# HumanRobot Interaction: When Investors Adjust the Usage of Robo-Advisors in Peer-to-Peer Lending

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## Robo-Advisor (RA) Overview

Robo-advisor (RA) is a service that provides automated, algorithm-based wealth-management advice without human planner

- Algorithms to invest in risk preference, budget, and goals.
- Augments investor intelligence in a personalized manner.
- Benefits:
  - More accessible (24/7 availability)
  - Lower fees (e.g., 0.25% vs. 220% standard).
  - Lower capital outlays for advice

| RA | AUM (2019) |
|---|---|
| Betterment | $16 billion |
| Wealthfront | $11 billion |
| Personal Capital | $8.5 billion |

**Theoretical Foundation:**

- Based on Markowitzs portfolio-optimization theory.[1]
- Aim: Diversified portfolio with greatest returns for each risk level.[2]
- Inputs: Returns and variancecovariance matrix of asset returns.
- Use of computer algorithms to optimize riskreturn tradeoff.
- Advanced methods: random forest, neural network, nonlinear shrinkage.[3]

[1] Friedberg 2019
[2] Markowitz 1952
[3] DAcunto et al. 2019, DHondt et al. 2019

**Expansion to P2P Loans:**

- Beyond traditional assets, some RAs explore peer-to-peer (P2P) loans.
- As of July 2018:
  - U.S. platforms (Prosper, Lending Club): >$23 billion loans.
  - Chinese P2P lending platforms: >$1,080 billion loans.[4]
- Challenge: Optimizing loan investment with limited info.
- Solution: RAs in mainstream P2P platforms assist lenders in choosing worthy loans.

[4] Jiang et al. 2020

## Human-in-the-Loop and Robo-Advisors

**Background:**

- Rise of intelligence-augmentation tools in daily life.
- Emergence of human-in-the-loop literature: importance of human engagement in algorithm design and refinement.[5]
- Interest: How investors use RA services and the impact of human participation in RA deployment.

**Research Gap:**

- Limited understanding of human and RA interaction.
- Uncertainty about the effectiveness of human intervention in RA-driven investments.

[5] Dietvorst et al. 2016, Xu and Chau 2018, Fu gener et al. 2019

**Study Context:**

- Collaboration with a NASDAQ-traded P2P lending company.
- Lenders can easily access and configure the RA service.
- Data provided: Transaction history, loan details, and mode of investment (manual or RA).
- Observed lender behavior: Mix of total reliance on RAs, occasional use, or no use at all.

## Research Questions

1. How does investors investment performance in the past influence their RA adoption when the service becomes available?
2. How do investors adjust their usage of RAs according to the RAs investment performance?
3. How does the adjustment affect investment performance?

## Key Findings on Robo-Advisor (RA) Usage

- Investors with more past defaults are less likely to try RA.
- RA usage is influenced by its recent performance:
  - Lower recent performance $\rightarrow$ decreased RA usage.
  - Higher recent performance $\rightarrow$ increased RA usage.
- Swift adjustments to RA usage based on its recent performance often lead to worse investment outcomes.

## Research Contributions

- One of the first studies investigating RA-augmented intelligence in P2P lending.
- Provides empirical evidence on how investment performance influences RA adoption.
- Reveals that users are affected by the recency effect when evaluating RAs.
- Uncovers a negative aspect of human-AI symbiosis: being too reactive can be counterproductive.

## Recommendations and Insights

- RAs need to increase transparency in their services.
  - Communicate RA objectives and inner workings.
- Potential misuse suggests that investors might not fully understand RA systems.
- A well-designed RA should anticipate and factor in user reactions in their algorithms.

# 2. Background and Research Context

## 2.1. Literature Review

- Initial studies on robo-advising focused on features[6] or IT components[7].
- Recent works highlight benefits, such as reduced fees and easy onboarding[8].
- This research extends by examining human-RA interactions and its effects on investment performance.
- Shifts focus from traditional assets to P2P loan investments.

[6] Lopez et al. 2015, Park et al. 2016, Jung et al. 2017
[7] Musto et al. 2015, Jung et al. 2018
[8] DAcunto et al. 2019, DHondt et al. 2019

## Extension to P2P Lending Literature

- Previous studies emphasize the borrower's side: credit ratings[9], demographics[10], and social media communications[11].
- Few works on lenders' behavior[12].
- This study is the first to explore lenders' use of RAs and associated performance.

[9] Iyer et al. 2016
[10] Duarte et al. 2012
[11] Ge et al. 2017, Xu and Chau 2018
[12] Paravisini et al. 2016, Jiang et al. 2020

## Relevance to Fintech Adoption Literature

- Initial fintech studies: ATM adoption[13], online banking[14], mobile payments[15].
- One study on RA adopters vs. nonadopters, finding no major demographic differences[16].
- This research delves into users' adoption and adjustment of RA usage and its effects.

[13] Hitt and Frei 2002
[14] Campbell and Frei 2010
[15] Schierz et al. 2010, Srivastava et al. 2010, Zhou 2013
[16] DAcunto et al. 2019

## Connection to Human-AI Collaboration

- Growing literature on humans viewing AI as collaborators[17].
- Studies on human-AI synergy in crowd-labeling[18], customer-service chatbots[19], and predictive models[20].
- This research contributes by examining a new form of human-in-the-loop case - humans adjusting AI usage.

[17] Fu gener et al. 2019
[18] Wang et al. 2017, Yin et al. 2021
[19] Schanke et al. 2021
[20] Xin et al. 2018

## 2.2. Research Context

### Borrower and Lender Process

- Borrowers undergo verification: demographics, financial status, credit history.
- Post online listing: loan amount, interest rate, loan purpose, etc.
- Platform assigns credit grade: AAA (highest) to F (lowest).
- Lenders transfer money, decide on loans to bid, amount to invest.
- Loan statuses: normal or delayed. No repayment guarantee by the platform.

## Robo-Advisor Service Introduction

- Platform launched free RA service in April 2015.
- Two-step process:
  - Machine learning methods (e.g., decision tree, SVM) assess loan risk. Inputs include loan and borrower characteristics.
  - Based on Markowitzs portfolio-optimization, RA selects loans fitting lender's risk preference.
- RA became highly popular: over half of the bids were by RAs after one year.

Table 1: Sample Description

| Variable | Mean | S.D. | Min | Median | Max | N |
|---|---|---|---|---|---|---|
| Gender | 0.73 | 0.45 | 0 | 1 | 1 | 4,370 |
| Age | 37.62 | 9.68 | 20 | 35 | 75 | 4,340 |
| Experience | 1.25 | 1.19 | 0 | 1 | 9 | 4,374 |
| BidAmount | 251.2 | 608.9 | 10 | 111.4 | 13698 | 4,374 |
| TotalAmount | 138,555 | 477,683 | 50 | 32,916 | 1.2e+07 | 4,374 |
| InterestRate | 15.96 | 3.75 | 7 | 16.35 | 23.64 | 4,374 |
| Term | 8.94 | 2.54 | 1 | 9.41 | 19.45 | 4,374 |
| RAAdopted | 0.63 | 0.48 | 0 | 1 | 1 | 4,374 |
| ReturnRate | 0.01 | 0.003 | -0.03 | 0.01 | 0.02 | 4,374 |

Note. The units of BidAmount and TotalAmount are Chinese RMB.

# 3. Data Description

Random sample: 4,374 lenders over 18 months (Jan 2015 - Jun 2016).

**Key Statistics:**

- 73% male lenders.
- Average age: 37.6 years.
- Avg. investment experience: 1.25 years.
- Avg. investment/bid: 251.2 RMB.
- Total avg. investment: 138,555 RMB.
- 63% used the RA service.

- Avg. interest rates: 15.96%. Avg. terms: 8.94 months.
- Monthly return rate: 1%.
- Positive skewness in BidAmount and TotalAmount; using logarithms in analyses.

## RQ1: Effect of Past Investment Performance on RA Adoption

- **Objective:** Investigate humanRA interaction from the adoption perspective based on investors past performance.
- **Potential Mechanisms:**
  - *Perceived Usefulness:* Investors with inferior past performance might see RAs as a tool to improve.[21]
  - *Perceived Risk:* Investors with more past defaults might perceive RAs as riskier.[22]
- **Contrasting Effects:** While perceived usefulness encourages RA adoption, perceived risk might deter it. Which effect dominates?

[21] Venkatesh et al. 2003

[22] Featherman and Pavlou 2003

## 4.1. Empirical Specifications

$$\begin{aligned}
\text{Prob}(RA_{\text{Adopted},i,T} &= 1|X) \\
&= \text{Logit}(\alpha_0 \\
&\quad + \alpha_1 \text{Previous_Investment_Performance}_i \\
&\quad + \alpha_2 \text{Previous_Investment_Characteristics}_i \\
&\quad + \alpha_3 \text{Controls}_i),
\end{aligned} \tag{1}$$

$$\begin{aligned}
RA_{\text{Share}_{i,T}} = \beta_0 & \\
&+ \beta_1 \text{Previous_Investment_Performance}_i \\
&+ \beta_2 \text{Previous_Investment_Characteristics}_i \\
&+ \beta_3 \text{Controls}_i \\
&+ \epsilon_i.
\end{aligned} \tag{2}$$

## Data Analysis and RA Service Launch Reaction

**Dependent Variables (Adoption Behavior):**

- *RAAdopted*: Whether lender used RA within $T$ months of launch.
- *RAShare*: Proportion of RA bids among all lender's bids in the period.

**Independent Variables:**

- *Previous_Investment_Performance*: Monthly return rate and number of defaulted loans (ln-transformed).
- *Previous_Investment_Characteristics*: Interest rate, terms, ln-transformed bid and total amounts.
- Calculated from January to March 2015 data.

**Control Variables:** Gender, age, experience.

**Table 2.** The Effect of Previous Investment Performance on RA Adoption

| | Panel A: Logit specification | | Panel B: Tobit specification | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Variable | $RAAdopted_{i,T=1}$ | $RAAdopted_{i,T=3}$ | $RAShare_{i,T=1}$ | $RAShare_{i,T=3}$ |
| $ReturnRate_i$ | −52.979 | −119.361 | −15.934 | −27.746 |
| | (76.178) | (79.433) | (20.159) | (21.655) |
| $\ln(\#Default)_i$ | −0.499** | −0.487** | −0.106** | −0.180*** |
| | (0.210) | (0.208) | (0.049) | (0.060) |
| $InterestRate_i$ | −0.080 | −0.042 | −0.025 | −0.016 |
| | (0.062) | (0.066) | (0.017) | (0.018) |
| $Term_i$ | 0.306*** | 0.265*** | 0.087*** | 0.088*** |
| | (0.041) | (0.039) | (0.010) | (0.010) |
| $\ln(BidAmount)_i$ | −0.078 | −0.057 | 0.029 | 0.011 |
| | (0.127) | (0.126) | (0.032) | (0.036) |
| $\ln(TotalAmount)_i$ | 0.195*** | 0.136** | 0.005 | 0.012 |
| | (0.059) | (0.058) | (0.016) | (0.017) |
| Lender characteristics | Controlled | Controlled | Controlled | Controlled |
| Observations | 924 | 984 | 924 | 984 |
| $R^2$ | 0.077 | 0.066 | 0.083 | 0.057 |

$^{**}p < 0.05$; $^{***}p < 0.01$.

## Analysis of RA Service Adoption Based on Past Performance

- *Panel A (Logit Specification):* ReturnRate coefficients insignificant; ln(Default) coefficients significant.
- 1% increase in Default leads to:
  - 39.3% decrease in odds of RAAdopted in 1 month.
  - 38.5% decrease in odds of RAAdopted in 3 months.
- *Panel B (Tobit Regression):* Significant negative effect of ln(Default) on RAShare.

**Implications:**

- Past investment performance affects RA adoption.
- Default, not ReturnRate, influences adoption;
- Defaults: salient, painful events; influence risk perception.[23]
- Lenders with defaults rely on personal judgment over RAs.[24]

[23] Tversky and Kahneman 1974
[24] Featherman and Pavlou 2003

**Table 3.** The Effect of Investors' Capability on RA Adoption

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Variable | $RAAdopted_{T=1}$ | $RAAdopted_{T=3}$ | $RAShare_{T=1}$ | $RAShare_{T=3}$ |
| *ReturnRate* | −52.634 | −118.154 | −15.678 | −27.049 |
| | (76.233) | (79.469) | (20.257) | (21.756) |
| ln(*#Default_Ultimate*) | 0.018 | 0.064 | 0.015 | 0.033 |
| | (0.138) | (0.140) | (0.031) | (0.037) |
| ln(*#Default*) | −0.514** | −0.540** | −0.118** | −0.207*** |
| | (0.241) | (0.243) | (0.053) | (0.066) |
| *InterestRate* | −0.082 | −0.050 | −0.027 | −0.021 |
| | (0.064) | (0.067) | (0.018) | (0.019) |
| *Term* | 0.305*** | 0.263*** | 0.086*** | 0.087*** |
| | (0.041) | (0.039) | (0.010) | (0.011) |
| ln(*BidAmount*) | −0.073 | −0.039 | 0.034 | 0.021 |
| | (0.136) | (0.135) | (0.034) | (0.039) |
| ln(*TotalAmount*) | 0.190*** | 0.119* | 0.001 | 0.003 |
| | (0.070) | (0.070) | (0.018) | (0.020) |
| Lender characteristics | Controlled | Controlled | Controlled | Controlled |
| Observations | 924 | 984 | 924 | 984 |
| $R^2$ | 0.078 | 0.066 | 0.083 | 0.058 |

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

## 4.3 Robustness Checks

### 4.3.1 Alternative Explanation:

- Concern: Investors capability, not performance, drives RA adoption.
- Solution: Replace ln(Default) with ln(Default_Ultimate).
- Result: ln(Default) remains significant; ln(Default_Ultimate) is not.

### 4.3.2 Coarsened Exact Matching (CEM):

- CEM used to further address endogeneity.[25]
- CEM produces datasets with lower imbalance.[26]
- Two groups: No defaults (control) vs. at least one default (treatment).
- 126 lenders matched; results in Table 4 and 5.
- Findings consistent with main model's results.

[25] Blackwell et al. 2009

[26] Iacus et al. 2012

**Table 4.** The Logit Specifications Before and After Matching

| | (1) | (2) |
|---|---|---|
| Treatment | Unmatched | Matched |
| *InterestRate* | 0.751*** | 0.020 |
| | (0.079) | (0.153) |
| *Term* | −0.177 | −0.172 |
| | (0.109) | (0.166) |
| ln(*BidAmount*) | −1.583*** | −0.917 |
| | (0.226) | (0.652) |
| ln(*TotalAmount*) | 1.574*** | 0.362 |
| | (0.159) | (0.288) |
| *Age* | −0.031* | 0.025 |
| | (0.016) | (0.056) |
| *Gender* | 0.187 | 0.341 |
| | (0.369) | (0.549) |
| *Experience* | −0.212 | −0.455 |
| | (0.161) | (0.327) |
| Observations | 984 | 126 |
| $R^2$ | 0.527 | 0.046 |

*$p < 0.1$; ***$p < 0.01$.

**Table 5.** The Effect of Treatment on RA Adoption

| | (1) | (2) |
|---|---|---|
| Variable | $RAAdopted_{T=3}$ | $RAShare_{T=3}$ |
| *Treatment* | −0.929** | −0.352*** |
| | (0.454) | (0.108) |
| Observations | 126 | 126 |
| $R^2$ | 0.032 | 0.060 |

**$p < 0.05$; ***$p < 0.01$.

# 5. Adjustment of RA Usage

**Research Question (RQ2):**

- Investigate investor interaction with RAs based on recent RA performance.
- Investors can enable or disable RA at any point.

**Recency Effect:**

- Emphasis on recent events.[27]
- Manifests among investors analyzing short-term data samples.[28]
- P2P lending platforms release monthly RA performance.
- Concern: Investors adjust based on short-term RA performance.

[27] Deese and Kaufman 1957, Murdock 1962
[28] Pompian 2011

## 5.1 Empirical Specification:

- One-year panel from May 2015.
- *RAShare*: Proportion of RA bids in month $t$.
- *RA_Performance*: RA investment performance of month $t-1$.
- *Manual_Performance*: Control for manual-bidding performance.
- Includes lender and month fixed effects.

**Table 6.** The Effect of Recent RA Performance on RA Usage

| | (1) | (2) | (3) |
|---|---|---|---|
| Variable | $RAShare_t$ | $RAShare_t$ | $RAShare_t$ |
| $RA\_ReturnRate_{t-1}$ | 1.494 (1.378) | | 1.078 (1.342) |
| $Manual\_ReturnRate_{t-1}$ | −0.136 (0.243) | | 0.082 (0.270) |
| $\ln(RA\_\#Default_{t-1})$ | | −0.015** (0.006) | −0.014** (0.006) |
| $\ln(Manual\_\#Default_{t-1})$ | | 0.026*** (0.008) | 0.026*** (0.008) |
| Investment characteristics | Controlled | Controlled | Controlled |
| Lender & month fixed effects | Yes | Yes | Yes |
| Observations | 12,895 | 12,895 | 12,895 |
| Lenders | 2,101 | 2,101 | 2,101 |
| $R^2$ | 0.170 | 0.172 | 0.172 |

**$p < 0.05$; ***$p < 0.01$.

## 5.2 Results

**Table 6 Specifications:**

- Two alternative *RA_Performance* measures.
- Column (1): *ReturnRate*
- Column (2): *ln(Default)*
- Column (3): Combination of both variables.

**Key Findings:**

- Investors react to *ln(Default)* over *ReturnRate*.
- *ln(Default)* from RA investments in month $t-1$ negatively impacts RA usage in month $t$.
- Suggests: More recent defaults in RA  Reduced RA usage.
- Specifically: 1% increase in *RA_Defaultt1*  1.4% decrease in *RASharet*.
- *Manual_Performance*: More defaults in manual bids  Increased RA usage.

**Table 7.** The Effect of Recent Overall Performance on RA Usage

| Variable | $RAShare_t$ |
|---|---|
| $ReturnRate_{t-1}$ | −0.139 (1.595) |
| $\ln(\#Default_{t-1})$ | −0.001 (0.007) |
| Investment characteristics | Controlled |
| Lender & month fixed effects | Yes |
| Observations | 12,895 |
| Lenders | 2,101 |
| $R^2$ | 0.169 |

**Table 8.** The Effect of RA Performance in Recent Two Months on RA Usage

| Variable | $RAShare_t$ |
|---|---|
| $RA\_ReturnRate_{t-1}$ | 1.695 (1.904) |
| $RA\_ReturnRate_{t-2}$ | −0.057 (2.055) |
| $\ln(RA\_\#Default_{t-1})$ | −0.017* (0.009) |
| $\ln(RA\_\#Default_{t-2})$ | −0.003 (0.010) |
| $Manual\_Performance_{t-n}$ | Controlled |
| Investment characteristics | Controlled |
| Lender & month fixed effects | Yes |
| Observations | 10,909 |
| Lenders | 18,18 |
| $R^2$ | 0.174 |

$^*p < 0.1$.

## 5.3 Robustness Checks

### 5.3.1 Alternative Explanation:

- Concern: Lenders adjust RA usage based on overall recent investment performance.
- Action: Replace recent RA performance with overall performance in Equation (3).
- Finding (Table 7): Overall performance metrics (*ReturnRatet1* and *Defaultt1*) don't significantly affect RA usage.
- Implication: Lenders focus on RA performance over overall investment performance.

### 5.3.2 A Longer Time Window:

- Action: Re-estimate Equation (3) considering both $t-1$ and $t-2$.
- Finding (Table 8): Only the most recent month's *ln(RA_Default)* negatively impacts RA usage.
- Consistency: Supports previous findings.

**Objective (RQ3):**

- Investigate: Does adjusting RA usage enhance investment outcomes?
- Implication: Should RA services incorporate human adjustments in their design?

**Background:**

- Investors actively modify RA usage based on recent RA outcomes.
- Pompian (2011): The recency effect might lead to suboptimal decisions.
- Typical RA focus: Long-term returns. But, investors' adjustments are often based on short-term, monthly performances.

# 6. Performance of RA Adjustment

## 6.1. Empirical Specifications:

- Econometrics model focuses on ReturnRate with several factors, including RAShare adjustment.
- Two samples used:
  - First: Focuses on completed loans. Measures RA share as RAShare_CoVi.
  - Second: Aggregated monthly performance, with RA share measured as RAShare_Std due to multicollinearity.

**Table 9.** The Effect of RA Usage Adjustment on Investment Performance

| Variable | (1) ReturnRate | (2) ReturnRate |
|---|---|---|
| *RAShare_Adjustment* | −0.001** | −0.002** |
| | (0.000) | (0.001) |
| *RAShare* | −0.000*** | −0.013*** |
| | (0.000) | (0.002) |
| Investment characteristics | Controlled | Controlled |
| Lender characteristics | Controlled | Controlled |
| Lenders | 1751 | 1205 |
| $R^2$ | 0.372 | 0.354 |

**$p < 0.05$; ***$p < 0.01$.

## 6.2. Results:

- Coefficients of RAShare_Adjustment are negative, indicating larger adjustments worsen return rate.
- Human intervention in RA usage may inadvertently disrupt performance.
- Algorithm-based decisions appear more optimal for long-term portfolio optimization.

## 6.3. Robustness Checks

**6.3.1. Coarsened Exact Matching (CEM):**

- Lenders divided based on RAShare_CoV into treatment and control groups.
- CEM used to match based on investment and lender characteristics.
- Significant and negative effects on ReturnRate found.

**Table 10.** The Logit Specifications Before and After Matching

| | (1) | (2) | (3) |
|---|---|---|---|
| Treatment | Unmatched | CEM_1 | CEM_2 |
| *RAShare* | −11.455*** | −0.894 | −0.554 |
| | (1.927) | (1.263) | (1.701) |
| *InterestRate* | 0.063 | −0.133 | −0.086 |
| | (0.077) | (0.151) | (0.199) |
| *Term* | −0.405*** | 0.026 | 0.082 |
| | (0.118) | (0.251) | (0.256) |
| ln(*BidAmount*) | 0.454 | 0.257 | 0.227 |
| | (0.280) | (0.564) | (0.702) |
| ln(*TotalAmount*) | −0.218 | 0.028 | 0.127 |
| | (0.214) | (0.252) | (0.289) |
| *Age* | −0.024 | 0.031 | 0.010 |
| | (0.023) | (0.039) | (0.042) |
| *Gender* | −0.280 | 1.207 | 1.252 |
| | (0.569) | (0.891) | (1.124) |
| *Experience* | 0.469** | 1.505*** | −0.411 |
| | (0.205) | (0.523) | (1.048) |
| Observations | 479 | 134 | 59 |
| $R^2$ | 0.836 | 0.240 | 0.044 |

**$p < 0.05$; ***$p < 0.01$.

**Table 11.** The Effect of Treatment on ReturnRate

| | (1) | (2) |
|---|---|---|
| *ReturnRate* | CEM_1 | CEM_2 |
| *Treat* | −0.007** | −0.012* |
| | (0.003) | (0.006) |
| *Constant* | 0.049*** | 0.052*** |
| | (0.002) | (0.003) |
| Observations | 134 | 59 |
| $R^2$ | 0.024 | 0.048 |

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

## 6.3.2. Causal Forest:

- Applied as an alternative matching method to CEM.
- RAShare_CoV treated as treatment variable. Regression trees built causal forest.
- Negative effect of adjustment on ReturnRate confirmed.

## 6.3.3. Adjustment Direction:

- RAShare_Adjustment measures intensity, not direction.
- Direction calculated for lenders with more than two adjustments.
- Results show direction of adjustment does not significantly impact relationship between RAShare_CoV and ReturnRate.

**Table 12.** The Moderating Effect of RA Adjustment Direction

| Variable | *ReturnRate* |
|---|---|
| *RAShare_CoV* | –0.002** |
| | (0.001) |
| *Direction* × *RAShare_CoV* | –0.001 |
| | (0.001) |
| *RAShare* | –0.011*** |
| | (0.002) |
| Investment characteristics | Controlled |
| Lender characteristics | Controlled |
| Lenders | 664 |
| $R^2$ | 0.461 |

**$p < 0.05$; ***$p < 0.01$.

## 7. Conclusion

**Research Questions and Answers:**

- **RQ1:** How does investors past investment performance influence their RA adoption?
  - Answer: Investors who have encountered more defaults are less likely to adopt RA services.
- **RQ2:** How do investors adjust their usage of RAs according to the RAs performance?
  - Answer: Investors swiftly adjust RA usage based on recent performance.
- **RQ3:** How does the adjustment affect investment performance?
  - Answer: Interventions based on swift adjustments undermine investment performance.

**Implications:**

- Intelligent systems should be more transparent.
- System designs should anticipate and account for user behaviors.
- Important to know when to include humans in the loop.

**Caveats:**

- Limited data on loan availability and RA recommendations.
- Unknown financial literacy of lenders.
- Focus is only on enabling and disabling RA services.

## Clear Structure

A well-structured research paper is pivotal for conveying complex ideas in a coherent manner. The structure should include:

- **Introduction:** This section lays the foundation, presenting theoretical backgrounds, research questions (RQs), key findings, and the paper's contributions.
- **Background:** A comprehensive literature review combined with a detailed context of the research.
- **Data Description:** A crucial part, offering insights into the nature, sources, and scope of the data used.

## Answering Research Questions

Each RQ should be addressed in a dedicated section, wherein:

- The RQ is clearly stated and explored.
- Empirical findings and analyses specific to the RQ are presented.
- Supporting arguments and evidence are provided to comprehensively answer the RQ.

# Robustness Checks

For each RQ and its corresponding analysis, robustness checks are essential. They ensure that the results are reliable and not artifacts of specific model specifications or sample selections.

- **Methodological Soundness:** Employ different methods or models to verify the consistency of the results.
- **Data Sensitivity:** Analyze how sensitive the results are to variations in the data set, such as considering different time periods or subsets of the data.
- **Alternate Explanations:** Explore and rule out alternative explanations to strengthen the validity of the findings.

## Contributions and Implications

Conclude with a discussion on:

- The implications of the findings for theory and practice.
- The contributions made to existing literature and knowledge.
- Future research directions based on the study's limitations and findings.

*Thanks!*