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RESEARCH NOTE

DOES BOT GENDER MATTER? THEORY AND EVIDENCE FROM A HIGH-TENSION SERVICE CONTEXT[1]

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Despite the increasing use of AI-powered voicebots, our understanding of how the choice of bot gender may impact service outcomes in high-tension service contexts, such as debt collection, remains limited. To address this gap, we drew on the tensions-based view of customer relationships and gender stereotype theory to hypothesize how and when voicebot gender matters in high-tension service contexts. We tested our hypotheses using a proprietary dataset of debt collection calls made by AI voicebots. We found that female voicebots increase the odds of a positive repayment intention by 28.3%. This gender effect is more pronounced when service encounters begin with higher tension, such as during weekdays or with initially uncooperative customers. We further show that the gender effect can be explained by the advantages of female voicebots in reducing behavioral and emotional tension during service interactions.

Keywords: Artificial intelligence, human-computer interaction (HCI), voicebot, tensions-based view, gender stereotype, high-tension service contexts

Introduction

High-tension customer service contexts, such as debt collection and service failure recovery, are "critical moments of truth" that significantly impact customer relationships and business performance (Heidenreich et al., 2015; Oliveira & Lumineau, 2019). Such high-tension service settings are characterized by heightened customer emotions, strained relationships, and potential conflicts (Edvardsson et al., 2011; Heidenreich et al., 2015), which often induce high turnover among human service representatives. Consequently, companies are increasingly exploring AI-powered voicebots to handle tense customer service interactions (Phillips & Moggridge, 2019). With the global chatbot market valued at 5.1 billion USD in 2023 (SNS Insider, 2024), business leaders, AI bot developers, and service managers increasingly face bot design issues that could directly impact service performance and influence future AI investment decisions.

In this paper, we focus on an important design dimension: the *gender* of AI voicebots. We are first interested in *whether* female voicebots have genuine performance advantages in high-tension service contexts. The human-computer interaction (HCI) literature has previously studied the effect of bot gender, primarily in friendly or neutral settings, such as virtual partners in healthcare (Borau et al., 2021), gaming assistance (Forgas-

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Coll et al., 2022), and sales recommendations (Benbasat et al., 2020) (see Appendix A for a review). However, the prior literature documents inconclusive evidence for the bot gender effect on customer perceptions and service performance measured by purchase intentions (Beldad et al., 2016; Qiu & Benbasat, 2010). Another notable void in the literature is that bot gender effects remain largely unexplored in high-tension service settings. Given prior studies, it remains unclear whether the female gender of voicebots has an impact on service performance overall, or whether, in certain contexts, such as high-tension service situations, female voicebots exhibit performance advantages.

It is crucial to address this question because, in practice, companies frequently default to using female voices and names in bot applications like Cortana and Siri (Cambre & Kulkarni, 2019). There have been suggestions that the preponderance of female bots is rooted in gender bias, with AI products being "created by men with a female stereotype in their heads" (Oliver, 2020). Given the research gaps identified above, it remains uncertain whether this design choice leads to tangible performance improvements or merely perpetuates a gender myth in AI. This is particularly critical in high-stakes, high-tension service contexts, where ineffective management of such contexts can have significant consequences, including customer churn and payment defaults (Hill, 1994).

Furthermore, existing studies are conducted in laboratory settings and lack evidence on the real-world impact of bot gender. Lab experiments may not be ideal for studying high-tension service settings because of inherent difficulties in recruiting participants with experience in high-tension service interactions and inducing authentic customer reactions in simulated situations. Existing laboratory studies primarily focus on how bot gender affects user attitudes and perceptions (e.g., likability, attractiveness) toward the *bot* (Lee et al., 2000), rather than on downstream business outcomes such as service performance. There is also a shortage of research on the impact of robot gender on real-world service outcomes. This research aims to fill these research gaps by focusing on real-world high-tension service outcomes, thereby providing more credible and direct support for business decisions in high-tension service contexts.

Our second goal is to elucidate the underlying mechanisms, i.e., *how* voicebot gender affects high-tension service outcomes. Although a few studies have examined gender effects through factors such as perceived humanness and competence (Ahn et al., 2022; Borau et al., 2021; Pitardi et al., 2023), they offer limited insights into the mechanisms by which voicebot gender may affect high-tension service outcomes. It is imperative to delve into the mechanisms specific to high-tension contexts, as uncovering such mechanisms would lend further credibility to the existence of gender effects in these settings rather than attributing the role of gender to a mere statistical artifact.

Finally, it is crucial to comprehend *when* gender effects are more salient. From a theoretical perspective, answers to this question shed light on the boundary conditions that govern the impact of bot gender. From a practical standpoint, understanding such factors enables the selection of personalized bot genders, thereby optimizing voicebot service performance.

In sum, our research aims to address the following three questions:

> ***Whether:*** Do female voicebots have real-world performance advantages over their male counterparts in high-tension service contexts?
>
> ***How:*** What are the mechanisms through which voicebot gender can affect service performance?
>
> ***When:*** When does the effect of voicebot gender become more pronounced?

We address the above questions in the context of AI voicebots for debt collection, a representative high-tension service setting characterized by stressful, unpleasant, and even threatening interactions with customers (Phillips & Moggridge, 2019). The debt collection industry is economically significant and growing fast, with a projected total value of USD 43.69 billion by 2027 (Industry Research, 2023). We collaborated with a prominent Chinese AI voicebot provider to obtain a unique dataset of debt collection calls made by AI voicebots. We focus on the effect of voicebots' gender on customers' repayment intention—i.e., whether the customer promised or agreed to repay their overdue debt during a debt collection call. Repayment intention is the most important performance metric in the debt collection industry (Roy, 2021). Prior research shows that repayment intention is a strong predictor of actual repayment (Mazar et al., 2018) and is commonly used as a proxy for actual payment (Li et al., 2024).

Theory and Hypotheses

We draw upon the *tensions-based view* (TBV) of customer relationships (Fang et al., 2011; Zheng et al., 2022) and *gender stereotype theory* (Prentice & Carranza, 2002) to develop hypotheses regarding the effect of bot gender, the underlying mechanisms, and moderating factors in high-tension service settings, as exemplified by debt collection calls (see Figure 1 for a summary of the hypothesized relationships).

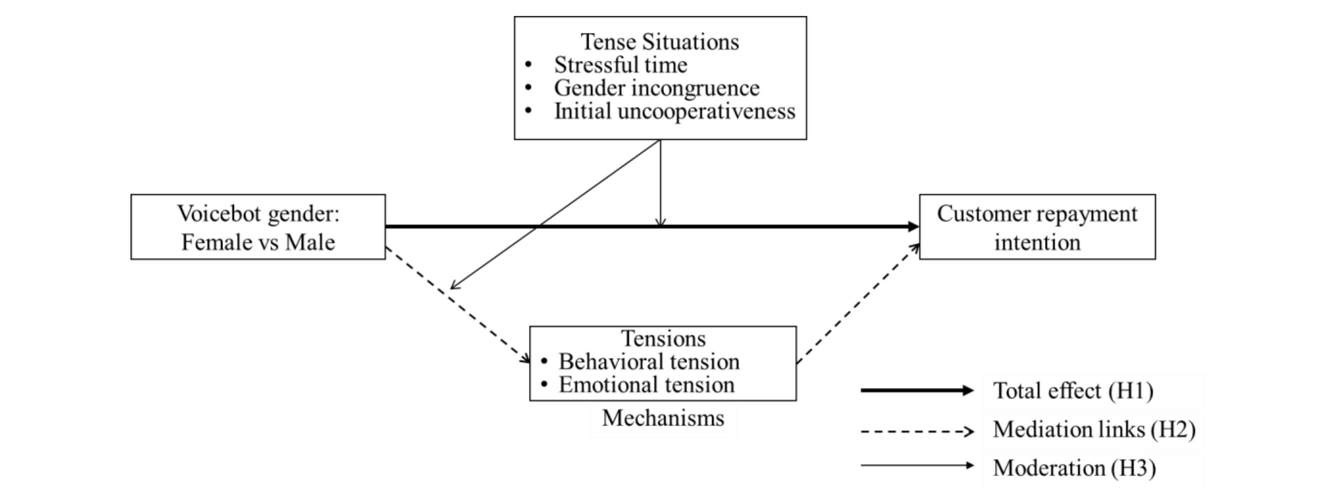

Figure 1. Conceptual Model

Gender Effects in High-Tension Service Contexts

Originally developed for business-to-business (B2B) relationships, the TBV explains the types of tension in a relationship and highlights their effects on relationship outcomes (Fang et al., 2011; Gnyawali et al., 2016). According to the TBV, *tension* refers to discomfort, dissonance, stress, strain, or conflict that arises from conflicting interests between actors, contradictory goals, or ambiguity in interactions (Tóth et al., 2018; Zheng et al., 2022). The TBV identifies three types of tension. *Behavioral tension* refers to the tension exhibited through actors' divergent actions, routines, and communication practices, such as the contrast between collaborative and avoiding approaches (Tóth et al., 2018; Zheng et al., 2022). *Emotional tension*, also known as psychological tension, refers to the tension exhibited through negative attitudes, perceptions, and emotions formed about other parties (Tóth et al., 2018; Zheng et al., 2022). *Structural tension* refers to the challenges and conflicts arising from how relationships are organized and governed in a network (Fang et al., 2011). The TBV literature has shown that, if not addressed, such tensions in a relationship can result in diminished relationship quality, partnership breakdowns, and poor business performance (Gnyawali et al., 2016; Oliveira & Lumineau, 2019).

Although the TBV has primarily been developed and tested in B2B settings, recent research has begun to apply it to business-to-customer (B2C) settings, such as customer-brand relationships (Alvarez et al., 2021) and business-and-customer co-creation (Tsiotsou & Diehl, 2022). Similar to B2B relationships, different types of tension may also arise in B2C interactions, and managing these tensions is vital for effective communication and achieving desirable service outcomes (Alvarez et al., 2021; Tsiotsou & Diehl, 2022). In the following, we argue that the gender of the AI voicebot gender may influence tension during service interactions and, consequently, service outcomes.

To explain the effects of bot gender on tensions in service encounters, we draw on *gender stereotype theory*, which posits that individuals unconsciously attribute specific traits and behaviors to others based on gender. Specifically, this theory suggests that traits associated with women typically include communality, friendliness, kindness, warmth, and empathy, whereas those associated with men include agency, aggression, assertiveness, dominance, and forcefulness (Fossa & Sucameli, 2022; Hentschel et al., 2019; Smith et al., 2016). Prior research shows that humans project gender stereotypes onto bots based on gender cues such as voice, name, and facial features (Ahn et al., 2022; Eyssel & Hegel, 2012). These projections significantly influence the dynamics between customers and bots, thereby shaping interactions and outcomes (Bernotat et al., 2021; Eyssel & Hegel, 2012).

Applying the TBV and gender stereotype theory to our research context, we first note that the customer-bot relationship in a collection call is inherently tense due to conflicting interests and a power imbalance, with customers typically in the lower-power position (Deville, 2015). In such tense interactions, the gender stereotypes that customers associate with the voicebot could influence their reactions. A male voicebot might invoke male stereotypes of dominance, aggression, and high power, which could amplify the perceived power imbalance between bot debt collectors and customers and heighten existing tension. By contrast, a female voicebot might invoke perceptions of warmth and kindness, which could soothe stressed customers and foster their cooperation, ultimately resulting in better collection outcomes (Harrington, 2018; Hill, 1994). Therefore, when customers encounter a female voicebot, they may experience less tension and be more inclined to cooperate, leading to higher repayment intention. Accordingly, we propose:

H1: *Female voicebots lead to higher repayment intention than male voicebots.*

Mechanisms for Gender Effects in High-Tension Service Settings

In high-tension service settings such as debt collection, we propose that bot gender can influence service outcomes by impacting the two types of tension identified by the TBV: behavioral tension and emotional tension. The TBV literature also identifies structural tension as being related to how relationships are organized and governed (Fang et al., 2011). We do not investigate structural tension in this study because the relationship structure in debt collection is predetermined and is relatively impervious to factors such as voicebot gender. Moreover, we focus on *customers'* behavioral and emotional tension, given that the behaviors and emotions of bot debt collectors are largely predetermined by design.

Mediating role of behavioral tension: In high-tension service contexts, *behavioral tension* can manifest as avoidance, interruption, or active resistance when the parties interact with each other (Custers, 2017). In debt collection contexts, such behavioral tension naturally arises from the inherent conflict of interest between customers and debt collectors, with customers interested in minimizing the amount they have to pay and avoiding harassment from debt collectors, and debt collectors aiming to maximize payment from customers by engaging in active outreach and persuasion.

We argue that the voice gender of bot debt collectors could impact behavioral tension during debt collection calls. If customers associate bots with masculine traits of agency, assertiveness, and aggression, they may respond more defensively and uncooperatively, exhibiting behaviors such as call avoidance, frequent interruption, antagonistic responses, and premature call termination (Prentice & Carranza, 2002). By contrast, if customers associate bots with feminine stereotypes such as friendliness and communality, they may correspondingly become more prosocial and have a more relational focus, which could increase their engagement and reduce their confrontational behaviors during communications (Siegel et al., 2009). Indeed, prior research has shown that female service bots are more effective at maintaining customer dialog and encouraging information sharing (Borau et al., 2021; Pitardi et al., 2023).

Reducing behavioral tension is crucial in high-tension service settings such as debt collection because active avoidance or antagonistic responses could disrupt communication or render it less effective. This could further lead to failed negotiations, diminished relationships, and, ultimately, poor service performance (Gnyawali et al., 2016; Oliveira & Lumineau, 2019). Therefore, we propose:

H2a: *Behavioral tension mediates the relationship between voicebot gender and customer repayment intention.*

Mediating role of emotional tension: Tense service interactions also lead to customers experiencing emotional tension, manifesting as anxiety, anger, frustration, and/or guilt, accompanied by negative attitudes such as distrust or animosity (Alvarez et al., 2021; Tóth et al., 2018; Vejnovic et al., 2024). In debt collection contexts, debtors' emotional tension typically stems from financial distress, the perceived power imbalance between the bot debt collector and the customer, and/or embarrassment related to being overdue in their payments (Custers, 2017; Deville, 2015).

We argue that bot gender can also influence high-tension service outcomes by affecting emotional tension. The perceived female stereotypes of warmth and empathy may be particularly valuable in alleviating the psychological strain related to debt collection (Ahn et al., 2022; Nass & Brave, 2005). Such perceptions can help customers feel emotionally supported and trusted (Bernotat et al., 2021; Cheng et al., 2022), thereby reducing their negative emotional reactions (Gelbrich, 2010). By contrast, the perceived dominance and forcefulness of male debt collectors may make customers feel pressured or judged, exacerbating their stress and negative emotions.

The reduction of emotional tension can significantly improve high-tension service outcomes. Prior research has demonstrated that high emotional tension significantly impairs customers' ability to process information rationally and make sound decisions (Forgas-Coll et al., 2022). When emotional tension is lower, customers can shift from an emotionally reactive state to a problem-solving mindset (Karimi et al., 2018). The latter enables customers to better comprehend and evaluate information during interactions, which is crucial for positive service outcomes. Therefore, we propose:

H2b: *Emotional tension mediates the relationship between voicebot gender and customer repayment intention.*

Moderation by Contextual Factors

Our tension-based explanation of bot gender effects suggests that the effects could be moderated by various contextual factors that contribute to the initial level of tension in a service encounter, resulting in what we refer to as "tense situations." In general, if a contextual factor leads to heightened initial tension, the advantages of female voicebots in deescalating tension and inducing more cooperative service outcomes will be amplified. Thus, we can expect a more pronounced advantage for female bots. Such contextual factors may emerge from circumstantial differences inherent in a service encounter or from individual differences specific to the customer. In the following, we identify three such contextual factors: two factors related to the service encounter circumstance—*stressful time* and *gender incongruence*—and one factor related to customer differences—their *initial uncooperativeness*.[2] We next discuss how these factors may moderate the gender effects.

Stressful time: When debt collectors contact customers during a *stressful time*, the overall tension in the interaction is likely to be high from the outset (Stokoe & Sikveland, 2020). For example, customers may experience greater stress when receiving debt collection calls on weekdays versus weekends, as they are often managing heavier workloads and experiencing greater mental and physical exhaustion (Binnewies et al., 2010). In these high-pressure scenarios, the perceived feminine traits of warmth and empathy can ease the pressure that customers feel, reducing overall tension in the interaction. Consequently, the positive effect of female voicebots on customer repayment intentions may be amplified.

Gender incongruence: Prior studies show that people feel more comfortable with and psychologically closer to individuals of the same gender (Benbasat et al., 2020; Eyssel & Hegel, 2012). Based on this, we posit that gender incongruence between the voicebot and the customer may lead to higher initial tension. Specifically, when a female voicebot interacts with a male customer, the gender incongruence may result in lower initial comfort and greater perceived psychological distance, resulting in elevated initial tension. Consequently, the advantage of female bots could be amplified in opposite-gender interactions.

Initial uncooperativeness: Customers who display initial uncooperativeness, manifesting as unfriendliness, hostility, or low trust, indicate a higher level of initial tension in the interaction (Kostopoulos et al., 2014). This uncooperative stance creates a challenging communication environment. In such tense situations, female voicebots' advantages become particularly pronounced. Female voicebots with perceived traits such as kindness may be better equipped to establish rapport, defuse tension, and encourage cooperation from initially uncooperative customers (Benbasat et al., 2020; Eyssel & Hegel, 2012).

In summary, these tense situations suggest heightened initial tension, which can magnify the benefits of female voicebots in alleviating emotional and behavioral tension. This, in turn, may result in a more pronounced gender effect on customer repayment intention. Therefore, we hypothesize:

H3: *The effect of voicebot gender on customer repayment intention and on (behavioral and emotional) tension is stronger when debt collection calls occur at* ***(a)*** *a stressful time,* ***(b)*** *with gender incongruence, and* ***(c)*** *with initially uncooperative customers.*

Methodology

Data

We leveraged a proprietary dataset comprising outbound debt collection calls made by AI voicebots obtained from a prominent AI voicebot provider operating in China. A typical debt collection call involves the voicebot's self-introduction, verification of the customer's identity to ensure accuracy, reminders regarding the overdue loan (including details such as the amount due), review of the potential consequences of non-repayment—such as additional fees and the impact on credit history—and, finally, an inquiry into the customer's intention to repay the debt. The AI voicebot provider offers client companies two different voicebot genders—female and male. Each gender includes a range of voice options that differ in tone and style. For example, some female voices are sweet and gentle, whereas others are light and enthusiastic. Importantly, the gender of the voice is easily identifiable to any listener. In our dataset, customers were contacted only once, within one to two days after their payment became overdue.

The voicebot is deployed at the level of the line of business (LOB), which corresponds to a specific business unit or a product line within a client company. Based on our interview, the deployment of a voicebot involves two steps. First, a designer from the voicebot provider collaborates with the client company to design the dialog flow and scripts to meet the LOB needs. Second, a gendered voice is chosen to serve both female and male customers within that LOB. The selection of gender may depend on factors such as the designer's preferences and the characteristics of the LOB. Furthermore, the gender of the bot may not always stay the same. Some LOBs experiment with different bot genders, especially during the early stages of deployment. In our dataset, even when a different gender was used, the dialog flow and scripts remained the same for a given LOB.

[2] We did not include bot-specific factors because our research questions call for holding bot design constant, except for bot gender. We did, however, examine whether other bot design differences (such as pitch and speech rate) may offer an alternative explanation to our findings (see Robustness Checks section).

Our unit of analysis was a collection call. We chose to focus on calls from LOBs that had used both female and male voicebots, resulting in six LOBs from five credit card companies. One credit card company had two LOBs because one of them was operated by a subsidiary for a different product line. For each LOB-voice combination, we randomly selected 1,200 connected calls from the dataset—if there were fewer than 1,200 connected calls, we included all of them.[3] This resulted in a total of 5,994 calls. We then removed calls answered by individuals other than the intended borrowers and calls where customers indicated that they had already repaid the debt. Furthermore, we removed 12 calls where the amount due was zero. Ultimately, we obtained a final dataset of 5,136 calls.

Our sample included 1,039 female and 4,097 male customers. A total of 74.8% of female customers and 74.9% of male customers were served by female voicebots. These near-equal proportions suggest that customer gender was independent of bot gender ($p = 0.949$).

Measurement and Model Specification

Our outcome variable of interest was the customer's intention to repay the overdue debt ($RepayInt_{ij}$), a metric commonly used by voicebot service providers and their clients. Although we did not have data on actual repayment, our interviews with client companies indicated that repayment intention serves as a strong proxy. If a customer promised or agreed to repay the loan, pay the minimum amount due, or pay later, we defined repayment intention as 1, otherwise as 0. Repayment intention was automatically classified by the voicebot provider using natural language understanding and manually verified by our research assistants. Because our dependent variable was binary, we adopted a logistic regression model to analyze the repayment intention associated with each call:

$$logit(RepayInt_{ij}) = \alpha + \beta FemaleBot_{ij} + \gamma Controls_{ij} + \varepsilon_{ij} \quad (1)$$

We used i to index the customer and j to index the LOB. Given that each customer was called only once, each call was uniquely indexed by ij. Our main independent variable was the voicebot gender ($FemaleBot_{ij}$), equal to 1 if the bot had a female gender, and 0 otherwise. In Equation (1), α and ε_{ij} are the intercept and the random disturbance, respectively. We were mainly interested in the coefficient β, which captures the effect of bot gender. We included several control variables in the model, including customer gender ($FemaleCust_{ij}$), total amount due ($AmtDue_{ij}$), time-of-day dummies—$Morning_{ij}$ (8 am-12 pm) and $Night_{ij}$ (5 pm-9 pm), city-tier dummies, LOB dummies, and week dummies. The city-tier dummies were based on the tier of the customer's city of residence, which ranged from 1 (the most developed) to 5 (the least developed) according to the well-known Chinese city-tier system. A city's tier, reflecting factors like population and affluence, approximates a customer's financial status and exposure to AI voicebots. The LOB dummies controlled for LOB-specific effects, and the week dummies controlled for time effects. The variable descriptions are given in Table 1.

Table 1. Descriptions of Key Variables (N=5136)

Variables	Description	Percentage of 1's (except for *AmtDue*)
RepayInt	Whether the customer explicitly promises to repay the overdue debt (Yes = 1, No = 0)	52.47%
FemaleBot	Whether the voicebot is female (female = 1, otherwise 0)	74.82%
FemaleCust	Whether the customer is female (female = 1, otherwise 0)	20.23%
BehavTens	Whether the customer interrupts the bot frequently (in over 85% of the dialogs)	8.8%
EmoTens	Whether the customer exhibits negative emotions during the interaction	21.16%
StressTime	Whether the call happens during weekdays	76.01%
GenderIncong	Whether the customer and the bot have opposite genders (can be calculated as *abs(FemaleBot-FemaleCust)*)	64.80%
InitialUncoop	Whether the customer behaves uncooperatively (e.g., refuses to provide information, remains silent, or acts unfriendly) during the first round of conversation with the voicebot	22.9%
AmtDue	Natural logarithm of the total amount due	Mean = 8.76, SD = 1.40, Min = 0.11, Max = 13.40
Morning	Whether the call happens in the morning (8 am-12 pm)	47.04%
Night	Whether the call happens in the evening (5 pm-9 pm)	14.17%

[3] We had 20 LOB-voice combinations in total, with each LOB using between two and six available voices. The distribution of calls was highly skewed among the 20 LOB-voice combinations, with one LOB-voice having 12,000 connected calls (71.5% of the total), four having between 400 and 1,200 calls, and 15 having fewer than 300 calls. To avoid over-representation from the LOB-voice with the most calls, and to preserve the data from the smaller LOB-voice, we used 1,200 calls, or 10% of all calls from the largest LOB-voice, as our sampling threshold. As a robustness check, we also tested alternative sampling thresholds of 300, 600, and 900 calls and obtained consistent results (available upon request).

Table 2. The Impact of Voicebot Gender				
	(1)	**(2)**	**(3)**	**(4)**
Variables	***RepayInt***	***BehavTens***	***EmoTens***	***RepayInt***
FemaleBot	**0.249**** (0.094)	**-0.341*** (0.143)	**-0.277**** (0.101)	0.180 (0.096)
FemaleCust	0.098 (0.076)	-0.089 (0.130)	0.111 (0.087)	0.101 (0.080)
AmtDue	0.007 (0.035)	-0.091 (0.057)	0.092* (0.044)	0.010 (0.037)
Morning	0.031 (0.068)	-0.041 (0.116)	0.020 (0.081)	0.026 (0.072)
Night	-0.136 (0.100)	0.277 (0.160)	0.318** (0.106)	-0.057 (0.105)
BehavTens				**-3.597***** (0.256)
EmoTens				**-0.775***** (0.077)
Constant	0.476 (0.388)	-2.109** (0.734)	-1.917*** (0.457)	0.836* (0.413)
LOB FE	Yes	Yes	Yes	Yes
City-tier FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Pseudo-R^2	0.079	0.039	0.024	0.176
N	5136	5136	5136	5136

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Robust standard errors in parentheses.

Mediation Effects

To investigate the proposed mechanisms, we introduced two mediation variables, $BehavTens$ (behavioral tension) and $EmoTens$ (emotional tension). Following the literature (Tóth et al., 2018; Vejnovic et al., 2024; Zheng et al., 2022), we operationalized these variables by measuring high-tension behaviors and emotions exhibited by customers during the interaction. Specifically, we used frequent interruptions and the presence of negative emotions as signals of behavioral and emotional tension, respectively. Interruptions and negative emotions were interpreted as behavioral and emotional manifestations of the underlying state of tension or conflict in interpersonal interactions (Barki & Hartwick, 2001). We defined $BehavTens_{ij}$ as whether the customer frequently interrupted the voicebot during a call ij. $BehavTens_{ij}$ took a value of 1 if the customer interrupted the voicebot in over 85% of the dialogues, and 0 otherwise.[4] The variable $EmoTens_{ij}$ is a binary indicator of whether customer i spoke negative-sentiment words during the interaction with voicebot j. We used a dictionary-based text analysis method[5] to detect negative words in the dialogues. If negative-sentiment words were found, $EmoTens_{ij}$ equals 1, otherwise 0. The correlation between $BehavTens$ and $EmoTens$ was 0.123, indicating that these two concepts are distinct. We tested the mediation effects using the procedure outlined by Zhao et al. (2010). Specifically, we estimated three regressions:

$$logit(BehavTens_{ij}) = \alpha + \beta FemaleBot_{ij} + \gamma Controls_{ij} + \varepsilon_{ij} \quad (2)$$

$$logit(EmoTens_{ij}) = \alpha + \beta FemaleBot_{ij} + \gamma Controls_{ij} + \varepsilon_{ij} \quad (3)$$

$$logit(RepayInt_{ij}) = \alpha + \beta FemaleBot_{ij} + \gamma BehavTens_{ij} + \delta EmoTens_{ij} + \theta Controls_{ij} + \varepsilon_{ij} \quad (4)$$

Moderating Effects

We operationalized the moderators as follows. To capture whether a call occurred during a stressful time, we used the variable *StressTime,* which is equal to 1 if the call occurred during a weekday, and 0 otherwise. We anticipated that customers would experience higher stress during weekdays

[4] We adopted binary coding for better interpretability. Moreover, the literature suggests that high-frequency interruptions could have a disproportionate effect compared to moderate or low-frequency interruptions (Speier et al., 1999). Binary coding allowed us to focus on high levels of emotional and behavioral tension and better accommodates the nonlinear relationships.

[5] We used the three most widely applied emotion dictionaries for text-mining in Chinese: the *National Taiwan University Semantic Dictionary*, the *Hownet Semantic Dictionary*, and the *Tsinghua Dictionary of Positive and Negative Sentiment Words*.

due to heavier workloads and resulting mental exhaustion (Sonnentag et al., 2010). To capture gender incongruence, we defined a variable, *GenderIncong*, which is equal to 1 if the customer and the voicebot were of different genders. The third moderator, *InitialUncoop*, is a binary variable indicating whether the customer behaved uncooperatively (e.g., refused to provide information, remained silent, or acted unfriendly) during the first round of conversation, which typically consisted of the bot's self-introduction and an identity verification question, followed by the customer's response—or lack thereof. We interacted these moderators with the main independent variable $FemaleBot$ in Equations (1)-(3), respectively, to test H3a-c.

Results

Main Findings

In Table 2, Column 1, we present the impact of female voicebot gender on customer repayment intention. The coefficient of *FemaleBot* is positive and significant (β = 0.249, $p < 0.01$), supporting H1, which states that the use of female voicebots leads to higher customer repayment intention. Specifically, compared with male voicebots, female voicebots increased the odds of positive repayment intention by 28.3%, an economically significant increase in repayment intention.

Mediating Effects

In Table 2, Columns 2-4, we present the results of the mediation tests. First, as expected, behavioral tension and emotional tension negatively affected customer repayment intention, as indicated by the negative and significant effects of *BehavTens* and *EmoTens* on *RepayInt* (−3.597, $p < 0.001$; −0.775, $p < 0.001$, respectively), as shown in Column 4.

Female voicebots negatively affected the two tension-based mediators, as indicated by the negative and significant coefficients of *FemaleBot* on *BehavTens* (−0.341, $p < 0.05$, Column 2) and *EmoTens* (−0.277, $p < 0.01$, Column 3), respectively. In addition, we conducted a causal mediation analysis (Hicks & Tingley, 2011) with 1,000 bootstrap replications, which is well-suited to binary or categorical variables. The results of the causal mediation analysis show that both behavioral tension ($p = 0.016$) and emotional tension ($p = 0.016$) significantly mediated the effect of voicebot gender on repayment intention. These findings support H2a-b, indicating that female voicebots increased repayment intention by alleviating behavioral and emotional tension.

Moderating Effects

We report the moderating effects in Table 3. First, as shown in Column 3, when calls took place during weekdays (*StressTime*), female voicebots were more effective at improving repayment intention (0.448, $p < 0.05$). Second, the coefficient of *FemaleBot* × *GenderIncong* is marginally significant (0.364, $p = 0.051$) and, interestingly, the coefficient of *FemaleCust* becomes significant (0.396, $p < 0.05$). Together, these results reveal that male customers had lower repayment intention (as indicated by the positive coefficient of *FemaleCust*), but their repayment intention increased when interacting with a female voicebot. Third, female voicebots were more successful in persuading initially uncooperative customers to repay (0.503, $p < 0.05$).

We report the effects of moderators on the mediation variables—behavioral and emotional tension—in Table 3, Columns 1-2. As shown in the table, calling customers at a stressful time significantly amplified the advantage of female voicebots in reducing behavioral tension (−0.974, $p < 0.05$), but not emotional tension, partially supporting H3a. The lack of significance regarding emotional tension might be because customers may have refrained from using negative words during service calls that were typically recorded, adding more noise to our emotional tension variable. As mentioned above, gender incongruence positively moderated the main effect of voicebot gender on *customer repayment intention*. However, gender incongruence did not influence the impact of voicebot gender on *behavioral* or *emotional tension*. Thus, H3b was only partially supported. A possible explanation for this finding is that gender incongruence moderated the gender effect on repayment intention through mechanisms other than alleviating tension. For example, prior research shows that men tend to be more generous in the presence of female observers (Siegel et al., 2009; Van Vugt & Iredale, 2013), which may extend to interactions where gender incongruence elicits similar social dynamics. Finally, we found support for H3c, where the advantage of female voicebots in reducing behavioral and emotional tension was significantly amplified by customers' initial uncooperativeness (−0.882, $p < 0.001$; −0.421, $p < 0.05$).

Robustness Checks

Selection Bias

One challenge to our estimations was the potential selection bias arising from the non-random assignment of bot gender—as discussed earlier, the choice of bot gender could depend on factors such as the AI designer's preference and characteristics of the LOB. To address such concerns, we focused on LOBs that used both female and male voicebots and introduced several control variables, LOB-fixed effects, and time-fixed effects. To further alleviate this concern, we employed the Heckman selection method and matching techniques, as recommended by Hill et al. (2021). We briefly discuss these approaches and findings below. We omitted some details of our implementation and results due to space constraints, but they are available upon request.

Heckman selection model: To account for potential unobserved factors that could have influenced the selection of bot gender, we employed the Heckman selection model. This approach allowed us to estimate the selection equation and then include the inverse Mills ratio derived from the selection equation in the main estimation, helping to control for non-random selection. We used customer gender, amount due, time of day, and stressful time in the selection equation, along with an instrumental variable, $DeltaRepay_{jt}$, calculated as the change in the average repayment intention for the voicebot of LOB j from time t-1 to time t-2. Results based on the Heckman selection model were similar to our main analyses. Moreover, the coefficient of the inverse Mills ratio was not significant, suggesting that selection bias may not be a concern.

Propensity score matching: Propensity score matching is one of the most popular approaches to addressing the selection bias problem. It ensures that treatment and control units have similar probabilities of receiving the treatment, given their observable characteristics, so that they are comparable. We included several observable covariates that could have influenced the selection of voicebot gender as matching variables, including customer gender, amount due, time of day, and the voicebot's prior performance metrics (number of calls, average call duration, and proportion of customers willing to repay). These metrics served as proxies for the voicebot's effectiveness and may have impacted future gender choices in interactions. Using the matched sample,[6] we reran all the analyses, and the results were mostly consistent with our previous findings.

Table 3. Moderation Effects

	(1)	**(2)**	**(3)**
Variables	***BehavTens***	***EmoTens***	***RepayInt***
FemaleBot	0.905 (0.506)	0.085 (0.239)	-0.327 (0.234)
FemaleCust	-0.146 (0.248)	0.111 (0.163)	0.396* (0.163)
AmtDue	-0.073 (0.059)	0.092* (0.044)	-0.032 (0.039)
Morning	-0.013 (0.117)	0.036 (0.081)	0.024 (0.073)
Night	0.233 (0.161)	0.303** (0.107)	-0.124 (0.110)
StressTime	0.786 (0.413)	0.083 (0.198)	-0.521* (0.203)
InitialUncoop	1.582*** (0.207)	0.218 (0.162)	-2.541*** (0.220)
FemaleBot × StressTime	**-0.974*** (0.427)	-0.305 (0.214)	**0.448*** (0.217)
FemaleBot × GenderIncong	-0.032 (0.293)	0.006 (0.191)	**0.364+** (0.187)
FemaleBot × InitialUncoop	**-0.882***** (0.245)	**-0.421*** (0.193)	**0.503*** (0.244)
Constant	-3.373***	-2.127***	1.135*
	(0.798)	(0.475)	(0.444)
LOB FE	Yes	Yes	Yes
City-tier FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Pseudo-R^2	0.070	0.026	0.181
N	5136	5136	5136

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, + $p = 0.051$; Robust standard errors in parentheses. *GenderIncog* is not included as a stand-alone variable in Table 3 because it causes multicollinearity issues and is redundant given the existing *FemaleBot* and *FemaleCust* variables.

[6] To enhance matching quality, we employed propensity score matching using the kernel matching method within each LOB. This approach ensured that the matching was performed among comparable units within each LOB, reducing potential confounding factors (Caliendo & Kopeinig, 2008). Samples that fell outside the common support region were excluded, ensuring that only comparable units were retained. The quality of the propensity score matching was assessed using indicators like pseudo-R^2, chi-square, and likelihood ratio, mean, and median biases (Kim et al., 2016). The matched sample consisted of 953 male bot calls and 1,800 female bot calls. Additionally, attempts to match across different LOBs yielded consistent findings, further validating the robustness of the matching procedure.

Causality of Mediation Variables

Another concern was whether the mediating variables—behavioral and emotional tension—truly caused repayment intention. While we measured mediation variables before repayment intention to limit reverse causality, omitted variables, such as the customer's unobserved attitude, may have impacted both tension and repayment intention, creating spurious mediation effects. We employed three approaches to mitigate this concern.

First, we controlled for confounding customer attitudes. An uncooperative customer may display behavioral and emotional tension and refuse to repay the loan. We approximated such customer attitudes using the variable *InitialUncoop*, which measures whether the customer was uncooperative in the first round of conversation. By controlling for *InitialUncoop*, we found that the effects of tension on repayment intention remained significant, supporting a causal relationship between tension and repayment intention.

Second, we conducted a sensitivity analysis for causal mediation analysis (Hicks & Tingley, 2011) to assess the robustness of the mediation effects to potential unmeasured confounders. We found that the average causal mediation effect became zero only when the sensitivity parameter ρ—representing the correlation between the residuals from the mediator and outcome models—reached -0.5 for behavioral tension and -0.3 for emotional tension. These values indicated a moderate level of robustness relative to other reported values in the literature, supporting the causality of our mediators.

Third, we employed the two-stage residual inclusion (2SRI) estimation method (Terza et al., 2008), an alternative to the two-stage least squares method for nonlinear models. We identified two instrumental variables each for behavioral and emotional tension: the average behavioral tension and emotional tension of the same voice within each voice gender, and the average behavioral tension and emotional tension of the same LOB in other calls within the sample. The results of the likelihood ratio test and the Wald test were both equal to 0, validating that these instrumental variables were not weak. The estimation results of 2SRI verified the causal effects of behavioral and emotional tension on repayment intention.

Acoustic Features as Alternative Mechanisms

Female voices are different from male voices on several acoustic dimensions, such as pitch. Prior studies have shown that acoustic features, including the speaker's *speech rate*, *pitch* (mean), *pitch variation*, *loudness* (mean), and *loudness variation*, can influence the perception of dominance and credibility (Chebat & El Hedhli, 2007). It is likely that the voice's acoustic features, not voice gender per se, drove the results. To account for such a possibility, we added the aforementioned five major acoustic features as additional controls. Our findings remained robust, which lent further support to our conclusions.

Discussion

Our study addresses a timely issue regarding how the choice of bot gender may impact service performance, particularly in high-tension service contexts. Drawing on the TBV of customer relationships and gender stereotype theory, we theorize whether, how, and when voicebot gender may play a role in high-tension service contexts. Our analyses of a bot-powered debt collection dataset largely confirm our theoretical predictions and yield several practical insights along the *whether, how,* and *when* dimensions introduced above. First (*whether*), female voicebots increase the odds of a positive repayment intention by 28.3%, confirming our theoretical prediction of female advantages in high-tension service contexts. Second (*how*), the effect of voicebot gender is mediated by behavioral and emotional tension, confirming our theoretical arguments about underlying mechanisms. Third (*when*), as predicted by our theory, female voicebots lead to higher customer repayment intention in high-tension situations, such as when calls occur during stressful times, between opposite genders, or with initially uncooperative customers, which further lends credence to our theory.

Contributions and Theoretical Implications

This study contributes to HCI research in two main ways. First, we extend traditional HCI research on bot gender, which has primarily focused on friendly or neutral settings (e.g., Benbasat et al., 2020; Borau et al., 2021), to high-tension service contexts. We theorize that female bots lead to improved service outcomes in such settings because customers' association of female stereotypes with bots can lead to reduced behavioral and emotional tension, which, in turn, can improve service outcomes. This tension-based framework offers a novel theoretical lens for understanding the role of gender in human-bot interactions that involve tension, moving beyond conventional explanations based on perceived attributes such as humanness or competence (Ahn et al., 2022; Borau et al., 2021). This context-centered theorizing approach opens new avenues for future research in this area. Although our study was empirically tested using debt collection, our findings have implications for other high-tension contexts such as service failure recoveries, payment disputes, and customer complaints. We hope our study paves the way for more research on such important yet understudied human-bot interaction contexts.

Second, our study offers one of the first pieces of real-world evidence on the impact of bot gender on service outcomes, complementing existing laboratory-based evidence on human perceptions of and attitudes toward robots (e.g., Bernotat et al., 2021; Qiu & Benbasat, 2010). The natural setting reveals how bot gender effects vary across different situation-specific factors—such as calling time—indicating that gender effects are more nuanced than previously theorized and that the optimal gender choice varies based on immediate circumstances, rather than remaining fixed within a given context. Therefore, in addition to drawing broad conclusions about bot gender effects for general contexts (Bernotat et al., 2021) or specific industry domains (Ahn et al., 2022; Forgas-Coll et al., 2022), researchers may want to delineate distinct factors favoring female or male robots that could be applied in many different settings.

Our study also makes significant contributions to the research on the TBV of relationships. First, we contribute to the emerging literature that extends the scope of TBV from B2B to B2C settings (Alvarez et al., 2021; Vejnovic et al., 2024). To our knowledge, we are the first to introduce TBV to the information systems literature. We hope our study opens a door to using TBV to study high-tension information systems phenomena, such as tense user-developer interactions, change management, and security- and privacy-related interactions. Second, the original TBV tends to be more descriptive and takes tension in a relationship as given (Fang et al., 2011). We demonstrate that design and contextual factors (such as gender and calling time) can influence the level of tension in a relationship and thus impact service outcomes. Our findings, therefore, encourage TBV researchers to adopt a more dynamic and proactive view of tension, examining the role of technology and other contextual factors.

Managerial Implications

With more organizations incorporating bots into their service operations, the interest in understanding consequential design choices for such bots is rapidly expanding. Our findings show that female voicebots have a sizable advantage over their male counterparts, dispelling the myth that the preference for female bots is merely a gender bias in the AI industry. Therefore, we suggest deploying female voicebots in high-tension service contexts and investing more resources in developing female voices. More broadly, our findings emphasize that social design elements are as crucial as technical features when organizations make AI development and investment choices.

In addition, recognizing that female voicebots work by reducing behavioral and emotional tension, managers should align other service elements to complement this tension-reduction mechanism. Beyond bot gender, AI vendors should leverage complementary design dimensions—such as communication styles, tones, and conversation strategies—to further enhance bots' ability to mitigate tension. Although our study focuses on high-tension service contexts such as debt collection, we expect our findings to be relevant for high-tension service episodes within otherwise low-tension service contexts, such as a sales pitch call to a highly uncooperative customer or a customer service call that leaves the customer waiting for a long time. We recommend that organizations identify such contextual factors and episodes that could benefit from deploying female voicebots.

Limitations and Future Work

Several limitations of this study require further research. First, we used repayment intention as our dependent variable. While repayment intention is highly correlated with actual repayment and is a key industry metric, research linking bot gender and actual repayment could further strengthen this line of investigation. Second, our estimated gender effects may have been biased by unobserved temporal confounders. Although our robust checks suggest that they did not present a significant threat, further research based on randomly assigned bot gender would further diminish such concerns. Third, we found that gender incongruence moderated the relationship between voicebot gender and customer repayment intentions, but it did not have a significant moderating effect on the relationship between voicebot gender and tension. Future research should further explore the mechanisms through which gender incongruence might influence customer-voicebot interactions. Finally, we had limited information on customers due to data privacy restrictions. A promising direction for future research would be to explore customer characteristics that alter the effects of bot gender.

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Appendix A

Table A1. Selected Review of Essential HCI Studies on Robot Gender			
Study	**Context**	**Method**	**Findings related to gender effects**
Ahn et al. (2022)	Industry: e-commerce Task: recommendation	Online experiment	1. **Gender effect:** Men/women are more persuasive for utilitarian/hedonic products. 2. **Mechanism:** Warmth mediates gender effects on recommendation evaluation for hedonic products; competence, for utilitarian products.
Beldad et al. (2016)	Industry: e-commerce Task: recommendation	Lab experiment	Gender's effects on credibility, trust, and purchase intention are insignificant.
Benbasat et al. (2020)	Industry: e-commerce Task: recommendation	Lab experiment	Women do not conform to male bots' advice, while men have no preferences.
Benbasat et al. (2010)	Industry: e-commerce Task: recommendation	Lab experiment	The main effect of gender on social presence is not significant. Female users prefer female bots.
Bernotat et al. (2021)	Industry: not specified Task: not specified	Lab experiment	Users trust female bots more. Gender-occupation fit positively affects user preference.
Borau et al. (2021)	Industry: healthcare Task: unspecified	Online experiment	1. **Gender effect:** Female bots are more likable. 2. **Mechanism:** Perceived humanness and warmth, but not competence, mediate the gender effect.
Crowell et al. (2009)	Industry: unspecified Task: self-introduction and asking questions	Lab experiment	Male-embodied and female-disembodied bots are more reliable than both male-disembodied and female-embodied bots.
Eyssel & Hegel (2012)	Industry: unspecified Task: (intended for) math or verbal tasks	Lab experiment	Female bots are perceived as more communal. The effect of gender-occupation fit on task fit evaluation is positive.
Eyssel et al.(2012)	Industry: unspecified Task: reading a sentence	Lab experiment	The effect of bot-user gender match on user attitude (e.g., acceptance, perceived humanness) is negative.
Forgas-Coll et al. (2022)	Industry: gaming Task: assistance	Lab experiment	The effect of gender-task fit is positive on user acceptance.
Lee et al. (2000)	Industry: unspecified Task: offering judge advice	Lab experiment	The effect of gender match is positive on opinion conformation. Female voice is perceived to be more socially attractive and trustworthy.
McDonnell & Baxter (2019)	Industry: banking or mechanics Task: assistance	Lab experiment	Male bots enhance user satisfaction, while gender-task congruence yields positive effects.
Nass et al. (1997)	Industry: unspecified task: assistance	Lab experiment	Praise from men is more convincing than that from women; men are more likable.
Pfeuffer et al. (2019)	Industry: math and finance Task: assistance	Online experiment	1. **Gender effect**: the perceived competence for female bots is higher. 2. **Mechanism:** The mediation effects of agentic, communal, and competence are insignificant.
Pitardi et al. (2023)	Industry: airport service Task: assistance	Online experiment	1. **Gender effect:** Gender match elicits positive affect. 2. **Mechanism:** Perceived control mediates gender effect only for consumers high on masculinity.
Powers et al. (2005)	Industry: dating Task: query	Lab experiment	Men engage more when communicating with female bots. Female bots are expected to be more knowledgeable.
Qiu & Benbasat (2010)	Industry: e-commerce Task: recommendation	Lab experiment	The effect of gender match on perception (e.g., social presence, usefulness) is insignificant.
Siegel et al. (2009)	Industry: nonprofit task: fundraising	Lab experiment	Men are more likely to donate when interacting with female robots, while women have no preference.
Tay et al. (2014)	Industry: healthcare, security task: medical advice; safety monitoring	Lab experiment	The effect of gender-occupation fit is positive on user attitude, evaluation, perceived behavioral control, subjective norms, perceived trust, and acceptance.
This study	**Industry: high-tension service task: debt collection**	**Archival data analysis**	**1. Gender effect: Female bots lead to higher repayment intention. 2. Mechanism: Behavioral and emotional tension reduction mediates the gender effect.**