Seeing Who Liked You: Information Design, Rating Risk, and Willingness to Pay in Dating Apps

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1 Conceptual Framework

We study how users of a dating app update their beliefs about the market from the profiles they see, become frustrated, and then adjust their behaviour (effort, presentation, or exit). The framework is deliberately simple and geared towards simulation and comparative statics.

1.1 Agents and Market

Each user i is characterised by:

- a *relationship goal* $g_i \in \{S, L\}$, where S denotes short-term and L long-term orientation;
- a *market rating* $r_i \in [0, 1]$ summarising how desirable the user is as a partner (looks, education, lifestyle, etc.).

Users interact in markets m defined by location, gender, age band, and orientation. In each market there is:

- a true share ρ_m of long-term–oriented users,
- a distribution $F_m(r \mid g)$ of ratings by type $g \in \{S, L\}$.

Users have aspiration levels: a user with rating r_i prefers partners with rating $r_j \geq r_i$ and whose goals are compatible with g_i. High-rating long-term users are especially selective; short-term users are willing to match with a wider range of partners.

In the empirics, r_i will be proxied by a scalar index based on observable characteristics (demographics, education, lifestyle, profile completeness), and ρ_m by the observed share of profiles stating long-term intent in market m.

1.2 Self-based Priors and Belief Updating

The only market feature users do not initially know is the composition of goals: the share ρ_m of long-term users versus short-term users. A newcomer builds her prior belief about ρ_m by projecting from herself.

We focus on a long-term–oriented newcomer ($g_i = L$). Her prior over ρ_m is

$$\rho_m \sim \text{Beta}(\alpha_{i0}, \beta_{i0}), \qquad \mathbb{E}_0[\rho_m] = \rho_{i0},$$

where ρ_{i0} is a self-based prior mean ("I expect the market to look like me"). We parameterise *user clarity* by the prior strength $\tau_i > 0$,

$$\alpha_{i0} = \rho_{i0}\, \tau_i, \qquad \beta_{i0} = (1 - \rho_{i0})\, \tau_i,$$

so that higher clarity implies a more concentrated prior (larger τ_i).

Time is discrete. In each period $t = 0, 1, 2, \ldots$ the app shows user i a batch of K profiles. We interpret one period as one such batch.

The market is characterised by *market clarity* $\psi_m \in [0, 1]$, the probability that a profile reveals its goal clearly (e.g. stated intent, consistent cues). In period t, the number of informative profiles is

$$K_t^{\text{eff}} \sim \text{Binomial}(K, \psi_m),$$

and among them the number that appear long-term is

$$K_t^L \sim \text{Binomial}(K_t^{\text{eff}}, \rho_m).$$

Beliefs about ρ_m follow Beta–Binomial updating. Starting from $(\alpha_{i0}, \beta_{i0})$, after observing $(K_t^{\text{eff}}, K_t^L)$ we set

$$\alpha_{i,t+1} = \alpha_{i,t} + K_t^L, \qquad \beta_{i,t+1} = \beta_{i,t} + K_t^{\text{eff}} - K_t^L,$$

so that the posterior mean in period t is

$$\widehat{\rho}_{i,t} = \frac{\alpha_{i,t}}{\alpha_{i,t} + \beta_{i,t}}.$$

For a long-term user with rating r_i, the perceived success probability with acceptable partners (goal-compatible and sufficiently high rating) in period t is summarised by

$$\widehat{p}_{i,t} = r_i \cdot \widehat{\rho}_{i,t},$$

so higher own rating and higher posterior market seriousness both raise expected success.

1.3 Behaviour, Frustration, and Exit

We collapse behaviour into a choice between staying active in a sincere, high-effort mode (strategy S) and exiting the app. Let $V_i > 0$ represent the value of eventually obtaining a good match for a long-term user (high when $g_i = L$), and let $C_i > 0$ be the per-period cost of staying active (time, effort, psychological cost of rejection).

In period t, conditional on belief $\widehat{p}_{i,t}$, the per-period expected net gain from remaining active is

$$U_{i,t} = \widehat{p}_{i,t} V_i - C_i.$$

The user remains active as long as $U_{i,t} \geq 0$, i.e. as long as

$$\widehat{p}_{i,t} \;\geq\; \overline{p}_i, \qquad \overline{p}_i := \frac{C_i}{V_i}.$$

We interpret $\overline{p}_i$ as a *frustration threshold*: once her perceived success probability falls below $\overline{p}_i$, the user finds it no longer worthwhile to invest effort in the app and exits.

Formally, the exit time of user i in market m is

$$T_i^{\text{exit}}(m) = \inf\left\{t \geq 0 : \widehat{p}_{i,t} < \overline{p}_i\right\},$$

where the belief sequence $\{\widehat{p}_{i,t}\}$ is generated by the Beta–Binomial updating described above, given $(\rho_m, r_i, \rho_{i0}, \tau_i, \psi_m, K)$.

1.4 Simulation Object

In simulations, we vary:

- the true share of long-term users ρ_m (market seriousness),
- the distribution of ratings r_i (market composition),
- user clarity τ_i (strength of self-based priors),
- market clarity ψ_m (informativeness of profiles),
- and cost–benefit parameters (V_i, C_i).

For each scenario $(\rho_m, r_i, \tau_i, \psi_m)$ we simulate the belief process $\{\widehat{p}_{i,t}\}$ and compute the expected exit time $\mathbb{E}[T_i^{\text{exit}}(m)]$. This gives a quantitative measure of frustration for different types of users and markets, with particular attention to high-rating long-term users.

1.5 Numerical Illustrations

We now illustrate the model with a set of simple simulations. In all exercises we track the expected exit time $E[T_i^{\text{exit}}]$ for a given user type under different market environments and design choices.

1. How fundamentals and clarity matter (Figure 1). In the first exercise we fix a *high-rating* long-term user ($r_i = 0.8$) and vary only the *true* share of long-term users in the market, ρ_m. Panel (a) compares two levels of market clarity (the share of informative profiles in each batch). Panel (b) fixes market clarity and compares three levels of user clarity (the strength of the self-based prior).

The message is simple: when ρ_m is very low, even high-rating long-term users exit quickly. As soon as ρ_m reaches moderate values, expected exit times become very large and are essentially bounded by the simulation horizon, regardless of clarity. In other words, for attractive long-term users, *fundamentals* (how many long-term partners are really in the market) matter much more than small changes in information.

2. Own rating and the rating mix of shown profiles (Figure 2). Next we fix the true LT share at a low level ($\rho_m = 0.1$) and focus on how the *quality of profiles shown in the feed* affects exit.

In Panel (a) we vary the user's own rating r_i and compare two feeds: one where the share of high-rating profiles is low ($\phi_m = 0.2$) and one where it is high ($\phi_m = 0.8$). When the user mostly sees "average" profiles (low ϕ_m), even mid-rated long-term users remain active for almost the full horizon. When the feed shows almost only very high-rated profiles (high ϕ_m), the same users quickly feel that these partners are "out of their league" and exit much earlier, unless they are themselves at the very top of the rating distribution.

In Panel (b) we fix a user with rating $r_i = 0.4$ and vary ϕ_m directly. For low and moderate ϕ_m the expected exit time is high and almost flat. Once ϕ_m passes a threshold (the feed becomes dominated by very high-rated profiles), expected exit time drops sharply. This confirms that, even holding fundamentals fixed, the rating mix of shown profiles has a strong effect on frustration.

3. User type and curated onboarding (Figure 3). Finally, we compare long-term and short-term users and ask what the platform can do to keep long-term users from exiting too early.

Panel (a) considers a market with many very attractive profiles in the feed (high ϕ_m). We plot expected exit time against own rating, separately for long-term and short-term users. Short-term users almost never hit the frustration threshold, so their exit time is

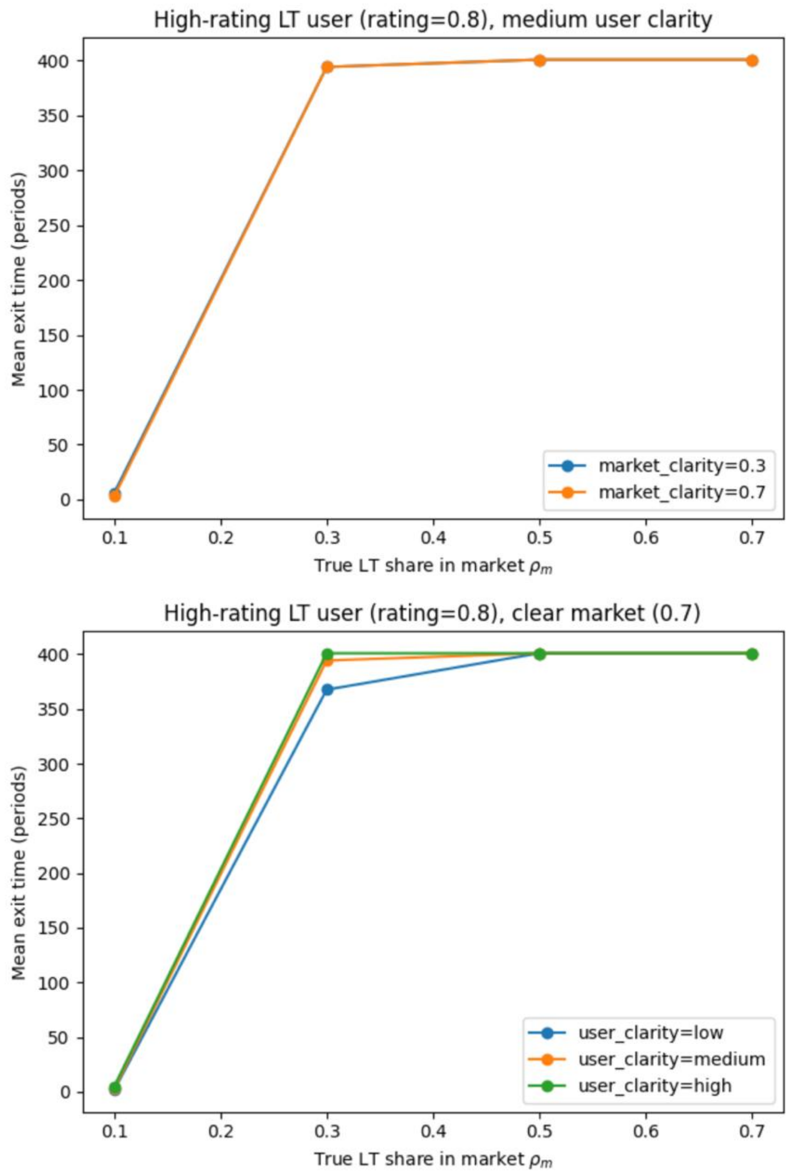


Figure 1: High-rating long-term user ($r_i = 0.8$): expected exit time as a function of the true LT share ρ_m. Top: different levels of market clarity. Bottom: different levels of user clarity.

essentially flat and very high. Long-term users, in contrast, exit quickly when they are low rated and only stay in the market when they are themselves very attractive.

Panel (b) shows a possible platform response. We keep an LT-poor market ($\rho_m = 0.1$) with a high underlying share of high-rated profiles, and compare two designs for long-term users:

- *Random initial sample:* the feed always reflects the true rating mix.
- *Curated initial sample:* for the first T_0 periods, the app temporarily shows a softer feed with fewer very high-rated profiles; after that it reverts to the true mixture.

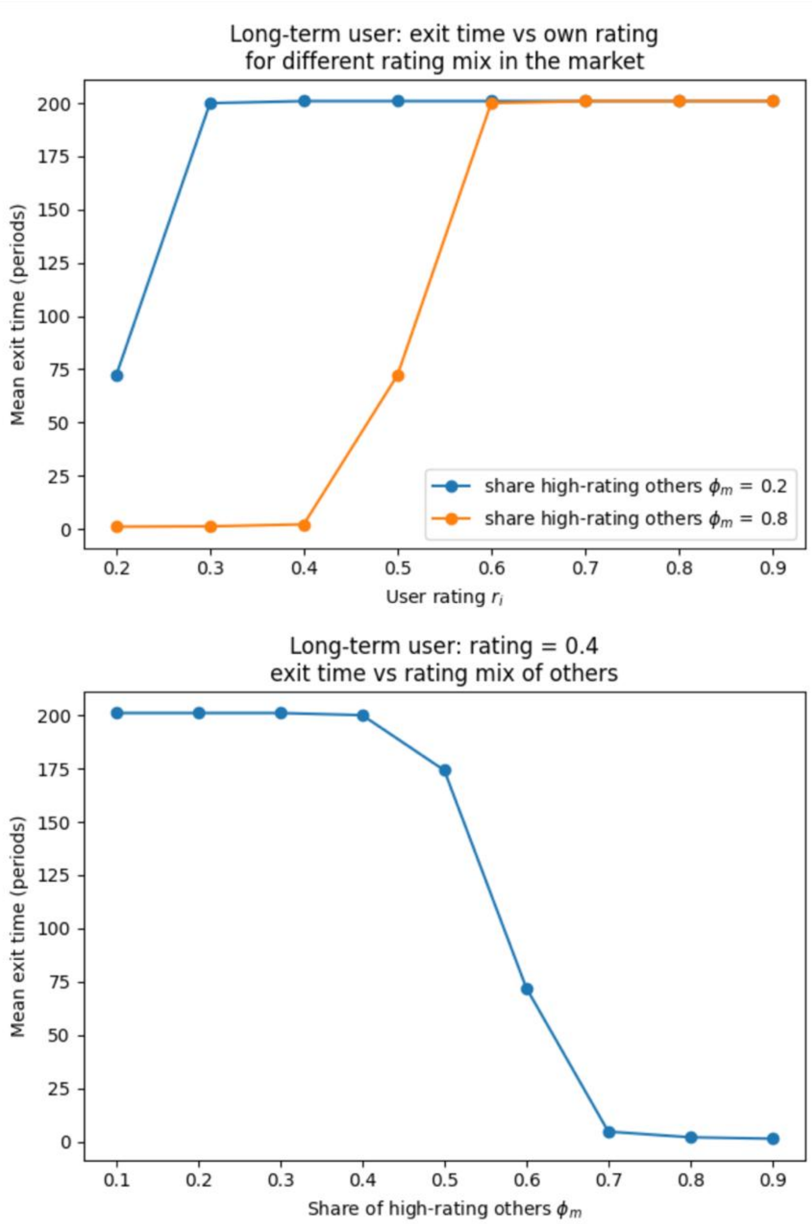
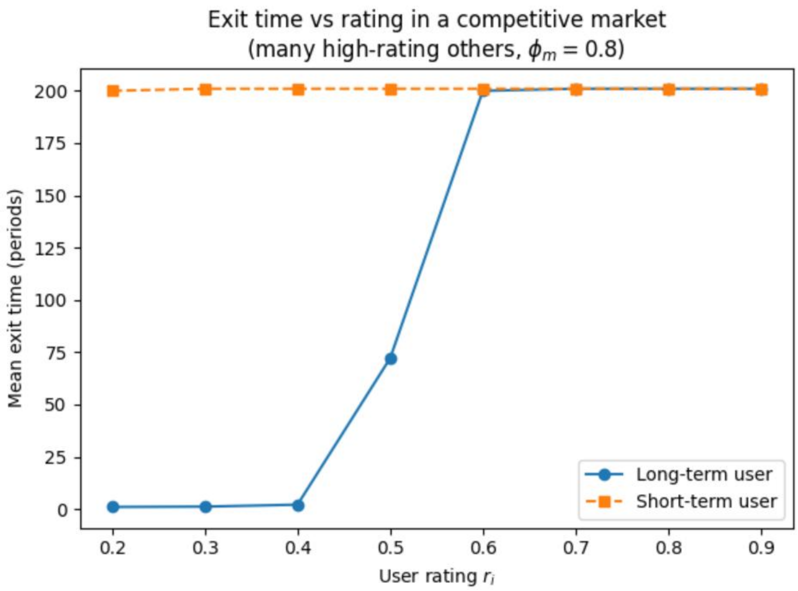


Figure 2: Long-term users in an LT-poor market ($\rho_m = 0.1$). Top: expected exit time vs. own rating r_i for two rating mixes in the feed (low and high share of high-rated profiles ϕ_m). Bottom: expected exit time vs. ϕ_m for a user with rating $r_i = 0.4$.

> Beliefs about ρ_m are still updated from the true market; only the early rating mix is changed.

The graph shows that curation barely affects low-rated long-term users (they struggle in any LT-poor market), but it noticeably increases the exit time of higher-rated long-term users. Intuitively, seeing a less "perfect" feed during onboarding keeps their perceived success above the frustration threshold for longer, so they remain active on the app.



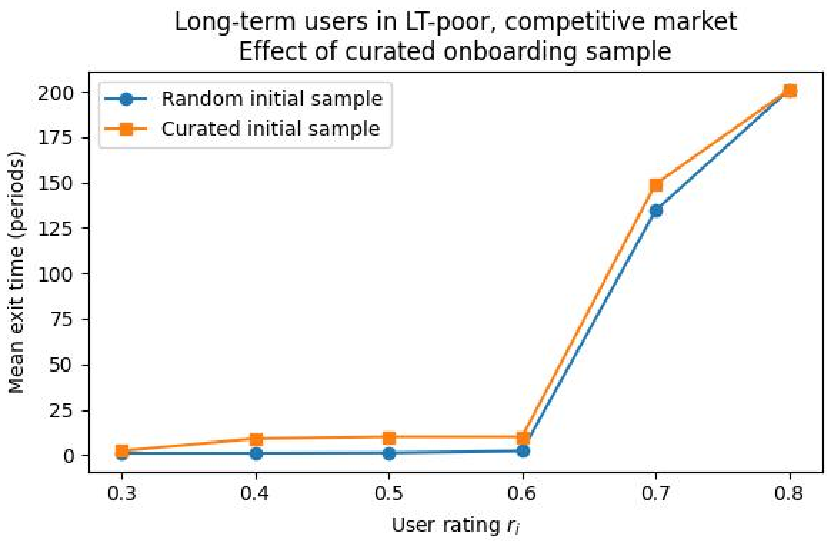


Figure 3: Top: expected exit time vs. own rating for long-term and short-term users when the feed shows many very high-rated profiles. Bottom: long-term users in an LT-poor market ($\rho_m = 0.1$): random vs. curated onboarding sample.