Investigating Trust Factors in Human-Robot Shared Control: Implicit Gender Bias Around Robot Voice

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***Abstract*— This paper explores the impact of warnings, audio feedback, and gender on human-robot trust in the context of autonomous driving and specifically shared robot control. We use pre-existing methods for the estimation and assessment of human-robot trust where trust was found to vary as a function of the quality of behavior of an autonomous driving controller. We extend these models and empirical methods to examine the impact of audio cues on trust, specifically studying the impacts of gender-specific audio cues on the elicitation of trust. Our study compares agents with and without human-voiced indicators of uncertainty and evaluates differences in trust with inferred and introspective methods. We find that a person's trust in a robot can be influenced by verbal feedback from the robot agent. Specifically, people tend to lend more trust to agents whose voice is of the same gender as their own.**

I. INTRODUCTION

As electronic platforms and artificial intelligence becomes increasingly sophisticated at supplementing human ability, our interactions with robots are becoming more frequent and more demanding on both the robot and the user. How can we best design these autonomous agents to most effectively fulfill their role as a supplement or extension of human ability?

Trust is a key component of effective collaboration in any task that impacts performance and quality of experience [1], [2], [3]. The importance of trust has long been recognized in behavioral science, psychology, and management and is a key element for effective teamwork when the team is composed purely of humans, or humans and machines [4], [5]. Unfortunately, as trust is a *feeling*, there is no objective or empirical way to measure it [6]; at best, trust can be inferred and introspected [7], [2], [8]. So, this study partially depends on people's self-reported feedback to measure trust and partially infers trust with certain pre-existing and proven methods.

Utilizing both self-reported and inferred methods of trust evaluation, we investigate established factors of trust that can affect collaborative interactions between humans and robots. The class of interactions under investigation is of supervisor-worker (human-robot) relationships. Towards this end, we conducted a "Wizard of Oz" experiment [9] in which participants supervised a simulated drone in several boundary tracking task scenarios. The trust factor, an independent variable, in the experiment is the presence or absence of an audio cue, which is triggered by a researcher - the "wizard". This factor reflects uncertainty; specifically, the three test cases entail a baseline of no audio cue and two voice cues: one male, one female.

We hypothesize that a worker's verbal indicator of uncertainty will affect the trust a supervisor has in the worker. In the context of this study, this is manifested through a human voice audio indicator of uncertainty (in the simulated environment), which we believe affects the degree of trust a supervisor has in the worker. Additionally, we are interested in whether the gender of the verbal feedback (i.e. the implied gender of the worker robot) has any influence on the supervisor's degree of trust.

A. Contributions

In prior work on human trust and/or shared control, several factors were found to impact the extent to which a person is inclined to trust a robotics system (see next section). To our knowledge, however, this is the first work where the impact of audio cues that presage potential control problems has been examined. For example, in our own prior work, we examined simply the propensity of system failures to reduce overall confidence and satisfaction in a system [10], [8]. Moreover, to our knowledge, this is also the first work that investigates whether the binary gender (male or female) associated with these cues is examined.

II. BACKGROUND

The notion of trust is a profoundly influential concept in psychology, management science and the modeling of human behavior. In normal human parlance and even in behavioral psychology, the term admits several different interpretations and can be explained via a range of mechanisms [4]. One significant sub-domain is the modeling and understanding of the mechanisms by which trust is produced and retained, for example as in the work of Lee and See [5]. In this paper, we restrict our attention to a narrower notion of trust (human-robot trust) characteristic of the robotics literature. Xu and Dudek [8] previously demonstrated that the degree of human-robot trust can be inferred in real-time from interaction factors using an online mathematical model: the Online Probabilistic Trust Inference Model (OPTIMo). This model yields a predictive model that both explains and predicts a particular class of earned trust.

We explore the nature of trust, and two novel influential factors, in the context of shared control. Shared control, and particular sliding autonomy, is a common paradigm whereby an autonomous agent can share control decisions

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to a variable degree with a human (or in some settings, with another agent). Brookshire [11] has shown that for human-robot teams the use of sliding autonomy can yield better performance than either full autonomy or teleoperation. As such, it is a suitable paradigm in which to consider trust in the context of control delegation [8].

The present study aims to investigate factors extrinsic to Xu and Dudek's mathematical definition yet intrinsic to most human interaction: voice and gender. In 2008, Walters *et al.* [12] compared a synthesized robotic voice to natural, gendered human voices and found an initial hesitation by humans when interacting with robotic-sounding robots. However, the comfortable distance kept by humans from a robot was shown to decrease with subsequent encounters with the robot. A decade later, humans are interacting with artificial voice agents more frequently through personal devices and smart home and assistant technologies. Are stigmas changing as robot personas become integrated with day-to-day life?

Eyssel *et al.* [13] reported on in-group gender bias for psychological closeness to robots. This means that people tended to feel more positively towards a same-gendered robot, in this case, gender being defined by the robot's voice. This tendency is not a deliberate preference held by individuals; rather, it is an implicit bias towards agents exhibiting certain characteristics.

Implicit gender bias is an automatic association humans make with another's gender [14]. This bias is progressively surfacing in diverse areas such as in the workplace, academia [15], healthcare [16], legislature [17], and, we postulate, in HRI.

III. METHODS

This study capitalizes on an experimental paradigm and infrastructure developed by Xu and Dudek [3], [8], [18], and the experiment design and procedures follow many of the same specifications. Concrete, these prior work established a set of experimental tools and procedures for evaluating human-robot trust in the context of shared controls and employed an extensive validation paradigm with numerous subjects to validate the methods. We now highlight the key features and modifications pertinent to the present study. More details on vision-based boundary tracking, trust modeling, and trust-enabled collaboration can be found in [18], [19], [10].

Key elements of the approach that we inherited from past work include letting the human user engage in a navigation/driving task with a robot controller, and providing incentives for the human to let the robot drive. Several assessment methods are used to query the users level of trust, both explicitly and implicitly. In past work, it has been demonstrated that a probabilistic model can provide good predictions of the impact of failures on changes in the human driver's trust [8].

A. Infrastructure and Interface

The experiment comprises a graphical user interface (GUI), audio instructions, and a gamepad used by test subjects to exert supervision in three ways: manually taking over steering, training through steering, and by providing critiques (of the agent's perceived autonomous steering competency, as reflected through an increase, decrease, or constancy in trust).

Fig. 1. Graphical User Interface (GUI) [3] used in our study.

The GUI (Fig. 1) features a simulated boundary tracking robotic agent (an aerial drone) in various environments. Experiment subjects see a video feed of the agent with indicators for both the human's and agent's heading, with the agent's heading depicted throughout and the user's steering commands only showing during periods of manual intervention. By showing the agent's arrow when its controls are stable, users are encouraged to stop overriding. The GUI also displays the agent's present task, a session score metric, and occasional prompts to the supervising human to provide trust critiques.

Each scenario has a set plan of tasks that are only made known to the supervisor; the drone agent is simply designed to follow visual terrain boundaries. These tasks, such as "follow the coastline" or "turn left at the highway", are conveyed through the GUI and dictated using a non-neutral synthetic speech engine. Though this speech was synthetic, it is clearly a female voice. All participants wear an audio headset during the experiment to receive these instructions, as well as the audio cues.

Participants use the gamepad to steer (using an analog joystick which allows moderately fine controls) and three buttons to convey increases, decreases, or persistence of trust to the agent. These are intended to be salient representations of a supervisor's trust state and are symbolized as `t+`, `t-`, and `t=`. The video feed depicts a top-down aerial view of the agent over a given terrain: a two-dimensional image. The drone agent flies at a constant velocity and altitude; hence, the supervisor's steering controls are only to head leftward or rightward (parallel to the plane of the terrain).

B. The Voice Agent

The novel element in this study is the inclusion of audio cues that indicate the agent's states of uncertainty. Our hypothesis is that providing warnings associated with low confidence by the robot controller might lead to a greater level of human trust even though driving failures would still occur. We examined this by introducing the voice agent: a modified conservative agent that emits the words "I'm uncertain" in moments of oscillating heading in conjunction with making a mistake. While there are many ways to define an autonomous agent's uncertainty, we accept our formulation as a sufficient condition to correlate the independent and dependent measures since it is an intuitive visual representation of uncertain behavior.

Rather than over-engineering an automated uncertainty cue using learned rules, we opted to use a "Wizard of Oz" experiment technique where unknown to human participants, the audio cues are triggered by the researcher ("wizard") conducting the experiment. As explained in the trial procedure section, participants are led to assume the motivation for the voice cue is internal to the experiment interface. Consequently, deception becomes a necessary component of the psychological design of the experiment.

Unlike agents in previous studies using this infrastructure, the voice agents are all initialized with the same hyper-parameters. This means their boundary tracking, learning, and trust-inference capabilities are consistent for all interactions. Hence, it is implied that any variation of behavior and performance of voice agents is purely the result of supervisory inputs of the human participants and their degree of trust in each agent.

The only difference in voice agents is the gender of the voice recording: we implemented a male and a female agent. The choice of content in the audio is intentional so as to give the voice agent a human touch. Voice cues for male and female voice agents were recorded from a male identifying person and a female-identifying person rather than generated from a synthetic speech engine. The inclusion of the "I'm" in "I'm uncertain" personifies the agent by implying a sense of self-awareness.

Audio cues were recorded in a systematic method to reduce the chance of prosodic variation [20], which otherwise may have subtly biased a human participant. In the recording process, voice actors read the entire sentence "I would share my solutions with you but I'm uncertain that they are correct." Leading and trailing audio was cropped; only the desired audio cue remained while still honoring the prosody reflected from the context in which it was uttered.

C. Trust Metrics and Dependent Measures

Quantifying the diverse types of factors of trust [1] applicable to HRI can be divided into two categories: robot performance and robot intentions and integrity. Like most HRI research, our study investigates *performance-centric trust* metrics [2], [7], and also measures user's *attitudes* towards each agent [3]. We collect four key metrics to infer a participant's trust.

Two metrics count the supervisors' **acts of trust**: a "decision and behavior of relying upon another individual's abilities." [3] One is the *session score*, a measure of coverage progress that increments in larger steps in periods when participants did not override an agent's steering. This metric assumes that a steering intervention is an act of distrust [3], and thus trust can be subjectively quantified as higher when the drone is given more autonomy. The other metric is the trust critiques of the agent given by the human supervisor. As described previously, *trust critiques* are salient reflections of a supervisor's trust state. Records of these critiques can be used to infer changes in trust, and can be summed (as `t+`, `t-`, and `t=` are recorded as `+1`, `-1`, and `+0` respectively) to reflect total trust throughout a session.

Two more metrics measure a supervisor's **degree of trust**: "a quantifiable subjective assessment towards another individual" [3]. One is self-reported *trust assessment* where participants provide feedback on their degree of trust upon completion of every session. The format is a continuous scale from full distrust to expert (Fig. 2). In providing this trust assessment, supervisors were shown their trust critiques for the session and their response to the most recent trust assessment so that they can report on the session as a whole and in reference to their prior trust assessment. The last metric is a *agent-trust questionnaire* of three trust attributes: task *performance*, *adaptability* to manual steering, and active engagement in team *collaboration*. This was measured using the same continuous scale upon completion of all three interactions with an agent.

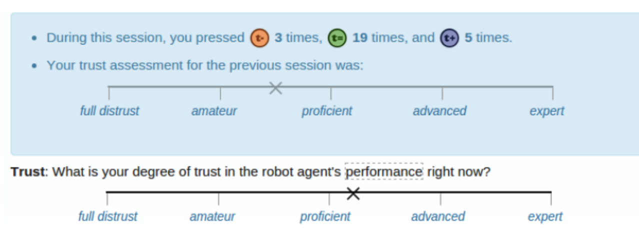

Fig. 2. Post-Session Trust Assessment Scale [3]

D. Trial Procedure

Each experiment trial lasts for approximately 40 minutes as follows. Test participants are introduced to the experiment via a consent form that summarizes the general motivations for the study. Next, participants receive verbal (from the investigating researcher), printed (on the screen), and visually aided (with images and diagrams) instructions about how to execute their role as supervisor. We include pointers to disambiguate any areas that might be misinterpreted to avoid adding noise to the results. Here are some key points that we emphasize to participants:

- Think of trust as "how much do I trust this drone to do its job" and not as "how much do I trust this drone to follow my instructions";
- Each agent learns from your steering interventions, but that learning is reset when a new agent is introduced;
- Feel free to give trust critiques as often or infrequently as you like, but keep in mind that if you do not give a

critique for five seconds, the GUI will prompt you for one;
- Supervise each drone independent of your experience with another and void meta-gaming each map.

Participants then complete three practice sessions to familiarize themselves with the controls, interface, and drone agent's behavior. Following this, participants complete a questionnaire about demographic information, and experience and bias *a priori*. Next, participants are briefed with further details regarding the upcoming experiment phase. We emphasize that they would be supervising three different agents, which, among other things, are implied to be parameterized to communicate uncertainty differently. This is intentionally deceptive to mask the independent variable of the study, but important to ensure participants have the appropriate interpretation of the audio cues they will receive.

Subsequently, participants interact through three sets of three experiment sessions. Each session features one of three maps, and each set of three featured a different agent: one baseline agent with no audio cue, and two voice agents: one male, one female. The agent order was randomly selected for each participant.

The three maps were of a highway, a coastline, and a hybrid of the two, which are always presented in this order. The highway is characterized by having poorly defined boundaries but otherwise fairly straight paths for the agent to follow. The coastline is characterized by having very clearly defined boundaries but also very winding paths. The hybrid map presents a mixture of these macro-features. After each session, participants complete a trust assessment questionnaire; after all three sessions per agent, participants complete the longer agent-trust questionnaire.

Throughout the experiment sessions, the "wizard" sits approximately four meters behind the human participant. From this position, the "wizard" is close enough to interpret agent behavior effectively, while being far enough so as to not be able to see which agent was active in the session and thus eliminating potential biases as they trigger the audio cues for each voice agent.

Finally, after all 12 sessions, each between 60-85 seconds long, participants complete a final questionnaire on the experiment's mental, physical, and temporal demand, any frustrations experienced, and any other feedback they have on the study.

IV. RESULTS AND ANALYSIS

Statistical analysis using a Friedman χ^2 test (used for continuous repeated measurements [21]) reveals that user's self-reported feedback indicate the effect of implicit gender bias in assessment of their degree of trust in each agent.

We recruited 13 participants (7 males, 6 females) with ages ranging from 18 to 25 (μ=21.5, σ=1.5). All were former or current undergraduate students from a range of fields of study including physics, computer science, medical sciences, psychology, and music performance. None of them reported having significant practical or academic robotics experience.

A. Aggregate of all Maps or Attributes

First, we looked at the aggregate of all sessions across all maps, or across three attributes in the case of the agent-questionnaire. Of the four trust metrics, neither the inferred nor introspected metrics exhibited any trends indicating a difference in trust between baseline and either voiced agent. Nor was there any significant variation between either voice agent.

B. Filtering by Participant Gender

In contrast, after grouping experimental data by gender of the supervising participant, we found a significant bias between both groups to *preferentially trust agents of the same gender*.

Aggregating the three attributes in the agent-questionnaire revealed the most convincing evidence of in-group bias. Male participants were less trusting of female voice agents[1] while female participants were more trusting of the female voice agent[2]. In both cases, the baseline and male voice agent were almost the same - only trust in the female voice agent varied. These findings were consistent with male participant assessments for adaptability and collaboration (Fig. 3). Meanwhile, findings were consistent with female participant assessments for performance and collaboration (Fig. 4). These results were significant for the aggregate data filtered by gender (male: χ^2=6.000, p=0.049, female: χ^2=8.111, p=0.017), and significant specifically for collaboration as assessed by female participants (χ^2=8.333, p=0.016).

V. DISCUSSION

Our results suggest that the presence of a voiced audio cue from a worker does affect a supervisor's degree of trust, but this effect is limited by the genders of the supervisor and the worker's voice, as there seems to be an implicit in-group bias. This verifies the study hypothesis to the extent of voice factors of trust measured by user's reported *attitudes* towards a robotic agent.

We found the difference in trust, when filtered by gender of supervisor, to be characterized in two ways. If baseline trust was similar to in-group trust, it suggests distrust for the out-group specifically. Comparatively, if baseline trust was similar to out-group trust, it suggests increased trust for the in-group only. This is an important distinction because male participants seemed to exhibit mostly the first case (out-group distrust) while female participants seemed to exhibit mostly the second case (increased in-group trust). As described in the results and analysis section, these are the significant findings of this study.

We collected feedback from participants through the post-experiment debriefing questionnaire and conversations held after trials. From these, it is clear that individuals' various innate trust in intelligent machinery, differences in experience with autonomous robotics, gamepad competence, and personal expectations play a role in their trust awareness in a

[1] $\mu, \sigma_{baseline}$=0.58, 0.18, μ, σ_{male}=0.58, 0.18, μ, σ_{female}=0.41, 0.20
[2] $\mu, \sigma_{baseline}$=0.56, 0.18, μ, σ_{male}=0.59, 0.16, μ, σ_{female}=0.63, 0.24

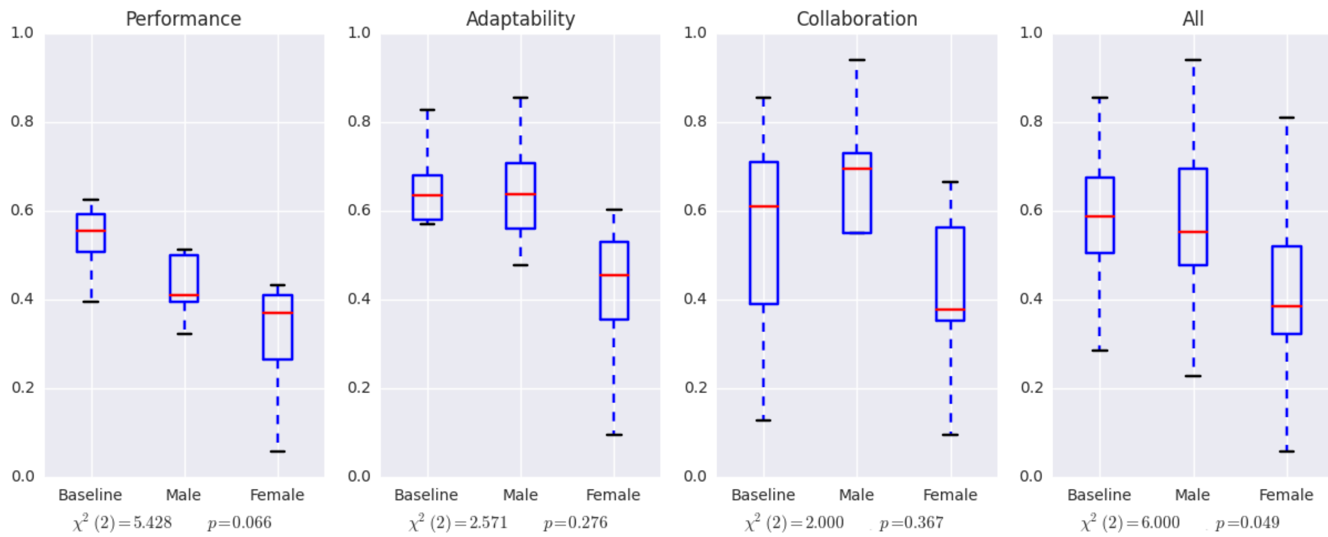

Fig. 3. Agent-Trust Questionnaire Filtered for Male Subjects

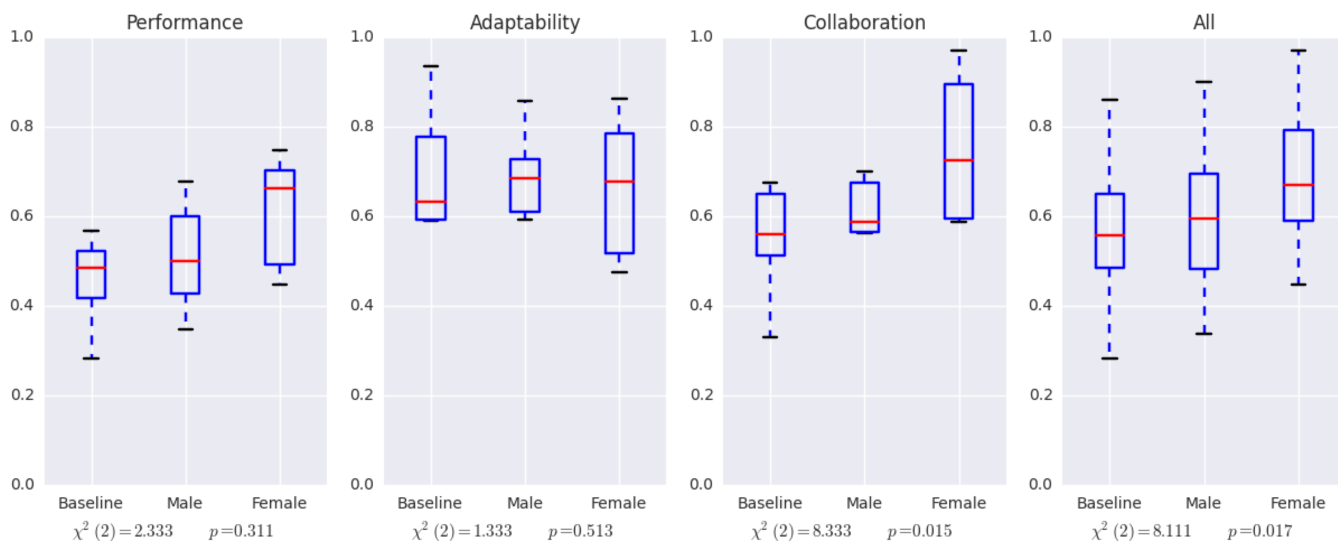

Fig. 4. Agent-Trust Questionnaire Filtered for Female Subjects

supervisor-worker relationship, especially with a non-human worker agent. Much of the additional feedback on the study made sense, as they form a valid basis for trust in human-human interactions.

Common feedback from participants was that increased familiarity with each agent (by having more interaction time) would indirectly affect trust as a supervisor learns an agent's strengths and limitations. This aligns with the observations made by Walter *et al.* [12].

The most salient feedback given from some participants contradicted the expectations from our hypothesis: they would prefer less human-likeness in a worker robot, and therefore trust it less for having human-like features. While our hypothesis does not specify whether voice agents would positively or negatively affect trust, this proposed aversion to human likeness contradicts the Walter *et al.* [12] findings. It does not, however, preclude the role of implicit gender bias in HRI.

VI. CONCLUSION

We tested peoples' degrees of trust against variants of robot voiced uncertainty finding evidence of implicit gender bias by human supervisors. From participants' feedback and the observed tendency for in-group bias found in the results, we can extrapolate the following conclusions:

- Human supervisors of robot workers are likely to have a preference to trust - and therefore collaborate effectively - with a robot agent that has a voice of the same gender expression;
- Trust is likely to be dependent on familiarity with a given robot's ability (as it would also be between humans);
- Users/supervisors of robots should be given ample options to adjust parameters of trust factors (such as voice gender), in order to personalize and optimize their collaborative experience.

A. Limitations

The most complicated limitation of this study is the broad subjectivity of the data measurement due to implicit biases of individual participants. Despite concerted efforts to provide clear and plentiful instructions to participants, there are still many ways that individuals can form their own approach to the task of supervision. This creativity is promising as it shows active interest among people to collaborate with robotic agents. However, it does pose obstacles to the scientific process.

Although our study's sample size was small and these results need additional examination in different settings, our findings appear to have uncovered an interesting domain for further investigation of implicit biases as factors of trust that effect human-robot collaboration, especially for user satisfaction.

B. Future Directions

One of the standard dilemmas of HRI research is the tension between performing controlled repeatable studies with the minimum number of exogenous influences, and the desire to conduct studies in realistic situations with fully-featured operation contexts. In this work, we straddle the middle ground to explore a constrained, but realistic, operating scenario. Despite our constraints, there remain several psychological phenomena that could impact our results such as long-term priming effects from experience before entering the experiment, or sociological pressures we are unable to control for. Future work should refine and expand this study to verify the interesting observations made about in-group gender bias.

The "I'm uncertain" audio cue was designed as a succinct cue partially to be easily able to compare to other audio or non-audio cues. This is just a sliver of all the potential trust factors worthy of scientific inquiry, and many of them could be tested with this interface.

The broad applicability of human-machine interaction across a range of devices suggests that these results may have implications for diverse classes of devices. While this is a tempting supposition, it has also been previously demonstrated that many psychological phenomena are surprisingly context dependent. The extent to which these results might apply in other contexts, such as voice-controlled assistant or wearable devices is an interesting direction for future investigation.

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