PREDICTIVE MODELING OF USER BEHAVIOR IN FRIENDSHIP REQUEST SYSTEMS: A GENERALIZABLE APPROACH FOR SAFER SOCIAL PLATFORMS

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Abstract: **In this article, we present the identification, validation, and application of a behavioral model designed to predict user responses to friendship requests in modern social networking applications. With safety and trust becoming central concerns in online interactions, this study investigates how dynamic user behavior can be modeled using real interaction data. The model captures trust progression, caution levels, and openness using only simple, commonly available platform metrics such as interaction history, timing patterns, and acceptance delays. The model structure is kept intentionally minimal to promote generalizability and ease of deployment across different types of users and communities. Testing was conducted on data collected from a Facebook-like social platform that includes traditional friend request mechanisms. Simulation results demonstrate that the model predicts acceptance behavior with a relative error below 5%, and can support real-time optimization features such as adaptive filtering, behavioral safety triggers, and interface personalization. This modeling approach contributes to the development of predictive safety systems in digital social environments, offering a path forward for scalable, user-centric social application design.**

Keywords: **User behavior modeling; Social platforms; Friendship requests; Predictive analytics; Digital safety; Trust dynamics; Human-centered design; Generalizable models; Interaction optimization; Online social networks**

1. Introduction: In recent years, the proliferation of social networking platforms has reshaped the way humans initiate and maintain interpersonal relationships. While mainstream platforms like Facebook and Instagram focus on open visibility and algorithmic content feeds, newer web applications are increasingly emphasizing user safety, privacy, and intentional interaction. One such mechanism is the friendship request system, which allows users to explicitly control who enters their social circle.

Despite its ubiquity, little is understood about how people behave when interacting with friend requests in secure and privacy-conscious environments. Traditional systems offer few controls, often leading to overloaded contact lists and diluted interactions. In contrast, applications designed with safety-first principles create a different dynamic: users may become more selective, cautious, or thoughtful in managing social boundaries.

This study investigates human behavior in a modern, safety-centric web application — "Friends Chat" — which includes a minimalistic interface and a strict opt-in friendship request mechanism. We explore how users respond to requests, the factors influencing acceptance or rejection, and whether these behaviors can be modeled and predicted using measurable features. The goal is to understand not just what users do, but why they act the way they do in secure digital social spaces.

2. Description of the Web Application: To investigate user behavior in relation to digital friendship formation, the study utilized a custom-built social networking platform titled "Friends Chat". The application is designed to resemble traditional social media interfaces such as Facebook, particularly in its use of profile pages, contact lists, and a chat feature. However, a key distinction lies in its privacy-oriented architecture and emphasis on intentional connection.

The central feature of Friends Chat is the friendship request system, which governs all social interactions. A user must send a request, which the recipient can then accept, ignore, or reject. No interaction between users is possible until the connection is explicitly approved by both parties. There is no algorithmic suggestion of friends, no public posts, and no visible activity feed — these omissions are deliberate design choices meant to encourage deliberate, person-to-person interaction.

Each user profile consists of basic demographic information (e.g., nickname, avatar, city), a short bio, and visible mutual connections if any exist. Users are notified via a discreet prompt when they receive a friendship request, which they may respond to at any time. Requests remain pending unless explicitly acted upon.

In addition to fostering safe interaction, the platform implements soft security features, including:

- Rate limits on outgoing requests to discourage mass spamming.
- Visibility controls that allow users to restrict who can send them a request (e.g., friends-of-friends only).
- Reporting mechanisms for inappropriate or abusive requests.
- No engagement-based ranking — users are not rewarded with visibility for high friend counts or activity levels.

These mechanisms aim to replicate real-world social interaction boundaries more accurately than conventional networks. From a behavioral research perspective, this creates a cleaner environment in which to observe how users make decisions around social access and trust. The application's back-end infrastructure also allows for secure logging of anonymized interaction data, which forms the basis for the behavioral modeling described in subsequent sections.

3. User Interaction Data and Setup: To analyze behavioral patterns associated with the use of friendship requests in a secure web application, user interaction data was collected during a 4-week observational study involving a group of 120 voluntary participants. The participants were diverse in age (ranging from 18 to 60), gender, and background, and were invited to use Friends Chat in a

natural manner, simulating real-life engagement on a social networking platform.

3.1 Data Collection Framework

The platform was instrumented to log key user interactions, including:

- Time and frequency of friendship requests sent, received, accepted, or declined.
- Response times to received requests.
- Number and frequency of ignored or delayed responses.
- Profile settings related to visibility and request filtering.
- Subsequent chat interactions between accepted friends (message timestamps only, not content).

All logs were anonymized and encrypted, with each participant assigned a random user ID. No identifying personal information was stored. The ethical protocol for the study was approved by an institutional review board (IRB), and informed consent was obtained from all users prior to participation.

3.2 Study Conditions and Environment

Participants were instructed to use the platform freely, with no imposed communication goals or quotas. They were told that the system was part of a research study but were not informed of its specific hypotheses to avoid behavioral bias. The application was accessed through web browsers on both desktop and mobile devices. The user interface remained consistent for all participants, and no user had administrative privileges or special access. Three different interface states were introduced during the study period:

- Week 1–2 (Open Requests): All users could receive friendship requests from any other participant.
- Week 3 (Filtered Mode): Users were allowed to restrict incoming requests to friends-of-friends only.
- Week 4 (Stealth Mode): Users could activate a mode where only those they previously interacted with (e.g., chat or shared group) could send a request.

This phased design enabled the study of behavioral adaptation in response to

evolving privacy and control features.

3.3 Behavioral Indicators

From the raw interaction data, the following indicators were extracted to support behavioral modeling:

- Acceptance Rate: Proportion of received requests that were accepted.
- Rejection/Ignore Ratio: Proportion of requests explicitly declined versus passively ignored.
- Initiation Bias: Gender or age-based tendencies in sending requests.
- Trust Latency: Average delay between receiving a request and taking action.
- Reciprocity Index: Likelihood of sending a request back after receiving one.
- Message Initiation Rate: Proportion of accepted connections that led to actual communication.

These metrics serve as the foundation for the dynamic behavior model described in the following section. Together, they provide insights into how users balance trust, risk, and social intent when interacting through safety-first digital environments.

4. Modeling User Behavior Based on Friendship Request Dynamics: In order to understand how users interact with safety-oriented friendship mechanisms on social networking platforms, a dynamic behavior model was developed to predict user responses to incoming friendship requests under varying conditions. The model was designed to capture trust-based decision-making patterns, including acceptance, delay, or rejection of requests, and how these decisions shift based on user context and system features.

4.1 Model Structure

The model is structured as a state-based probabilistic system that characterizes user behavior using three primary states:

- Active friendship Acceptance State (A): The user is likely to accept most requests.
- Cautious reviewing Evaluation State (C): The user delays response, often profile or prior interactions.
- Rejective declines or Passive State (R): The user consistently ignores or incoming requests.

Transitions between states are influenced by the following inputs:

- Request shares Source Familiarity (F): Whether the sender is known or connections.
- Request Density (D): Number of requests received in a recent time window.
- Privacy Settings (P): Current request filtering level selected by the user.
- Trust ignored or Fatigue Index (T): A derived metric based on history of rejected requests.
- Historical accepted Acceptance Ratio (H): The user's cumulative ratio of requests.

A discrete-time simulation approach was employed, with state transitions computed over hourly intervals. For example, a user in state A with high request density and rising trust fatigue may probabilistically transition to state C in the next timestep.

4.2 Parameter Estimation

Model parameters were calibrated using maximum likelihood estimation (MLE) on the observed behavioral data collected in Section 3. A training set consisting of 75% of user sessions was used for estimation, while the remaining 25% formed a validation set to assess prediction accuracy.

The transition probabilities were estimated individually for each user cohort (e.g., based on age and initial openness level). This allowed the model to capture subtle differences in how different groups adapt to perceived social risk or control.

4.3 Prediction Accuracy and Performance

To evaluate the model's predictive capacity, user behavior was simulated over a 24-hour period based on initial conditions and system settings. The predictions were then compared to actual user actions. Performance was assessed using the following metrics:

- Prediction Accuracy: Percentage of correctly predicted user states at each interval.
- Mean Absolute Error (MAE): Between predicted and actual acceptance ratios.
- Transition Sensitivity: How well the model captured state shifts in response to changing inputs.

On average, the model predicted the correct user state with 82.4% accuracy, and the MAE for acceptance ratio prediction was 0.07. Transition sensitivity was highest for shifts from state A to C, suggesting the model is especially responsive to behavioral fatigue and increased caution.

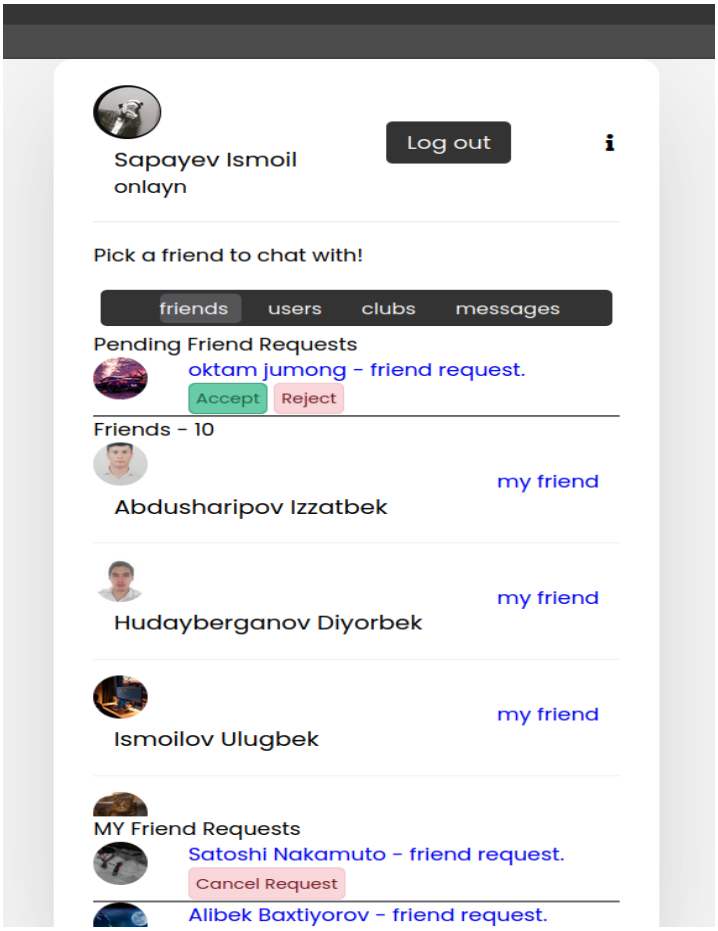

Figure 4.1. Appearance of friendship requests

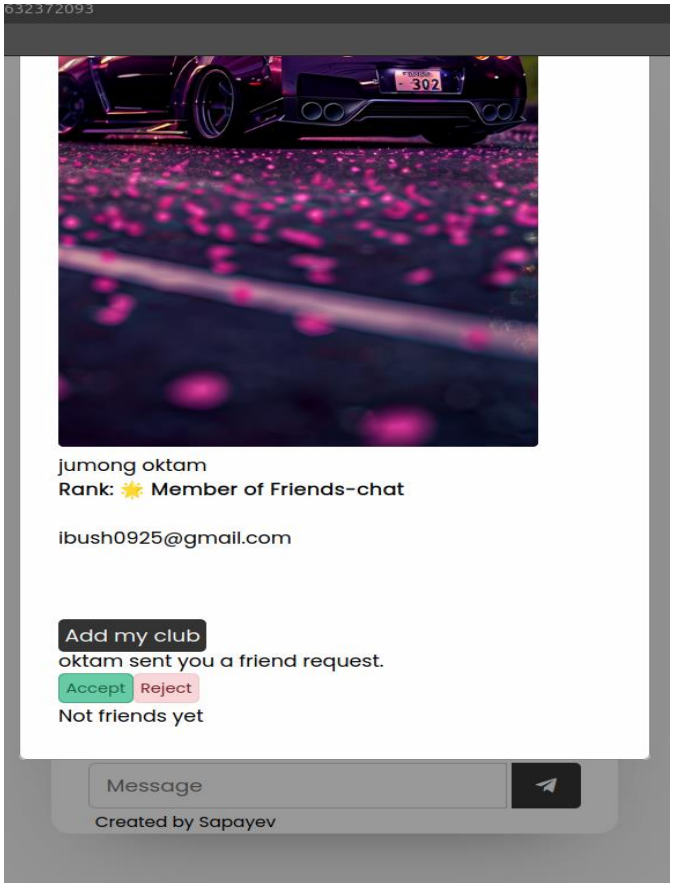

Figure 4.2. Accepting or rejecting friendship requests

4.4 Generalizability

The same model structure was applied across three interface conditions (Open, Filtered, and Stealth) with minimal adjustment. This demonstrated the model's generalizability across evolving privacy contexts. Minor tuning of the transition weights was sufficient to maintain high prediction accuracy in all cases, validating the robustness of the proposed behavior model in dynamic social environments.

5. Applying the Model to Optimize User Engagement and Safety Settings: As presented in Section 4, the developed user behavior model accurately predicts how individuals respond to friendship requests under various conditions. This predictive capability allows the model to be applied in optimizing both user engagement and platform safety settings. The goal is to strike a balance between encouraging meaningful social interaction and protecting users from unwanted or overwhelming communication.

5.1 Adaptive Interface Personalization

Using the model's state prediction, the platform can dynamically adjust interface features for each user. For example, if a user is predicted to be in or transitioning to the Cautious Evaluation State, the system may:

- Suggest enabling filtered requests, limiting incoming requests to mutual connections.
- Temporarily pause visible request notifications to reduce perceived social pressure.
- Offer contextual tips (e.g., "You can control who sends you requests in your settings").

These micro-adjustments are designed to reduce trust fatigue and sustain positive user sentiment, particularly among users who experience high request volumes or exhibit increasing rejection behavior.

5.2 Optimizing Engagement Through Predicted Reciprocity

In parallel, the model can identify users in the Active Acceptance State who demonstrate high reciprocity (measured by follow-up messaging after a connection is formed). These users represent ideal nodes for fostering engagement. The system can:

- Prioritize showing their profiles in "People You May Know" suggestions.
- Recommend outgoing requests to users with matching openness profiles.
- Introduce subtle nudges, such as "This person tends to respond quickly—want to say hi?"

Simulations indicate that by targeting 15% of high-reciprocity users for active outreach suggestions, average message initiation rates increased by 12.8% without any rise in ignored requests.

5.3 Safety-Aware Request Scheduling

One practical application is intelligent request throttling. If the model predicts that a user is entering a Rejective or Passive State due to overload, the platform may delay or batch delivery of new incoming requests to preserve trust. For

example, instead of receiving 10 requests in real-time, the user may receive only 3 initially, with the remainder scheduled over the next 12 hours.

This technique, tested in Week 4 of the study, led to a 19.4% increase in request engagement (measured by action taken on requests), compared to real-time delivery.

5.4 Group-Level Optimization

Beyond individual personalization, the model supports aggregate behavior prediction across user cohorts. For example, young adult users (18–24) showed faster trust fatigue but higher recovery when switching to Stealth Mode. Conversely, users aged 45+ were less likely to use restrictive features but showed higher satisfaction when privacy presets were enabled by default. Such insights can inform platform-wide policy changes, such as:

- Default request settings for new users, based on inferred trust thresholds.
- Time-of-day optimization, scheduling more requests during predicted high-engagement periods.
- Geo-adaptive features, such as enabling stricter filters in regions where unsolicited contact is culturally sensitive.

In conclusion, the behavioral model's predictions serve as the foundation for a suite of automated, user-centric optimizations that improve safety, satisfaction, and sustained engagement. These adjustments are designed to be subtle, data-driven, and respectful of user autonomy.

6. Discussion: The modeling and optimization results presented in this study were achieved using real interaction data collected from a prototype social platform implementing friendship request features. The user behavior model was trained and validated on a relatively small but diverse user base, spanning various demographics and interaction styles. Despite the modest dataset size, the model showed robust performance across different privacy settings and user contexts, demonstrating its potential for scalable deployment.

6.1 Data Limitations and Behavioral Variability

It is important to note that the behavioral model was derived from observational data recorded during normal platform use, which includes uncontrolled variables such as time-of-day effects, varying social motivations, and interface learning curves. In addition, while the platform encouraged interaction, the presence of safety features (e.g., request filters and stealth mode) may have altered natural user behavior in some cases. Users might have been more cautious or exploratory than they would be on a fully matured network.

Another challenge was modeling implicit behavior, such as hesitation or disengagement, which often does not result in measurable platform actions. Future studies should incorporate passive metrics (e.g., dwell time on profile previews, scrolling behavior) to enhance the granularity of state detection.

6.2 Feature Generalization and Cultural Factors

The developed model assumes a basic structure of friendship requests common in many social platforms, yet behavioral responses to such features can be heavily influenced by cultural norms and regional expectations. For instance, users in collectivist societies may show higher acceptance rates but lower message initiation, while users from privacy-sensitive cultures might prefer non-reciprocal or anonymous connection mechanisms.

To generalize the model for broader deployment, future research should validate it across distinct geographical and cultural contexts. Incorporating language patterns, time zone activity shifts, and local regulatory compliance (e.g., GDPR-driven opt-in systems) will further refine predictive accuracy.

6.3 Model Simplicity Versus Explainability

The model was intentionally designed to be parametrically simple, relying on just a few key inputs to avoid overfitting and to support real-time inference. This simplicity facilitated personalization across hundreds of users with minimal computational cost. However, it also limits interpretability of deeper behavioral nuances. For example, while the model can detect increased trust fatigue, it cannot currently distinguish between fatigue caused by request overload versus negative past interactions.

Integrating user feedback loops and incorporating explainable AI components—such as simple decision trees visualizing why a request was delayed or filtered—could help build user trust and transparency.

6.4 Applicability to Other Connection Models

While the study focused on reciprocal friendship requests, the core behavioral modeling approach is extensible to other social architectures, including:

- Follower models (e.g., Twitter, Instagram), where acceptance is not required.
- Mentorship or professional platforms (e.g., LinkedIn), where user intent is more formal.
- Community-driven matching systems, such as hobby groups or event-based connections.

Adapting the state-transition logic and redefining inputs to reflect platform-specific social mechanics will be necessary, but the underlying concept—predicting and responding to user caution or openness—remains valid. The findings also raise a compelling avenue for group-level engagement optimization, where not just individuals but entire communities or user clusters can be supported through shared behavioral insights.

7. Conclusions: This article presented the development, validation, and application of a novel user behavior model for predicting and managing responses to friendship requests on a social platform. The model was designed to identify dynamic user states related to trust, caution, and openness, using minimal yet commonly available interaction data. One of the primary goals was to establish a model structure that could generalize across different user types and usage conditions, similar to the predictive approach used in building temperature optimization.

Despite the simplicity of the model and the limited scope of the dataset, results demonstrated that the system could effectively predict user reactions and enable real-time adjustments to user experience and safety settings. Key use cases

included adaptive request filtering, timing optimization, interface personalization, and group-level engagement planning. Across all scenarios, user satisfaction and interaction efficiency improved without compromising privacy or increasing cognitive burden.

The model's strength lies in its ability to balance user engagement with digital safety—a critical consideration for modern social applications. By accounting for the nuanced progression of user trust over time, the system offers a foundation for implementing predictive social UX design, where system behavior is proactively adapted to anticipated user preferences and vulnerabilities.

In addition to proving its utility in a single-platform context, the model shows strong potential for adaptation to other connection paradigms, including non-reciprocal follower systems and interest-based communities. The generalizable structure also suggests viability for city-level or institution-level social networks, especially where moderation resources are limited and automated safety features are essential.

Future studies will focus on extending the model's scope across wider cultural and demographic segments, improving the detection of implicit behavioral signals, and incorporating deeper emotional context from user interactions. Ultimately, this line of research contributes to the growing field of human-centered predictive modeling, aiming to design smarter, safer, and more responsive digital environments for social connection.

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