*Review of Economic Paper:*

**Contests with Revisions**

By: Emmanuel Dechenaux, Shakun D. Mago

Josh Mercurio

Economics 5314: Behavioral & Experimental Economics

Baylor University Hankamer School of Business

Dr. Jason Aimone

December 9, 2023

**Introduction**

In many business decisions, information is constantly controlled and contained for the benefit of the parties involved. Deals worth millions of dollars can fall through if details are leaked to the public before dates specified in NDA agreements. When one player has information about the other player’s choice or strategy, it can create a strategic imbalance between the two parties. Information leakage in mergers can increase the takeover premium giving managers incentives to discretely give away valuable information (<https://www.intralinks.com/company/news-press/leaking-information-ma-deals-boosts-deal-values-average-us21m>) and traders can use that information to generate returns.

Dechenaux and Mago (2023) examine how test subjects react to the possibility of information leakage. The motivation of this study is to better understand the strategies of players in these situations. For example, the observing player will be able to adjust their strategy to perfectly capitalize on the other player’s strategy. The observed player can take advantage of their choices being observed by committing a pre-action. The researchers explored the effects of probabilistic strategic asymmetry in rent seeking competitions - which are extensively applied to analysis of advertising, political races, litigation, M&A activity, and R&D - with a group of students at Purdue University. They found that the value of flexibility increases as the probability of information leakage increases and that there is a strong discouragement effect for the potentially disadvantaged player in the all-payer auction. The rent dissipation affected the all-pay auctions to an extent that expenditures were significantly less than that of the lottery contest.

**Literature Review**

All payer auctions  
  
Lottery Contests  
  
Uncertainty  
  
Information leakage  
  
Risk Preferences

**Literature Review**

Artificial intelligence (AI) is rapidly changing the world and accelerating growth in almost every industry (Foodman, 2023). As it becomes more prominent, it is important to understand how individuals interact with AI and how that differs from human interactions. One group of interest is older individuals who stereotypically have a tense relationship with technology (Niemelä‐Nyrhinen, 2007).

Due to its recency, there is not extensive literature on the interaction between AI and age; however, such research has been conducted about other technological novelties. In 2011, researchers examined the relationship between age and trust in the internet. They found that the most important indicators of trust were experience with the technology and general attitudes toward technology. When these factors are controlled for, the relationship between age and trust in the internet becomes nonsignificant (Blank & Dutton, 2011). Applying these findings to AI, we can hypothesize that it will take more time for older individuals to become trustworthy of AI, as they will need time to experience it firsthand. This implies that current studies, such as this one, are likely to find lower levels of trust toward AI from older individuals; however, once enough time has passed, the trust levels will likely increase.

Other research has explored what AI characteristics garner trust from humans. Borau et al. (2021) found that female chatbots were perceived as more human and trustworthy than their male counterparts. While the current study does not include gendered bots, the idea that specific characteristics of AI alter human perception and trust is relevant. Makovi et al. (2023) showed that their participants believed that bots “behave as if they had preferences, be it for money (the currency in our experiment), or for real-life currencies like collecting likes on social media or avoiding sanction and bans in online communities such as Wikipedia” (p. 2, pp. 2). These perceived humanlike characteristics could influence the trust levels of participants.

In a technological era where AI continues to integrate with society, understanding bot-human relations is essential. Older individuals have a history of taking longer to trust new technology, and subsequentially, may have a different experience with AI than their younger counterparts (Blank & Dutton, 2011). The current study expands the literature by examining the relationship between age and trust in AI.

**Experimental Design**

The environment for the original study included online experiments with 7,917 US students who were 18 years of age or older and recruited on the crowdsourcing marketplace Amazon Mechanical Turk. Five studies were performed; the results of each are summarized in Table 1 below. The experiments were built on one another sequentially, starting with a questionnaire regarding how participants thought about the preferences of bots. Studies 2, 4, and 5 were online experiments using currency to compare how humans interact with each other in comparison to interacting with bots. Study 3 was another questionnaire, which explored the participants’ thoughts about interaction norms and trust.

**Table 1**

*Summary of Experiments*

|  |  |  |
| --- | --- | --- |
|  | Study | Findings |
| 1. | A questionnaire asking how much participants agreed about the preferences of bots and humans to see if currency works in this study | People believe bots behave as if they have preferences for money and other currencies, so currency should work in this study |
| 2. | Document differences in the way humans treat bots vs. humans with sharing currency, as well as the difference in the way they treat other humans who interact with bots vs. humans | * humans earn less trust when sharing with bots * bots gain less trust when sharing with humans * humans gain less trust when punishing humans who did not share with bots |
| 3. | Questionnaire for Trustor about beliefs in what Helpers or Punishers should do (“norms”) and how much to trust them | The perceived consensus around the norms of sharing and punishing correlates with the trust that norm-followers gain over non-followers |
| 4. | Same as Study 2 except Trustors are informed before the decision that 93% surveyed said Helpers should share with Beneficiaries making norm consensus salient | The consensus information affects the trust earned by bots who share with humans: their trust-gain climbs to 55 percentage points, compared to 44 percentage points in Study 2 |
| 5. | Similar to Study 4 except where Trustors are randomly assigned to either receive a message about the norm-consensus or receive no message at all before they make their trust decisions | The consensus information affects the trust earned by people who shared with bots: their trust-gain climbs to 46 PP, compared to 37 PP |

The institution for the study included the form of communication, choice architecture, and rules governing the game. The researchers communicated with the participants via text to inform them whether their counterpart was a bot or a human. People were referred to as “MTurk workers,” and bots were referred to as “Bot.” Participants had a binary choice to share or not as they split their resources evenly between themselves and beneficiaries.

The roles of the participants are illustrated in Figure 1 below and included Beneficiaries, Helpers, Punishers (each of which can be played by a human or a bot), and Trustors (only played by humans). Helpers were given monetary resources and chose to share with Beneficiaries or not. Punishers observed the Helpers’ behavior and could penalize the Helper if they disagreed with the sharing decision. The Trustor observed the actions of either the Helpers or Punishers and then played a trust game with them. The Trustor could send a portion of their own endowment to their counterpart, the money sent was tripled, and the Helper/Punisher was then able to send a portion back to the Trustor.

The behavior observed from the experiments indicated that actors earned trust by sharing and by punishing those who did not share, but the trust-gains were less pronounced when bots were involved. Trust-gains generally increased when participants were informed that there was a high consensus about the norm of sharing, which suggests that people might alter their behavior once informed. Findings also suggest that participants actively think about how their behavior toward bots is viewed and interpreted by other people.

**Empirical Replication**

Replicating the results of Malkovi et al. (2023) was relatively simple because the code and data provided were straightforward. We were able to run the code and produce all the charts shown in the paper. All graph characteristics, including color, were completed using R code, creating paper-ready pictures. The only graph that was not replicated exactly was Figure 3. The code produced a graph depicting the trust levels of the trustor when the punisher did/did not punish. The figure in the paper had the “trust level of the Trustor when the Punisher punishes” on top and the “trust level of the Trustor when the Punisher does not punisher” on the bottom. The code, however, created a graph with the values flipped. This was a minor change that did affect the story told by the figure.

Looking at the graphics in the paper, we did not expect the replication to be so easy. The graphs are high quality, color-coded, and simple to interpret. We assumed the code would allow us to produce the same results but were unsure how the final product would look; however, the code included everything necessary to create publishable graphs. Even Figure 3 – the only graph different from the paper – merely had a superficial difference.

It is important to note that the graphs in the paper mostly included boxplots and illustrations of confidence intervals. This may be part of the reason replication was so simple. Had there been more complex analyses or figures, it may have been harder to produce similar results.

**Alternative Approach and Results**

We hypothesize that age affects human-machine interaction. Specifically, aligning with previous literature, older individuals will be less trusting of bots. To investigate the impact of age on participants’ willingness to trust bots, we performed multiple regressions, using the same data collected by Malkovi et al. (2023). A logit regression analyzed how age affected whether Player 1 – the giver in the ultimatum game – decided to trust or not when the punisher was a bot. The results show that when the punisher is not a bot (a human), an increase of one year in age increases the probability of trust by 4.5% (*p* =.011). However, when the beneficiary is a bot, an increase of one year in age only increases the probability of trust by .69% on average which is 3.8% (*p* =.056) less. This implies that while older individuals are more trusting than their younger counterparts, they are less trusting of bots than younger people.

 A second logit regression evaluated the impact of age on whether Player 3 – the punisher – punishes when either the helper or the beneficiary is a bott. We find that when there are only human players, an increase of one year in age decreases the probability of punishment by 0.61%, although this result is statistically nonsignificant at the 10% level. When the Beneficiary is a bot, the probability of punishment decreases by 179% (*p* =.001). On average, when each additional year of age increases the probability of punishment by 2.46% (*p* =0.66) when the Beneficiary is a bot. When the Helper is a bot, an increase of one year in age increases the probability of punishment by 1.17%; this result is also nonsignificant at the 10% level.

**Conclusion**

Understanding how humans interact with technologies is essential in our increasingly digital world. Discerning human-technology interaction helps to ensure the effectiveness, usability, and satisfaction of intercommunications between humans and technology such as chatbots. There are benefits of relying on chatbots instead of humans in many situations, which means that chatbots are here to stay. Society is adopting this phenomenon, but general acceptance is still evolving, and there are differences in trust levels across age groups when interacting with chatbots.

Studies such as this are helpful to learn where society stands on the acceptance of interacting with technologies. Questions seem to remain regarding how to further advance trust levels of communicating with chatbots. Additional research could assist with finding these answers, but experiments will need to be tailored for different age groups.

**References**