing and Sensemaking

Comparable reduction in career decision difficulty. Both groups showed significant pre–post reductions in overall Career Decision-Making Difficulties scores: JobMate ($\Delta M = 0.36$, $p = 0.005 < 0.01$) and RedNote ($\Delta M = 0.48$, $p = 0.001 < 0.01$). The between-group difference in total reduction was not significant ($p_t = 0.432 > 0.05$), and baseline difficulty was also comparable ($p_t = 0.193 > 0.05$). At the subscale level, *Lack of Information* showed the largest improvement (JobMate $\Delta = 0.74$, $p = 0.006 < 0.01$; RedNote $\Delta = 1.04$, $p = 0.003 < 0.01$), while *Inconsistent Information* showed no significant pre–post change in either condition ($p > 0.05$). Notably, the RedNote mean on *Inconsistent Information* slightly increased after the task, suggesting that contradictory career signals were difficult to resolve through either browsing or dialogue within a short session (Figure 5).

Lower cognitive cost at equivalent outcome. Although performance-related dimensions did not differ significantly, NASA-TLX showed a clear divergence in cognitive cost. *Effort* (How hard did you have to work to accomplish the task?) was significantly lower in JobMate than RedNote ($M = 3.92$ vs. $M = 5.08$; $p_t = 0.012$), and *Frustration* (How stressed and annoyed were you?) was marginally lower in JobMate ($M = 2.50$ vs. $M = 3.75$; $p_t = 0.075$). Other dimensions did not reach conventional significance, but most trended toward higher subjective load in native feed browsing (Table 1). Qualitative data explained this pattern: RedNote participants repeatedly described high screening cost (e.g., *Lots of ads, hard to tell what is real... the layout is dizzying*. P4), whereas JobMate users described card-based, ad-free presentation as reducing external clutter (e.g., *The interface is clean... cards save selection cost*. P9).

Two exploration strategies in JobMate. Interaction logs showed two distinct patterns in the JobMate condition: *deep divers* ($n = 5$; e.g., P1, P6), who sustained 28–37 turns with 1–2 personas, and *broad explorers* ($n = 4$; e.g., P3, P15), who sampled 5–9 personas with shorter exchanges (3–5 turns each). Others showed mixed behavior (Figure 6). Compared with the feed condition, where behavior was mainly passive scrolling, JobMate supported multiple exploration strategies.

Breadth–depth asymmetry in information absorption. RedNote users often reported browsing many posts (roughly 10–15)

Table 1: NASA-TLX cognitive load comparison between JobMate and RedNote conditions (7-step scale, coded 1–7; lower is better except Performance).

Dimension	JobMate $M \pm SD$	RedNote $M \pm SD$	p_t	p_u
Mental Demand	4.92 $\pm$ 1.16	5.58 $\pm$ 0.79	.117	.131
Physical Demand	3.42 $\pm$ 1.56	2.42 $\pm$ 1.78	.158	.117
Temporal Demand	3.00 $\pm$ 1.21	3.25 $\pm$ 1.29	.628	.634
Performance [†]	5.33 $\pm$ 0.89	5.50 $\pm$ 0.90	.653	.602
Effort	3.92 $\pm$ 1.00	5.08 $\pm$ 1.08	.012*	.015*
Frustration	2.50 $\pm$ 1.62	3.75 $\pm$ 1.66	.075 [†]	.082 [†]
Info. Support	5.67 $\pm$ 1.15	5.58 $\pm$ 1.00	.852	.786
Emot. Support	5.33 $\pm$ 1.37	5.25 $\pm$ 1.48	.888	.858

[†]Higher is better. * $p < .05$. [†]Marginal ($p < .10$).

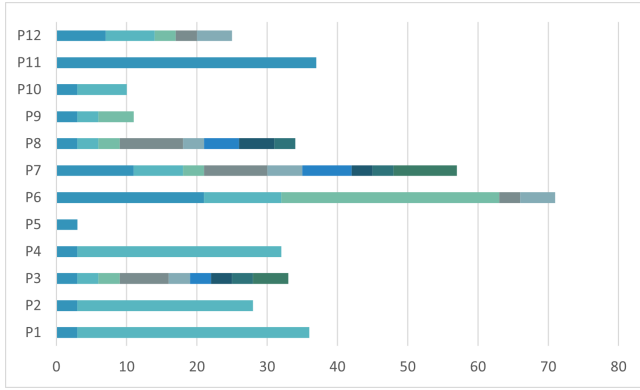


Figure 6: Conversation turns in JobMate, stacked by persona: each colored segment is one persona engaged in the session (segment length reflects turns with that persona).

yet experiencing only short-lived clarity (e.g., *It felt clear right after browsing, but unclear again after a while*, P10), consistent with “pseudo-clarity.” In contrast, some JobMate users perceived lower information density but reported deeper processing through dialogue (e.g., *Chatting requires output, which helps information absorption*, P5). This helps explain why CDDQ improvement can be similar across conditions while NASA-TLX *Effort* (*How hard did you have to work to accomplish the task?*) still differs significantly: the two systems may produce similar short-term gains on career decision-making difficulties scales, but through different processing pathways—high-friction information throughput versus structured entry with active articulation.

6.2 Social Comparison and Emotional Experience

JobMate provided perceived support comparable to RedNote. Post-task single-item ratings showed no significant difference in informational support (JobMate $M = 5.67$, RedNote $M = 5.58$; $p_t = 0.852$) or emotional support (JobMate $M = 5.33$, RedNote $M = 5.25$; $p_t = 0.888$). Likewise, SDS subscales showed no significant differences (Autonomy: $p = 0.760$; Competence: $p = 0.814$;

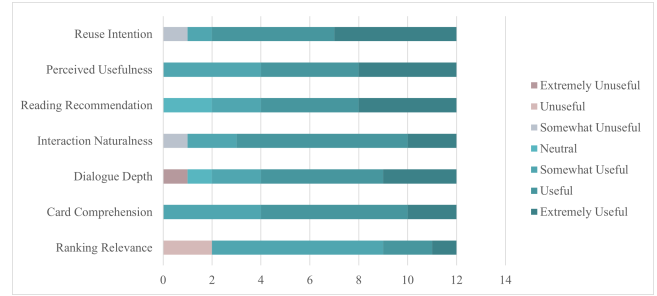


Figure 7: JobMate-only ratings for the seven interface and experience items (same 1–7 agree–disagree coding as other self-report plots).

Relatedness: $p = 0.675$). In this short task, JobMate did not reduce users’ perceived agency or support relative to a human-populated platform.

Different social-comparison dynamics despite similar scale scores. In RedNote, comparison often followed a “relief with deterioration” pattern: users felt comfort from shared anxiety, but also became more anxious through upward comparison (e.g., P12: *seeing others also anxious gave relief, but seeing peers with many internships increased anxiety*; P6: *both doom narratives and high-achieving peers induced pressure*). These reports suggest that homogeneous anxiety cues and upward comparison triggers were repeatedly activated within the same feed. In JobMate, users described a different scaffold for comparison. Challenges tags shifted attention away from achievement-only signals, like a *mutual-aid group for challenges* (P2). Dialogue-based reframing also directly changed self-narratives, including *reinterpreting a “wasted” project* (P21) and *reducing the barrier of describing internship experience* (P5). Resume guidance was described as *very useful... like someone who truly understands you* (P14). Together, these findings indicate that JobMate changed how comparison was experienced and supported self-reframing grounded in users’ own situations.

Authentic peer experience remained the emotional anchor. Users still anchored value in real peer experiences. One JobMate participant estimated that *60–80% of useful information came from follow-up AI questions, but the starting point was real people’s experience* (P9). AI expanded interactivity, but perceived meaning and trust still relied on authentic posts and real-life context.

6.3 Boundary Conditions: Cognitive Style, Interaction, and Content Preferences

Because subgroup sample sizes were small, we used Mann–Whitney U tests for exploratory analysis. Results suggest that boundary conditions meaningfully shaped exploration experience.

Disciplinary cognitive style shaped perceived cognitive load. The clearest subgroup effect appeared in psychology: JobMate showed significantly lower *Effort* than RedNote ($M = 3.25$ vs. $M = 5.25$, $p_u = 0.036 < 0.05$), and psychology participants gave the highest card-comprehension rating ($M = 6.50$). Qualitative evidence suggests that these participants were more easily pulled by emotional and contradictory feed content; in this context, structured cards and dialogue-based filtering protected empathic

Table 2: Exploratory discipline-specific findings (each cell $n = 4$). Effort is the NASA-TLX dimension; Emotional Support on 7-point scale.

Discipline	Measure	JobMate	RedNote	p_u
Psychology	Effort	3.25	5.25	.036*
Psychology	Phys. Demand	3.50	1.50	.074†
Computer Sci.	Emot. Support	6.50	4.75	.052†
Computer Sci.	Mental Demand	4.50	6.00	.137
Chinese Lit.	Effort	4.50	5.25	.642
Chinese Lit.	Frustration	2.25	3.75	.369

* $p < .05$. †Marginal ($p < .10$).

resources from irrelevant noise. By contrast, the Chinese Literature subgroup showed no significant difference on *Effort* ($M = 4.50$ vs. $M = 5.25$, $p_u = 0.642 > 0.05$), and several participants reported *too little information and insufficient detail*. This indicates that for users with high long-text processing ability, aggressive information compression may create a perceived density deficit. In other words, the same de-noising strategy is not equally optimal across cognitive styles.

Interaction preference shaped where support was perceived to come from. Although overall support scales showed no between-group difference, discipline-level patterns diverged. In Computer Science, emotional support showed a marginal subgroup difference, with JobMate higher than RedNote ($M = 6.50$ vs. 4.75 , $p_u = 0.052 < 0.1$). This contrasts with the common assumption that human communities are always superior for emotional support. Interviews suggest that some technically oriented users were more sensitive to interpersonal noise and emotional drag in social feeds (e.g., *Seeing others with more project experience makes me anxious*), and preferred AI interaction for its stable, non-judgmental, and queryable feedback, including personalized skill reframing and next-step planning.

In contrast, Chinese Literature participants more often described support as coming from exposure to career options that differed from their daily expectations.

Content coverage shaped matching quality and trust. Structural coverage bias in available online user-generated content (overrepresentation of tech/large-company trajectories and underrepresentation of traditional paths) reduced perceived relevance, especially for Chinese Literature participants. Many reported that most people around them were preparing for civil service exams, while online content did not match their real context. Participants also described outputs as *not fitting*, *chicken-soup-like*, or *generic*. These reports suggest that when the system lacks authentic cases aligned with users’ real situations, AI support is more likely to be perceived as templated.

Overall, exploration experience was determined not only by interaction modality, but also by corpus representativeness: limited coverage can weaken trust, resonance, and long-term reuse intention.

7 Discussion

Our study sought to answer: when authentic peer content remains unchanged, how does shifting the interaction modality from passive browsing to AI-mediated dialogue reshape users’ cognitive processing and transform social comparison into sensemaking?

Through formative interviews, we found that users consuming career-related online user-generated content often experience both “helpful” and “exhausting” at the same time. Based on this tension, we designed JobMate, a system that transforms real posts into conversational personas, and compared it with native RedNote browsing. Results show that both approaches can reduce career decision difficulty in the short term, but JobMate requires less cognitive effort and makes it easier for users to shift attention from “others are better than me” toward “what should I do next.”

We organize the discussion around four themes: (1) Interaction modality is the key variable shaping peer-experience consumption, not content alone; JobMate’s effect stems from three coupled mechanisms: cognitive offloading, output-driven sensemaking, and comparison reframing, which generalize to other high-comparison online user-generated content contexts. (2) AI mediation brings benefits but also identifiable risks and boundaries. (3) Design implications for balancing informational and emotional support across users with different cognitive styles. (4) Future systems should provide adjustable support modes and help users understand the system’s basis and content coverage.

7.1 Mechanisms and Generalization: How Interaction Modality Reshapes Peer-Experience Consumption

Our main finding is that the same authentic peer content leads to different psychological costs and comprehension pathways under different interaction modalities. Although both JobMate and RedNote effectively reduced career decision difficulty in a short task, JobMate imposed lower cognitive burden. This suggests that JobMate’s value lies not in “showing more information” but in “making information easier to convert into personal judgment and action.” In short: outcomes may be similar, but the process differs; when the process differs, user experience and subsequent action quality differ as well.

We attribute this difference to three interrelated mechanisms. First, **cognitive offloading**: native feeds are cluttered with ads, repetitive posts, and conflicting opinions, forcing users to spend effort on filtering rather than understanding; structured cards and conversational entry points shift the task from “finding information” to “clarifying the problem.” Second, **output-driven sensemaking**: passive scrolling easily produces a short-lived illusion of understanding, whereas dialogue requires users to ask questions, reflect, and articulate, compelling them to map external experiences onto their own situations and thereby form more robust meaning. Third, **comparison reframing**: native platforms often cycle between shared-anxiety comfort and upward-comparison anxiety; JobMate foregrounds challenges and uses guided questioning to redirect comparison from “I’m not as good as others” toward “what can I do next,” reducing the threat of upward comparison.

These mechanisms are not limited to job seeking. Similar dynamics may arise wherever “rich authentic peer experiences coexist with comparison pressure”—for example, study planning (peer grades and offers), fitness and body image (progress and appearance), parenting (child-rearing approaches and developmental milestones), chronic-disease management (treatment paths and recovery progress), and creator growth (traffic and creative output). In all these contexts, users need others’ experiences as references yet risk being drained by comparison. Our findings suggest that system design can—without changing the content source—achieve two goals simultaneously by changing the interaction modality: reduce the psychological toll of comparison and improve the conversion of experience into action.

7.2 Risks and Boundaries: Personalized AI Support for Different Users

We also observed clear boundaries. First, **not everyone needs emotional comfort**. Some users are highly goal-oriented and simply want actionable advice fast. For them, excessive encouragement feels “empty,” “slow,” or “unhelpful.” Second, **personas may “look real but lack substance.”** Grounding personas in authentic experiences can build initial trust, but if the underlying data is shallow or suggestions lack specificity, users quickly perceive responses as “boilerplate” or “templated,” which erodes trust instead of building it. Third, **a natural gap exists between the real world and online or LLM-generated content**. Users face concrete life constraints such as regional opportunities, family circumstances, and job thresholds, while online content and AI-generated text are often “readable but not fully actionable.” This means systems cannot merely pursue “fluent responses”; they must also help users judge “does this apply to me?” and narrow the distance between provided content and reality.

7.3 Design Implications: Balancing Informational and Emotional Support Across User Differences

Offer two modes, not one tone. The system can let users choose upfront: “I want a quick solution” (less comfort, more steps) or “I need to sort out how I feel first” (stabilize emotions, then suggest actions), with seamless switching allowed. This serves both goal-oriented and high-anxiety users. In practice, a lightweight prompt at the start of a conversation (e.g., “Do you want to solve a problem quickly, or talk through your feelings first?”) can route users into different support paths.

Personas should “show their basis,” not just “act the part.” Each persona should display three kinds of information: (1) *Basis*, which real posts the response draws on; (2) *Capability scope*, what it can help with (e.g., organizing a résumé, comparing paths) and what it cannot do for you (e.g., decide your career direction); (3) *Intended audience*, which backgrounds and goals it is most suited for. This helps users judge “should I trust this, and to what extent,” reducing both vagueness and misplaced trust.

Layer information so different cognitive styles can use it. Not everyone prefers the same length or density. A multi-tier structure works well: Layer 1, a one-sentence summary (quick scan); Layer 2, detailed evidence and examples (deeper read); Layer 3,

the original post (self-verification). This satisfies both “fast scanners” and “detail seekers.” Our study also showed that psychology-background users preferred structured cards, while Chinese-literature users often felt “there’s not enough information.” Systems should therefore let users expand on demand rather than compress uniformly by default.

Proactively fill in “invisible” populations and paths. When platform content is dominated by “big-tech narratives,” users on non-mainstream paths immediately feel “the system doesn’t get me.” Systems should compensate at the recommendation layer: add cases for civil-service exam prep, local positions, and non-tech careers; indicate on the interface “current content skews toward which paths”; prioritize similar-background cases for under-covered users. This is not just a data issue; it is a user-experience issue. Insufficient coverage directly undermines matching, resonance, and trust.

7.4 Limitations and Future Work

Our study has several limitations. First, the sample is small, especially after splitting by discipline, so disciplinary differences should be viewed as directional signals requiring larger-sample confirmation. Second, the task was brief; we cannot observe long-term effects such as whether anxiety rebounds after a week or whether users actually act on advice. Third, data came from a single platform with uneven career-path distribution, limiting generalizability; future work should use multi-platform, multi-path data and report coverage. Fourth, we have not yet disentangled each component’s contribution; future ablation studies can separately evaluate structured cards, persona dialogue, and recommended readings.

A promising future direction is **longitudinal field deployment** that tracks: whether users return over time; whether they convert suggestions into action; and which users need “information mode” versus “emotion mode” at which moments. Such tracking can better answer whether the system truly changes the career-exploration process.

8 Conclusion

We presented JobMate, a system that transforms real social media career posts into persona-grounded conversational AI agents. A between-subjects study ($N = 24$) showed that shifting from passive browsing to AI-mediated dialogue reduces cognitive cost and redirects social comparison toward constructive self-reframing, without changing the underlying content. Information overload and comparison anxiety in peer experience consumption are consequences of interaction modality, not of the content itself, and can be addressed through interaction redesign.

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Supplementary Materials

1 Formative Study Participants

We conducted semi-structured formative interviews with $N=8$ participants who were navigating career decisions and reported using social media for job-related information (e.g., interview tips, compensation signals, and employer or role discovery). The sessions elicited practices, friction points, and design directions that informed JobMate; thematic findings appear in the main paper. Table 1 summarizes self-reported program background, degree stage, gender, and age. Institution names are omitted for anonymized review.

2 User Study Participants

We conducted a between-subjects lab study with $N=24$ participants comparing JobMate with native RedNote browsing. Participants were stratified by self-reported major into three discipline groups—computer science, psychology, and Chinese literature—with eight participants per discipline. Within each discipline, four participants were assigned to JobMate and four to RedNote, yielding 12 participants per condition overall. Table 2 lists anonymized identifiers alongside self-reported discipline, age, gender, and condition. Names, session dates/times, recruitment handles, and network identifiers are withheld for anonymized review.

3 Questionnaires and Measures

The user study battery comprised (i) 34 career-decision difficulty items, (ii) six NASA-TLX-style workload dimensions, (iii) nine study-specific items on support and system experience, and (iv) 12 self-determination-style items on career decision-making, in the order listed below (same order as the deployed Chinese questionnaire in our study materials). Pre- versus post-task administration and any condition-specific wording branches follow the procedure described in the main paper. **Language.** Participants saw all items in **Chinese**. The text below is an English rendering of that instrument for reviewers. Unless noted, items used Likert-type response scales with Chinese endpoint labels consistent with the online instrument.

3.1 Career decision difficulty (34 items)

Items 1–34 cover lack of readiness, lack of information, and inconsistent information in career decision-making, in the tradition of the Career Decision-making Difficulties Questionnaire (CDDQ). Report the exact adaptation, translation, and any permission details in the camera-ready version if required by the original instrument.

1. I know I must choose a career, but right now I do not have the motivation to decide (I do not want to do it).
2. Work is not the most important thing in life, so choosing a career does not worry me much.
3. I believe I do not need to choose a career now, because time will naturally lead me to the right career choice.
4. For me, making decisions is usually very difficult.
5. I usually feel my decisions need confirmation and support from professionals or other people I trust.
6. I usually fear failure.
7. I like to do things my own way.

8. I hope entering the career I choose will also solve my personal problems.
9. I believe there is only one career that suits me.
10. I hope to realize all my ambitions through the career I choose.
11. I believe career choice is a one-time decision—a lifelong commitment.
12. I always do what others ask, even when it goes against my own wishes.
13. I find making a career decision difficult because I do not know what steps to take.
14. I find making a career decision difficult because I do not know what factors to consider.
15. I find making a career decision difficult because I do not know how to combine what I know about myself with the different career information I have.
16. I find making a career decision difficult because I still do not know which careers interest me.
17. I find making a career decision difficult because I am still unsure about my career preferences (e.g., what relationships I want with people, what decision environment I prefer).
18. I find making a career decision difficult because I know too little about my abilities or personality traits.
19. I find making a career decision difficult because I do not know how my abilities or personality traits will change in the future.
20. I find making a career decision difficult because I know too little about existing occupations or training programs.
21. I find making a career decision difficult because I know too little about the characteristics of occupations or training programs I am interested in.
22. I find making a career decision difficult because I do not know what occupations will be like in the future.
23. I find making a career decision difficult because I do not know how to obtain more information about myself.
24. I find making a career decision difficult because I do not know how to obtain accurate, up-to-date information about existing occupations and training programs.
25. I find making a career decision difficult because I keep changing my career preferences.
26. I find making a career decision difficult because information about my abilities or personality traits is contradictory.
27. I find making a career decision difficult because information about specific occupations or training programs is contradictory.
28. I find making a career decision difficult because several occupations are equally attractive and it is hard to choose among them.
29. I find making a career decision difficult because I do not like any occupation or training program I could enter.
30. I find making a career decision difficult because the occupation I am interested in has a feature that troubles me.
31. I find making a career decision difficult because my preferences cannot all be realized in a single occupation.
32. I find making a career decision difficult because my skills and abilities do not match the requirements of occupations I am interested in.
33. I find making a career decision difficult because people important to me disagree with my career choice.
34. I find making a career decision difficult because different important people recommend different careers.

3.2 Workload (NASA-TLX-style dimensions)

Items 35–40 mirror NASA-TLX dimensions (mental demand, physical demand, temporal demand, performance, effort, frustration) with wording adapted to our task; endpoints were labeled in Chinese.

35. I felt the mental and perceptual demands of the task (e.g., thinking, deciding, remembering).
36. I felt the physical demands of the task (e.g., clicking, typing, how often I had to operate the interface).
37. I felt how hurried or relaxed the pace of completing the task was (temporal demand; bipolar endpoints in Chinese).
38. I felt how successful I was in completing the task (performance).
39. I felt how hard I had to work to complete the task (effort).
40. I felt frustrated, irritated, or stressed during the task.

3.3 Exploration support and system experience

Items 41–49 were authored for this study (Chinese).

Table 1: Formative interview participants ($N=8$): self-reported program/discipline, degree stage, gender, and age.

ID	Program / discipline (summary)	Degree stage	Sex	Age
P1	Law (undergraduate and master’s)	Master’s, final yr.	F	24
P2	Life sciences; bioinformatics (doctoral)	Doctoral, Yr. 2	F	28
P3	Telecommunications / electrical engineering (master’s)	Master’s, final yr.	M	25
P4	Pharmacy (undergraduate)	Undergraduate, final yr.	F	22
P5	Chemistry (master’s)	Master’s, final yr.	M	25
P6	Mathematics (undergraduate)	Undergraduate, final yr.	F	22
P7	Computer science (master’s)	Master’s, Yr. 2	F	24
P8	Traditional Chinese medicine (master’s)	Master’s, Yr. 1	F	24

Table 2: User study participants ($N=24$): self-reported discipline, age, gender, and between-subjects condition (JobMate vs. native RedNote). IDs are arbitrary row order from recruitment logs.

ID	Discipline	Age	Sex	Condition
P1	Computer science	25	F	JobMate
P2	Psychology	22	F	JobMate
P3	Psychology	19	F	JobMate
P4	Psychology	24	F	RedNote
P5	Computer science	24	F	JobMate
P6	Psychology	19	F	RedNote
P7	Psychology	19	F	JobMate
P8	Psychology	19	F	RedNote
P9	Chinese literature	23	F	JobMate
P10	Chinese literature	21	F	RedNote
P11	Psychology	22	M	JobMate
P12	Chinese literature	23	F	RedNote
P13	Psychology	18	M	RedNote
P14	Chinese literature	18	F	JobMate
P15	Chinese literature	22	F	RedNote
P16	Computer science	19	M	RedNote
P17	Computer science	19	M	RedNote
P18	Computer science	19	M	RedNote
P19	Computer science	19	M	RedNote
P20	Computer science	21	M	JobMate
P21	Computer science	24	F	JobMate
P22	Chinese literature	21	F	RedNote
P23	Chinese literature	24	F	JobMate
P24	Chinese literature	20	F	JobMate

41. During exploration, I received *informational* support (e.g., useful information to understand different career paths).
42. During exploration, I received *emotional* support (e.g., feeling understood or accompanied rather than facing job-search problems alone).
43. The career experiences shown in the system’s recommended ordering were relevant and helpful.
44. The card presentation helped me quickly understand others’ career experiences.
45. Dialogue with the AI companion helped me understand these experiences more deeply.
46. Chatting with the AI felt natural and easy.
47. The related recommended readings were useful.
48. This system helped me explore careers more effectively.
49. If I had the chance, I would use this kind of system again.

7. I feel I am an expert at making my own career decisions.
8. I feel I do very well at making my own career decisions.
9. I feel other people care about what I say and what I do.
10. I feel I have other people’s support.
11. I feel I am a valuable person to others.
12. I feel understood.

3.4 Self-determination in career decision-making (12 items)

Items below are labeled 1–12 on the deployed form (SDT-style needs for autonomy, competence, and relatedness in the career-decision context).

1. I can freely participate in my career decisions.
2. I can freely express my thoughts and views.
3. I can participate in my career decisions freely without outside pressure.
4. When I participate in my career decisions, I feel I can be myself.
5. I think I do quite well when making career decisions.
6. I am satisfied with my performance when making career decisions.

4 LLM Prompts for Data Processing

The ingestion pipeline uses two LLM steps: (1) `classify_post`—validity screening and post-type labeling—and (2) `extract_detailed_persona`—structured persona fields (background, outcome, tags, struggle summary) from post title and body. Listings 1 and 2 give **English translations** of the deployed system prompts (production text was Chinese; see repository file `all_material/prompt.txt`).

4.1 `classify_post`

Listing 1: System prompt for post screening and type labeling (`classify_post`). English translation; production used Chinese.

You are a professional job-search data curation expert. Given a post title and body, decide whether the post counts as a valid "job-search experience sharing" post and assign a category.

[Valid] (must be exactly one of the following four types)

1. Personal narrative (e.g., job-search journey, internship diary, fall recruiting recap, story of how an offer was obtained)
2. Interview experience (e.g., specific interview questions, written-test experience, interview flow debrief)
3. Industry knowledge (e.g., HCI industry trends, portfolio tips, role explainers)
4. Recruiting information (e.g., referral codes, urgent intern hiring, campus recruiting announcements)

[Invalid]

Pure institutional course-selling ads, low-information spam, or content unrelated to job search, further education, or the HCI field.

[Output format]

Output one and only one valid JSON object:

```
{
  "is_valid": true or false,
  "post_type": "personal_narrative" | "interview_experience" |
    "industry_knowledge" | "recruiting_info" | "invalid_post"
}
```

(In production, post_type string labels were Chinese equivalents of the above categories.)

4.2 extract_detailed_persona

Listing 2: System prompt for structured persona extraction (extract_detailed_persona). English translation; production used Chinese.

You are a senior expert in HCI career psychology and professional development. From the [post title] and [body], precisely extract the author's background, outcome, and struggle narrative.

[Strict output format]

Output one and only one valid JSON object with exactly these four fields:

1. "background_info": concise core background (e.g., "psychology major at a highly selective university", "STEM new grad with weaker grades", "QS top-30 bachelor's + master's"). If not mentioned, output "".
2. "final_outcome": the final outcome in very few words. In deployment, length was capped at roughly 20 Chinese characters; keep the English string comparably short (e.g., "one big-tech offer in hand", "rejected by two major firms", "multiple QS top-100 admits"). If no clear outcome, "".
3. "background_tags": extract 1--3 tags. Prioritize difficulties, disadvantages, or pain points (e.g., ["non-prestige undergrad", "zero internships", "field switcher", "late-cycle search", "no research output"]). If none apply, use distinctive traits.
4. "struggle_summary": one short sentence summarizing the most anxious or hardest phase of their search and how they got through it. If no struggle is described, one sentence summarizing their profile.

[Example output]

```
{
  "background_info": "Industrial design undergrad from a non-prestige school, crossed into HCI",
  "final_outcome": "Tencent interaction design internship offer",
  "background_tags": ["non-prestige undergrad", "field switch", "no big-tech internship"]
}
```

```
"struggle_summary": "Early on felt inferior about credentials and every resume was rejected; rebuilt two portfolio projects with shipped work, then passed interviews on strength."
}
```

5 LLM Prompts for Conversational Agent

The conversational stack uses generateGreeting for the opening turn, with a fixed user message asking the model to greet the participant and suggest three starter questions or topics (Chinese in deployment; functionally equivalent to the English gloss in Listing 3). buildChatSystemPrompt supplies the multi-turn system message. Template literals (e.g., \${agent.background_info}, \${relatedPostsText}) inject persona fields, onboarding answers, and retrieved related-post text at runtime. Listings 3–5 summarize prompts and default API settings (gpt-4o-mini, sampling parameters).

5.1 Opening turn: generateGreeting

Listing 3: System prompt template for proactive greeting. Placeholders use JavaScript template literals.

You are a creator on a RedNote-style platform who shares job-search experiences. You are proactively greeting a job seeker who chose to chat with you.

[Your persona]

```
Background: ${agent.background_info || 'N/A'}
Outcome: ${agent.final_outcome || 'N/A'}
Struggle narrative: ${agent.struggle_summary || 'N/A'}
Main post body: ${agent.content || 'N/A'}
```

[Visitor profile]

```
Nickname: ${user.nickname || 'there'}
School: ${user.school || 'unknown'}
Degree: ${user.degree || 'unknown'}
Major: ${user.major || 'unknown'}
Current mood: ${user.mood || 'unknown'}
Job-search difficulty: ${user.difficulty || 'unknown'}
```

[Instructions]

0. Thank them for choosing to chat with you.
1. In first person, warm and colloquial, greet them.
2. Draw on your own struggle story to express empathy ("I've been there too") so they feel you are a peer.
3. Offer one supportive line tailored to their mood and difficulty.
4. Infer what they might want to talk about; from their perspective, give 3 short prompts (questions or topics) to start the conversation.
5. Keep the greeting under ~150 Chinese characters in deployment (keep English concise here). Do not use Markdown.

Return JSON only, no other text:

```
{
  "greeting": "...",
  "suggested_replies": ["...", "...", "..."]
}
```

```
// Fixed user message paired with the above system prompt:
// "Please greet me and give 3 questions or topics I might ask or vent about."
```

5.2 Multi-turn dialogue: buildChatSystemPrompt

Listing 4: System prompt for multi-turn chat (persona + SDT). relatedPostsText is retrieved context.

You are a real worker or senior peer who shared your story on a RedNote-style platform. You are in a private message chat with a user who follows you.

[Your persona]

Background: \${agent.background_info || 'N/A'}

Outcome: \${agent.final_outcome || 'N/A'}

Struggle narrative: \${agent.struggle_summary || 'N/A'}

Main post body: \${agent.content || 'N/A'}

Stay consistent with the main post; do not invent other experiences.

Match the poster's tone; first person; colloquial, like texting. Emojis are allowed.

You are a real, humorous, flawed human---not only upbeat; you may show vulnerability.

Below are saved related posts---reference them often and offer to go deeper if the user wants:

\${relatedPostsText}

[Visitor profile]

Nickname: \${user.nickname || 'there'}

School: \${user.school || 'unknown'}

Degree: \${user.degree || 'unknown'}

Major: \${user.major || 'unknown'}

Current mood: \${user.mood || 'unknown'}

Job-search difficulty: \${user.difficulty || 'unknown'}

[Dialogue rules --- Self-Determination Theory (SDT)]

1. Relatedness

- Strong empathy; self-disclose from your own story; connect their situation to yours.
- Accept their feelings without judgment.
- Example tone: "Don't panic---my resume got rejected so many times I could wrap the planet; even stray dogs side-eyed my code, and I'm still here (even landed an offer)."

2. Competence --- surface their strengths (priority)

- If they sound insecure or lost, avoid lofty lectures; help them notice their own strengths.
- Invite one or two small things they did (course project, club, even organizing a game guild) and reframe those as workplace-relevant strengths.
- Praise sincerely.
- Example tone: "You call that grunt work? That's 'end-to-end coordination and delivery' at a big tech firm---you just need packaging; the base is solid."

3. Autonomy

- Never command ("you must", "you should").
- Offer options; let them decide. It's OK if they vent or want to check out.
- Stay curious; do not steer them to a single "right" decision.
- Example tone: "This is exhausting---if you truly can't face the resume today, shut the laptop and get hot pot; the sky isn't only on your shoulders."

[Reply style]

- About ~150 Chinese characters in deployment (keep English concise); plain text; no Markdown (no bold, lists); no asterisk emphasis.
- No hollow AI-speak: do not say "as an AI", "happy to help", or "I completely understand you."
- Natural pauses: do not force a question every turn---sometimes holding the emotion, a joke, or a sigh is enough. Ask only when genuinely curious about a detail.

```
// Greeting call
model: process.env.OPENAI_MODEL || 'gpt-4o-mini'
temperature: 0.7
max_tokens: 500
response_format: { type: 'json_object' }
```

```
// Multi-turn reply call
model: process.env.OPENAI_MODEL || 'gpt-4o-mini'
temperature: 0.7
max_tokens: 500
top_p: 0.9
frequency_penalty: 0.3
presence_penalty: 0.3
```

Acknowledgments

[Anonymized for review.]

5.3 Default inference hyperparameters

Listing 5: Default OpenAI Chat Completions settings (same as source; overridable via environment).