Conversational Dynamics: ***When*** Does Employee Language Matter?

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Abstract

Firms increasingly use text analysis for marketing insight. While this has begun to shed light on *what* firms should say to customers, *when* in a conversation to say those things is less clear. Take customer service: agents could adopt a certain speaking style early in a conversation, at the end, or throughout. How can firms identify *when* specific language will be beneficial? To examine this question, we introduce a Sparse Functional Regression with Group-Lasso approach and apply it to language features related to the "warmth/competence trade-off." Prior work suggests an affective (i.e., warm) speaking approach will lead employees to be seen as less competent, so more cognitive language (which is linked to competence) should be prioritized. In contrast, analysis of nearly 20 hours of recorded service conversations (over 12,000 conversational turns) indicates conversational outcomes are better when both approaches are used, but each deployed at specific times. Satisfaction and purchases are higher when agents speak affectively at the beginning and end of a conversation but lower when agents use such language during the middle "business" portion. The opposite pattern holds for cognitive language. Our approach demonstrates the importance of considering language's temporal flow, deepens understanding of person perception, and provides insight into improving conversational outcomes.

Keywords: Conversational Dynamics, Sparse Functional Regression, Group-Lasso, Language, Customer Service.

1 Introduction

Language is central to marketing. Ad copy shapes customer attitudes, sales language affects purchase, and customer service language drives satisfaction and retention (cf. Pogacar, Shrum and Lowrey 2018). Managers and scholars have long considered how service employees should speak to customers (e.g., Parasuraman, Zeithaml, and Berry 1985; Blanding 1989), for example, and recent advances in text analysis have enabled a deeper understanding of what specific words and speaking styles matter, in customer service and more broadly (Berger et al. 2020).

But while it's clear that *what* companies and employees say matters, might *when* they say it also play an important role? Interactions between employees and customers usually involve multiple conversational turns. When calling customer service, for example, or speaking with a salesperson, the customer says something and the employee responds. Research suggests that employees should ask questions (Drollinger, Comer, and Warrington 2006; Huang et al. 2017), use concrete language (Packard and Berger 2020), or speak in a rational, logical way (Singh et al. 2018), but they could do so at any point in an interaction. Should employees use such linguistic approaches throughout, or might doing so at certain points be more beneficial? And could doing so at other points actually have a negative effect?

The present research proposes a method to examine not only whether certain language features or speaking styles matter, but *when*. We combine functional data analysis (FDA; e.g., Foutz and Jank 2010) with machine learning to address the unique challenges of temporal dynamics in conversational language. While conversations are a central feature of the marketer-consumer interface, they involve a noisy series of back-and-forth turns with potentially dramatic moment-to-moment variation in content and importance (Zhang, Wang, and Chen 2020). This can make them remarkably difficult to analyze. Our approach tries to account for these challenges, recovering time-based functions of language effects for important marketing outcomes.

To demonstrate the approach and its potential value, we apply it to the two most important dimensions of person perception — warmth and competence (Fiske, Cuddy and Glick 2007). These dimensions are seen as diametrically opposed. Trying to be warmer, or more affective, makes people seem less competent or agentic. Conversely, acting more rationally makes people seem less emotionally engaged (Godfrey, Jones and Lord 1986; Holoien and Fiske 2013; Wang et al. 2017). Consequently, prior research suggests pursuing only one of these modes in a given social or customer service interaction (Kirmani et al. 2017; Li, Chan, and Kim 2019; Marinova, Singh, and Singh 2018).

In contrast, we suggest that both aspects may be valuable, but at different points in a conversation. In the case of customer service calls, affective language may be pivotal to warmly establishing rapport. Later in the conversation, however, shifting to a more analytic, cognitive style while attempting to competently address the customer's needs may be more beneficial. Finally, closing with affective language may help leave customers feeling good about the interaction. Dynamic modeling of interactions at the level of conversational turns allows us to test such predictions. Customer satisfaction and future purchase quantity are higher when employees speak more affectively at certain points in the conversation, and more cognitively in others, whereas using these language features at the wrong conversational moments is costly.

This paper makes three main contributions. First, we extend work on linguistics in marketing, identifying *when* in a conversation what service employees say matters. In conversation, the time-varying interactional and circumstantial features that affect both conversational content and outcomes often inhibit inference making (Zhang, Mullainathan, and Danescu-Niculescu-Mizil 2020). Our functional approach helps address these challenges by simultaneously accounting for language and paralanguage dynamics, for both agent and customer, as well as potential agent and customer synchronicity. To address the circumstantial challenge, we capture various static features of the agent, customer, and their interaction that may drive conversational content and/or outcomes.

Second, our approach helps address the difficulties of examining dynamic conversational features as predictors of static outcomes. Modeling conversational dynamics involves two major challenges — high dimensionality and sparsity. Each moment of human conversation contains a variety of verbal and vocal features, leading to a "wide" data situation in which the number of variables may be similar to or even greater than the number of observations. This is especially true given the difficulty of obtaining large conversation data sets.[1] To accommodate such high-dimensionality within functional data analysis (FDA; Ramsay and Silverman 1997), we apply Group-Lasso machine learning (Yuan and Lin 2006; Meier et al. 2008; Yang and Zou 2015) to regulate the functional regression and select the best-fitting functional and scalar predictors.

Linguistic features are also inevitably irregular and sparse. Someone may use lots of emotion in one conversational turn, for example, but little the next. What's more, specific language features may not appear at all in many conversational turns (proportion = 0), leading to sparsity in observations. The irregularity and sparsity of conversational features represent a challenge to classical FDA which requires dense and regularly-spaced measurements per observation. To address this, we model the sparse functional data as random trajectories realized from latent smooth functions, and apply Karhunen-Loève expansion to the smoothed trajectories to obtain eigen scores for subsequent Group-Lasso regression.

Third, we provide deeper insight into the relationship between the affective and cognitive language styles linked to warmth and competence. While prior work suggests that speakers should be *either* affective or cognitive, but not both, our dynamic approach reveals that the warmth/competence "trade off" may not be so stark. We find that rather than prioritizing just one dimension, prioritizing each dimension at different times within an interaction may be best.

[1] Due to privacy issues, transcription costs, intensive data cleaning and editing demands, etc.

The rest of the paper is organized as follows. In Section 2, we briefly discuss the literature in which our examination is grounded. Section 3 describes the details of the conversational data for the current research and the measurement of language features. Section 4 sets out our modeling and analysis strategies. Section 5 presents the results of *when* within a conversation more affective versus cognitive agent language matters, and tests the robustness of the main results with alternative language measures and counterfactual simulations. Finally, Section 6 highlights managerial opportunities, discusses potential limitations, and notes opportunities for future research.

2 Talking to Customers

2.1 Service Language in Marketing

Talking to customers is important. American companies spend over a trillion dollars a year on staffing, training, and supporting their frontline sales and service. This is the single largest strategic investment for most firms, and nearly three times what they spend on marketing communications (Cespedes and Wallace 2017; Morgan 2017). What's more, these costs are likely to rise, as channel complexity and technology make it harder than ever to deliver great service (Ramachandran et al. 2020; McBain 2020).

Consistent with its importance, academics have spent much time and effort trying to understand and improve frontline interactions. Thousands of articles have studied service quality (for reviews, see Ladhari 2008; Parasuraman and Zeithaml 2002; Snyder et al. 2016). From surveys exploring how consumers evaluate salespeople (e.g., Zeithaml, Berry, and Parasuraman 1996) to experiments testing how service initiatives shape customer attitudes (e.g., Bolton and Drew 1991). From empirical tests of service actions (e.g., apologies and compensation; Smith, Bolton, and Wagner 1999) to models examining how customer service interactions drive financial outcomes (Rust and Chung 2006).

Recent advances demonstrate how words can impact service interactions. Ordenes and colleagues (2014), for example, found that sentiment analysis could be enhanced by linking it to language's topical content (e.g., firm vs. product). Other work finds that employees can boost customer satisfaction and purchase by using more concrete language (e.g., referring to the customer's order as a "t-shirt" rather than the "item" or "that"; Packard and Berger 2020), replying in complete sentences (Castleberry et al. 1999), or using different types of personal pronouns (e.g., saying "I" rather than "we" are happy to help; Packard, Moore, and McFerran 2018).

But while these examples demonstrate the importance of customer service language, they all focus on *what* rather than *when*. Should customer service agents speak concretely all the time, for example, or might this approach be more beneficial at certain conversational points than others?

2.2 When Language Matters in Customer Conversations

We examine *when* customer service language matters in the context of the so-called "warmth/-competence trade-off." Warmth and competence are two universal dimensions of social cognition, accounting for almost all of how people characterize one another (Fiske, Cuddy and Glick 2007). Warmth is described as the "expressive function," capturing affective expression and attention to emotions. Competence is the "instrumental function" focusing on agency, rationality and cognitive efficiency (Abele and Wojciskzke 2007). Above all else, people evaluate one another on these two fundamental dimensions (Judd et al. 2005).

Importantly, however, a great deal of research suggests these two dimensions are inversely related. Trying to be affectively-engaged impedes perceptions of competence, while acting in a more rational, cognitively-oriented manner makes people seem less warm. This trade-off has led to suggestions that people should try to be warm or competent, but not both (Godfrey, Jones, and Lord 1986; Holoien and Fiske 2013; Wang et al. 2017).

In marketing, research suggests that companies should prioritize a more cognitive, competence oriented approach (Kirmani et al. 2017). Work on handling customer queries, for example, finds that frontline worker's "relating" (i.e., affective or warm) language and non-verbal behaviors have a null or negative effect on customer attitudes on their own, and impede or even nullify the positive effect of more important "resolving" (i.e., cognitive or competent) language and behaviors (Marinova et al. 2018; Singh et al. 2018). Similarly, service employees who use emoticons in digital service contexts are perceived as warmer, but less competent (Li, Chan, and Kim 2019), leaving solution-oriented customers feeling less satisfied.

But should service agents always prioritize a rational, cognitive manner of speaking? And given other work encouraging employees to speak affectively to show they care (e.g., de Ruyter and Wetzels 2000; Parasuraman et al. 1985; Spiro and Weitz 1990), might there be a way to do both?

2.3 A Potential Solution to the Warmth/Competence Trade-off?

Rather than speaking either affectively *or* cognitively, we suggest that it may be important to consider *when* within customer interactions each is beneficial.

In customer service calls, for example, rather than diving straight into finding a solution at a conversation's beginning, affective language may be important. Human conversation commonly, and ideally, starts with some relationship-building before turning to the speaker's specific goals (Gabor 2011; Kaski, Niemi, and Pullins 2018; Placencia 2004). When employees and customers interact for the first time, such as in retail or call center interactions, affective language may be particularly helpful at building situated rapport (DeWitt and Brady 2003; Gremler and Gwinner 2000).

But such affective engagement will only go so far. Eventually the employee must move to addressing the customer's needs. Here, competence should be important, so shifting to a more analytic, cognitive communication style may be valuable.

Finally, given the work on recency and end effects (Greene 1986), closing with affective language may help leave the customer feeling positive about what's just happened. Attempting to summarize what has just transpired in a positive and polite way signals that a conversation should be approaching its end (Bardovi-Harlig et al. 1991; Schegloff and Sacks 1973).

Dynamic modeling of conversational turns test these predictions. Analysis of over 12,000 conversational turns examines *when* more affective or cognitive employee language is associated with increased customer satisfaction and purchase.

3 Data

A large US online fashion retailer provided recordings of 200 customer service calls. A professional transcription company converted the recordings to text, treating each conversational turn as a separate record (e.g., turn 1 (agent): "How can I help you?", turn 2 (customer): "I can't find ..."). Part of the conversation was inaudible for fifteen of the 200 recordings provided, leaving the turns from 185 conversations for analysis. Overall, this resulted in a final data set of 19.1 hours of live service conversations containing 12,410 conversational turns. The average conversation lasted 6.19 minutes (SD = 3.97) and included 66.75 turns (SD = 44.49).

3.1 Independent Measures: Agent Affective and Cognitive Language

Following prior work examining warmth- and competence-related constructs (Decter-Frain and Frimer 2016; Berry et al. 1997; Marinova et al. 2018; Singh et al. 2018), we measure affective and cognitive language through Linguistic Inquiry and Word Count (LIWC; Pennebaker et al. 2015).[2,3] As noted previously, warmth is conveyed through emotional expression. Using affective words like *happy* (e.g., "I'm happy you like the pants"), *great* ("That's great"), or *horrible* ("That's horrible") signals that an agent is considering a customer's emotional state or expressing their own. Consequently, following the work cited above, affective language is measured through LIWC's affective processes module, which contains 1,388 words and word stems[4] related to emotional expression (e.g., happy, great, horrible).

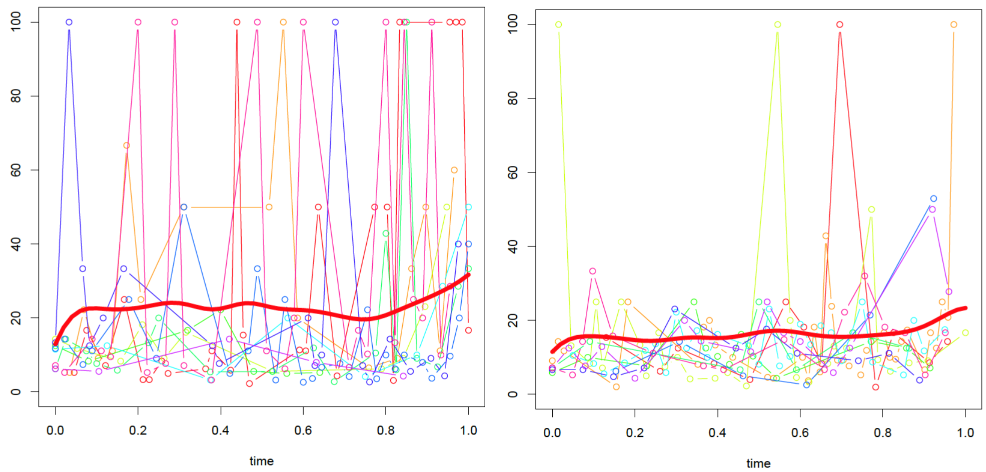
Cognitive language involves rational expression suggesting instrumentality, intelligence, and agency. Using cognitive words like *diagnose* (e.g., "Let's diagnose the cause") or *think* ("I think that will do it") signals that an agent is cognitively working to address the customer's needs. Consequently, following the work cited above, cognitive language style is measured through LIWC's cognitive processes module, which contains 780 words and word stems related to this construct (e.g., diagnose, think, and solve).

Figure 1 illustrates agents' average use of affective and cognitive language over conversational time (standardized to $[0, 1]$). It also includes language from a random sample of 10 calls, which indicates the irregularity in language feature use. While one might wonder whether agents strategically trade-off affective and cognitive language, this does not appear to be the case. Affective and cognitive language are uncorrelated at turn level ($r = -0.02$, $p > 0.1$) and only weakly correlated at call level ($r = -0.17$, $p < 0.05$). Further, examining the mean levels of affective and cognitive language suggests that service agents did not prioritize a cognitive, solving interaction style supported by prior research, instead using more affective language overall ($\mathrm{M}_{\text{affective}} = 22.74$ vs. $\mathrm{M}_{\text{cognitive}} = 16.03$, $p < 0.001$).

[2]Note that prior literature uses a variety of terms interchangeably for affective and cognitive components of interpersonal language, behavior, and perception (e.g., warmth and competence, communion and agency, relating and resolving).

[3]The Marinova et al. (2018) and Singh et al. (2018) papers customize the LIWC dictionaries and provide new names for their linguistic features of warmth ("relating") and competence ("resolving"). Using this custom adaptation of the LIWC dictionaries produces similar results (see Section 5.6).

[4]Word stems capture tense and part of speech variations of a single root. For example, the stem "bother*" captures bother, bothers, bothered, and bothering.



(a) Agent Affective Language

(b) Agent Cognitive Language

Figure 1: Means (red lines) and Samples of Linguistic Features (proportion of words) over Conversational Time

3.2 Dependent Measures: Customer Satisfaction and Purchase

We examine the relationship between agent language dynamics and two closely related customer outcomes. First, the firm provided their measure of customer call satisfaction: perceived employee helpfulness (1 = not at all helpful, 4 = very helpful, measured at the end of the call). Perceived helpfulness represents a crucial performance-based measure of customer satisfaction (Cronin and Taylor 1992; Parasuraman et al. 1991). Second, the firm provided a behavioral measure — the number of orders placed in the 30 days following the service interaction.

3.3 Control Variables

To account for alternative explanations, we control for a variety of call, agent, customer and interaction factors likely to be associated with our dynamic predictors and outcome measures, and do so at both the static and dynamic levels. The ability to consider a large number of such features is critical for inference given the interactional and circumstantial nature of conversation (Zhang et al. 2020). The Group-Lasso mechanism we apply to the sparse functional regression results in automatic variable selection to retain the statistically meaningful subset of controls.

3.3.1 Static Controls

Topic The content of the call could impact agent's language, or customer satisfaction and purchase, so we control for this in two ways. First, we include dummy variables for the four call reasons captured by the firm (*Order*, *Shipping*, *Return*, *Product*). Second, to provide a more fine-grained measure, we use the customer's language to uncover the hidden mixture of call topics via a latent Dirichlet allocation topic model (Blei et al. 2003). Assessment by perplexity and interpretability supports 13 topical controls, each of which captures the proportion of the call's language corresponding to that topic (*Topic* 1, ..., *Topic* 13).

Complexity The complexity of the call could shape agent's language, and their ability to successfully solve the issue, so we control for complexity in two ways. First, two judges listened to each call and indicated perceived difficulty or severity of the call on a five-point scale (*Severity*). Second, given that complex issues may require more discussion, we control for call length using the total number of words spoken (*Length*).

Resolution Whether the agent was able to resolve the customer's issue during the call likely impacts both how both the agent and customer speak, as well as customer satisfaction. To account for this, two different judges read the transcript of each call and indicated whether or not the customer's main issue had been resolved (*Resolved*; yes = 1).

Agent Observables Experience could shape both how agents speak to customers and customer satisfaction, so we control for this in two ways. First, to control for organizational experience, we include how many days agents have been with the firm (*Agent Tenure*). Second, to account for direct experience with customers, we control for the total number of calls they have handled (*Agent Calls*), which is only moderately correlated with job tenure ($r = 0.38$, $p < 0.05$). The firm also provided the agent's gender, which we include as a dummy variable (*Agent Female*).

Customer Observables Experience with a firm can shape customer satisfaction and behavior (e.g., loyalty effects; Neiderhoffer and Pennebaker 2002), so we control for this in two ways. First, we use the number of days since the customer's first purchase with the firm (*Customer Tenure*). Second, we include their lifetime expenditure with the firm in dollars (*Customer LTV*). We also include two demographics variables provided by the firm, including dummies for which of five geographic regions a customer resides in (*Customer Region*), and a dummy for customer gender (*Customer Female*).

The customer's attitude about other aspects of the firm could impact how they interact with the agent, their satisfaction towards the agent in the particular interaction, and their subsequent purchase behavior. To control for these possibilities, we include measures of their attitude towards the website (*Attitude Web*) and the shopping experience (*Atttitude Shop*), which were captured by the firm after the customer satisfaction measure at the end of the call.

Finally, in our model examining post interaction purchases, we control for each customer's baseline buying behavior using the number of orders placed up to 30 days prior to the conversation (*Orders 30 Pre*).

3.3.2 Dynamic Controls

Additional Agent Language Features Beyond affective and cognitive language, other dynamic facets of employee language may color how customers perceive or speak to them. We include turn-level measurement of LIWC's other main psychological process dictionaries, including social processes, perceptual processes, drives, temporal orientation, and informal language (*Social*, *Percepual*, *Drives*, *Time*, *Informal*; Pennebaker et al. 2015).

Agent Paralanguage In addition to what was said, one could wonder whether how things were said (i.e., accompanying paralinguistic features) might drive our effects. The extent to which a speaker modulates pitch and intensity (i.e., volume) while talking, for example, has been linked to persuasion (Van Zant and Berger 2020). Consequently, we control for these two paralinguistic features using phonetics software (*Pitch* and *Intensity*; Boersma and van Heuven 2001).

To isolate the impact of agent's language, it is also important to control for how it may be shaped by customer language. How someone speaks can impact their conversation partner, but also may reflect things that the conversation partner said previously (Zhang et al. 2020). People sometimes mimic or match a conversation partner's way of speaking, especially if they want to please that partner (Cheng and Chartrand 2003). Agents may use more affective language to respond to customers who are already speaking emotionally, and customers may adopt agents' language when discussing technical or detailed steps that need to be taken to competently (i.e. cognitively) solve an issue. We control for these possibilities in three ways.

Agent-Customer Synchronicity First, we control for the possible dynamic influence of customer language on agent language with a moment-to-moment measure of linguistic synchronicity (i.e., mimicry). Specifically, we follow Zhang, Wang, and Chen (2020) and create a synchronicity measure using the R^2 of the moment-to-moment regression from customer language on agent language. Figure A1 in the Web Appendix summarizes the linguistic synchronicity across the 185 conversations. We include this call-level measure in the controls to accommodate the instantaneous linguistic mimicry that may happen between the agent and the customer.

Customer Affective and Cognitive Language In addition to moment-to-moment synchronicity, an agent might mimic or otherwise repeat something the customer said much earlier in the conversation. Further, *when* within a conversation the customer uses more affective or cognitive language could shape the extent to which the agent tends to mimic that language. To account for these kinds of mimicry, which would not be captured by moment-to-moment synchronicity, we include the customer's own affective and cognitive language over the course of the conversation as dynamic controls.

Other Major Customer Language Features Beyond affective and cognitive language, other aspects of customer language may color how employees respond to them in subsequent moments or even later in the conversation, so we control for this using turn level measurement of the same main psychological process dictionaries applied to employee language (*Social*, *Percepual*, *Drives*, *Time*, *Informal*).

Overall, our model incorporates two language predictors (agent affective and cognitive language) related to the two most important dimensions of person perception, 34 static controls, and 18 dynamic language and paralanguage controls. See Web Appendix Table A1 for summary statistics for all the variables (independent measures, dependent measures, and controls).

While we cannot rule out endogeneity with certainty, controlling for an extensive variety of factors that might shape the relationship between agent affective and cognitive language and our outcome measures helps mitigate such concerns. What's more, the temporal relationship between the predictors and outcome measures casts doubt on reverse causality.

4 Empirical Modeling Approach

4.1 Functional Data Analysis

To flexibly characterize the relationship between dynamic conversational features (e.g., affective and cognitive language) and static conversational outcomes (i.e., customer satisfaction or purchase behavior), we begin our modeling efforts with the semiparametric tools from functional data analysis (FDA; Ramsay and Silverman 1997). Functional data has seen growing applications in marketing to help address dynamic modeling challenges. For instance, Sood et al. (2009) used functional regression to forecast new product penetration, demonstrating FDA's superiority over the Bass model in predicting diffusion. Foutz and Jank (2010) applied functional analysis to detect the shapes of virtual stock trajectories predictive of the pre-release demand of motion pictures. Hui et al. (2014) developed a Bayesian functional linear regression to relate continuous consumer attitude measurement to the overall judgement of a TV show. Xiong and Bharadwaj (2014) explored the impact of temporal variations in online buzz volume on new product performance, illustrating the enhanced predictive power resulting from FDA.

We extend FDA to human conversation. We consider time-varying measurement of a conversation feature (e.g., affective or cognitive language) within the n-th conversation as a trajectory $X_n(t)$, $n = 1, ..., N$, that is randomly drawn from an underlying stochastic function. The following functional regression relates the static outcome of the interaction y_n to the dynamic language measurement $X_n(t)$,

$$y_n = \alpha + \int_0^1 \beta(t) \left[X_n(t) - \mu(t)\right] dt + e_n, \tag{1}$$

where α is the intercept, $\mu(t) = \mathbb{E}[X_n(t)]$ the mean function of $X_n(t)$, e_n the i.i.d. Gaussian error term, and $\beta(t)$ the sensitivity curve of our interest that characterizes the dynamic impact of a linguistic feature at different moments during a conversation. We standardize the varied conversation lengths to a common interval $[0, 1]^5$.

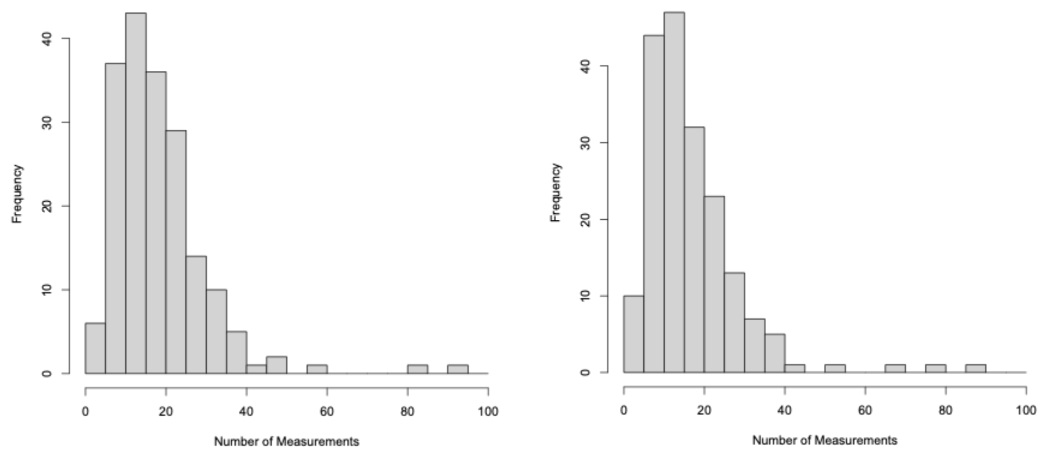
4.2 Sparseness and Irregularity in Conversational Dynamics

As noted previously, before applying the functional regression model, several major challenges specific to conversational data need to be addressed. First, while virtual stock markets (Foutz and Jank 2010) and continuous user dials (Hui et al. 2014) provide evenly-spaced and dense measurements, conversational language occurs over a series of spontaneous conversational turns and tend to be *irregularly-spaced* across time. For example, some turns ("Hi, my name is Chris and thanks for calling customer service. How can I help you today?") are longer than others ("My phone is broken."). Further, given the use of fixed dictionaries to measure language features, a certain conversational feature may not appear every moment, resulting in *sparse* measurement of the feature. Figure 1 and Figure 2 illustrate the irregularity and the sparseness in our conversation data. Except for a handful of calls that contain close to 100 measures of these language features, most interactions have only 10 to 30 measurements. Consequently, functional regression for conversation must be able to handle the irregular and sparse measurement of conversational features.

Second, human conversation is complex, containing a large variety of dynamic linguistic and paralinguistic features, as well as static observables. To control for their influence, we need to deal with a "wide" data situation in which the number of (functional and scalar) variables may be comparable to or even greater than the number of observations (conversations). As noted, compared with the 185 call observations in the data, there are two focal language variables (agent affective and cognitive language), 18 dynamic language controls, as well as 34 static controls. The dynamic linguistic features alone translate to close to 100 regressors after the functional Karhunen-Loève expansion.

Moreover, as dependent variables may be recorded as nonlinear responses such as count

[5]Conversation length is also included as a control in the main model.



(a) Agent Affective Language (b) Agent Cognitive Language

Figure 2: Sparseness in Linguistic Measurements of Conversation

data (i.e., purchase quantity post call), we need to include an appropriate link function to generalize the functional linear regression specified in (1).

To address these challenges, we employ recent developments in statistics and machine learning to extend the conventional functional regression model in (1). In particular, we consider a dynamic language feature as a continuous trajectory $Z_n(t)$ over the course of conversation n. Across multiple conversations, we obtain a sample of measured trajectories that are assumed to be independently drawn from an underlying stochastic function, with unknown mean function $\mu(t) = \mathbb{E}[Z_n(t)]$ and unknown variance function $\Sigma(t_1, t_2) = \text{Cov}[Z_n(t_1), Z_n(t_2)]$. Due to measurement errors arising from using language dictionaries, the actual observation for the m-th measurement, $m = 1, ..., M_n$, of the n-th conversation is given by

$$X_n(t_m) = Z_n(t_m) + \varepsilon_n(t_m), \tag{2}$$

where t_m indicates the time of the sequential conversational turn at which the measurement was taken, and the measurement error ε_n is i.i.d. drawn from $N(0, \sigma^2)$. In call n, the M_n measurements are irregularly-spaced and sparse. We assume M_n is exogenous and control for its effect in our model.

For each functional variable, we apply scatterplot smoothing and surface smoothing, both via local linear regression, to estimate the mean and covariance functions respectively (Yao et al. 2005; Wang et al. 2016; Chen et al. 2017).[6] We use the entire sample simultaneously in the smoothing to allow information shrinkage across observations to accommodate the data sparseness discussed above.

After smoothing, we apply Karhunen-Loève expansion to obtain eigen components of the conversations, $\{X_n(t)\}_{n=1}^{N}$, namely,

$$\Sigma(t_1, t_2) = \sum_{i=1}^{\infty} \lambda_i \phi_i(t_1)\phi_i(t_2), \tag{3}$$

and so

$$X_n(t) = \mu(t) + \sum_{i=1}^{\infty} \omega_{ni}\phi_i(t) + \varepsilon_n(t), \tag{4}$$

where $\phi_i(t)$ is the i-th eigen function, λ_i the associated eigen value, and ω_{ni} the i-th eigen score of the n-th conversation. If we expand the unknown $\beta(t)$ curve onto the same eigen bases,

$$\beta(t) = \sum_{i=1}^{\infty} b_i \phi_i(t), \tag{5}$$

thanks to orthogonality, the functional regression in (1) can now be simplified to

$$y_n = \alpha + \sum_{i=1}^{\infty} b_i \omega_{ni} \approx \alpha + \sum_{i=1}^{I} b_i \omega_{ni}. \tag{6}$$

In the above, the truncation I, or the actual number of eigen components to appear in the regression, is determined using the Akaike information criterion (AIC).[7]

[6] For both the smoothed mean and covariance functions, we choose the commonly-used Gaussian kernel and obtain the smoothing bandwidth via the generalized cross-validation bandwidth selection (Speckman 1988).

[7] Alternatively one could use other criteria such as leave-one-out cross-validation. We tried different metrics and obtained the same truncation point.

4.3 High Dimensionality in Conversational Dynamics

From the data we obtain a number of dynamic and static features that are possibly interdependent. Therefore, we write the following generalized functional regression model to accommodate additional functional and scalar variables with nonlinear responses,

$$\mathbb{E}\left[y_n \mid \{X_{ln}\}_{l=1}^{L}, \{W_{jn}\}_{j=1}^{J}\right] = g^{-1}\left(\alpha_a + \sum_{l=1}^{L} \int_0^1 \beta_l(t)\left[X_{ln}(t) - \mu_l(t)\right] dt + \sum_{j=1}^{J} \gamma_j W_{jn}\right), \tag{7}$$

where L and J denote the number of functional and scalar predictors respectively, W_{jn} is the j-th scalar control for the n-th call, γ_j represents the regression coefficients, and $g(\cdot)$ indicates the link function for the nonlinear dependent variable. Besides using agent observables as controls, we further capture agent heterogeneity with a random intercept α_a for every agent.

Applying the smoothing procedure and Karhunen-Loève expansion to the functional components of the data, we obtain a simplified generalized regression as follows,

$$\mathbb{E}\left[y_n \mid \{X_{ln}\}_{l=1}^{L}, \{W_{jn}\}_{j=1}^{J}\right] = g^{-1}\left(\alpha_a + \sum_{l=1}^{L} \sum_{i=1}^{I_l} b_{li}\omega_{lni} + \sum_{j=1}^{J} \gamma_j W_{jn}\right), \tag{8}$$

where the truncation I_l is determined by AIC for each functional variable $X_l(t)$.

As mentioned, it is possible that the total number of variables $(L+J)$ becomes comparable to or larger than the number of observations (conversations), thus we will not include the full set of functional and scalar controls, as such a model is likely to overfit the noise and become less useful in producing meaningful inference from the data. Therefore, we need to regularize the regression such that the controls can be automatically selected to yield efficient model inference.

However, conventional variable selection methods like stepwise regression (e.g., Foutz and Jank 2010) are not applicable in our context for two reasons. First, solutions from stepwise regression are path-dependent as the approach is a *greedy* algorithm that finds local optima in every step, but often fails to reach generally optimal variable selection. This fundamental limitation of stepwise regression is usually termed as the lack of oracle properties in variable selection (Zou 2006). Second, stepwise regression does not allow *group-wise* variable selection, whereas the selection of functional variables corresponds to selecting from the L groups of eigen scores in (8). That is, for a given functional variable $X_l(t)$, either $\{b_{li}\}_{i=1}^{I_l}$ are all suppressed to zero or they are all selected to enter the regression. Similarly, categorical control predictors associated with multiple dummies (e.g., call reasons and customer regions) also require group-wise variable selection.

To overcome the wide data challenge, we utilize Group-Lasso regularization (Yuan and Lin 2006; Meier et al. 2008; Yang and Zou 2015) to avoid path-dependency and to retain the functional and categorical variable grouping after selection. The shrinkage and variable selection method, Lasso (Tibshirani 1996), has been widely applied in statistics and machine learning for high dimensional data analysis. Yuan and Lin (2006) proposed a generalization of Lasso for group-wise variable selection and regularization. In our context, to answer the research question around affective and cognitive language, we keep the two functional predictors unpenalized in the L1 regularization procedure (Chen et al. 2016). That is, assuming the controls in our model can be divided into D non-overlapping groups, Group-Lasso attempts to minimize

$$\frac{1}{2}\left\|g(\mathbb{E}[y]) - \alpha_a - \boldsymbol{b}_A\boldsymbol{\omega}_A - \boldsymbol{b}_C\boldsymbol{\omega}_C - \sum_{d=1}^{D}\boldsymbol{b}_d\boldsymbol{\omega}_d\right\|_2^2 + \lambda\sum_{d=1}^{D}\sqrt{\dim(\boldsymbol{b}_d)}\,\|\boldsymbol{b}_d\|_2\,, \tag{9}$$

where subscripts "A" and "C" denote the affective and cognitive language components respectively. The Group-Lasso procedure suppresses a subset of groups of coefficients to zero to encourage a simpler and more efficient generalized linear model. Computationally, solving the above penalized least squares is expensive, therefore we follow Yang and Zou (2015) and implement the groupwise-majorization-descent (GMD) algorithm to achieve fast computation of Group-Lasso, for the selection of functional and scalar variables simultaneously. To determine the optimal value of penalty parameter λ, we first calculate the maximum penalty parameter λ_{max} such that none of the penalized groups are active in the model. Then we construct a multiplicatively decaying grid for possible λ values starting at λ_{max}, and use leave-one-out cross-validation to pick the best penalty parameter from the grid.

5 Results

5.1 Dynamic Effects of Agent Language on Customer Satisfaction

The ultimate result is represented by the $\beta_l(t)$ curves estimated from the sparse functional regression in (8). Predictors have a positive (negative) relationship with the outcome of interest when a given $\beta_l(t)$ curve and its confidence interval lie above (below) zero. We examine the relationship between agent affective and cognitive language and both customer satisfaction and purchase.

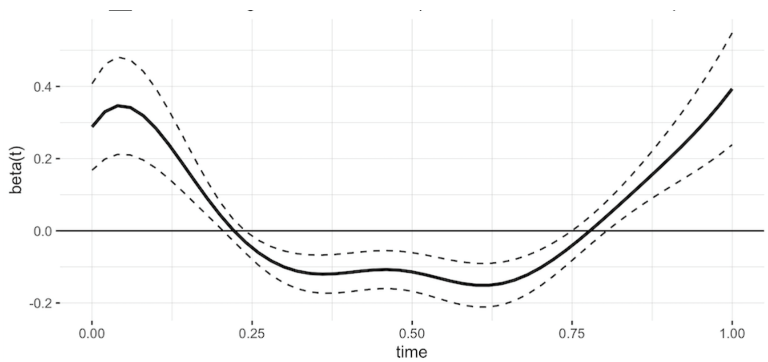
As predicted, the model estimates for agent affective language (Figure 3a) reveal a positive relationship (pointwise 95% confidence interval above zero) between agent affective language and customer satisfaction at the conversation's beginning and end (48.75% of the conversation). In contrast, customer satisfaction is higher when agents avoid affective language (pointwise 95% confidence interval below zero) during the middle of the call (51.25% of the conversation). Approximately two-thirds (63.59%) of the positive conversational contribution for agent affective language occurs at the start of the conversation, with the remainder (36.41%) at the conversation's end.

The beta curve for agent cognitive language is quite different (Figure 3b). While customer satisfaction is higher by using affective language at the start of the call, speaking more rationally during this time appears to be costly. Cognitive language's positive conversational impact (94.33% of its positive contribution) instead arises in the middle of the conversation.

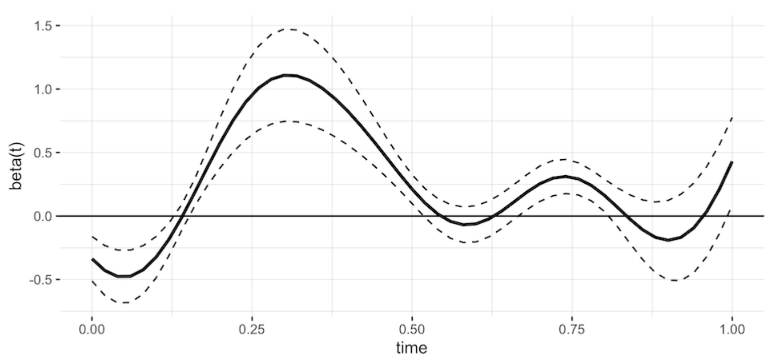
Parameter estimates for the customer satisfaction model are provided in Table A2 in the Web Appendix. The beta curves remain similar when we exclude the control variables (see

Web Appendix Figure A2).

Note that the average employee does not seem to follow the beta curves revealed. Instead, affective language is at its lowest point at the start of the call (Figure 1a), when it is particularly important, while cognitive language was near its lowest point between 10% and 40% into the conversation (Figure 1b), which is when customer satisfaction seems most likely to benefit from such language.



(a) Agent Affective Language

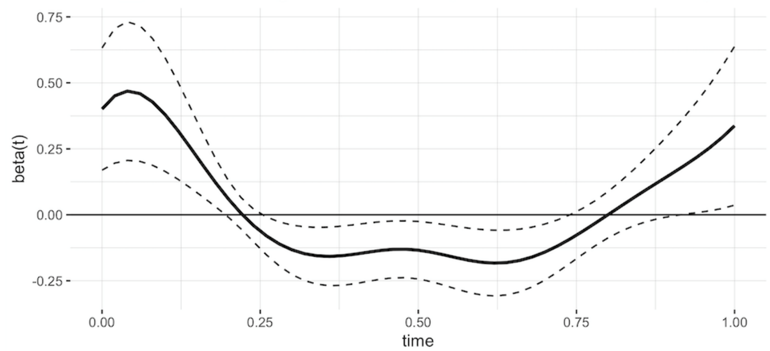


(b) Agent Cognitive Language

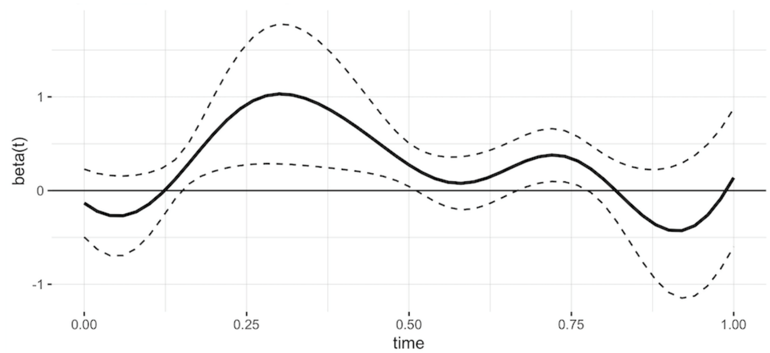
Figure 3: Beta Curves for Agent Affective (a) and Cognitive (b) Language in Relation to Customer Satisfaction (dotted lines: pointwise 95% confidence intervals)

5.2 Dynamic Effects of Agent Language on Customer Purchase

While the customer satisfaction measure is useful given its occurrence immediately after the service interaction, more satisfied customers should also make more purchases (Zeithaml et al. 1996). Are the dynamic effects of agent affective and cognitive language sufficiently robust that they might be linked to post-call purchases over a longer period of time?



(a) Agent Affective Language



(b) Agent Cognitive Language

Figure 4: Beta Curves for Agent Affective (a) and Cognitive (b) Language in Relation to Customer Order Count within 30 Days Post Interaction

We apply a functional Poisson regression model to estimate the relationship between agent affective and cognitive language and downstream customer purchase behavior. That is, we use a Log link function in (8) to relate the predictors with the mean of the order count. The Poisson model includes the same sets of functional and scalar variables as in the functional linear regression, and adds a control for each customer's baseline buying behavior using the number of orders they placed up to 30 days prior to the conversation (*Orders 30 Pre*).

Results are similar to those observed for customer satisfaction (Figure 4; parameter estimates are provided in Web Appendix Table A3).[8] Replication with purchase is valuable due to not only its behavioral (rather than self-reported) nature and its direct financial impact, but also its stronger inference of causality thanks to the greater time lag between it and the dynamic language predictors (i.e., up to 30 days).[9]

5.3 Relative Contributions of Affective and Cognitive Language

One might wonder whether affective or cognitive language is more important overall. To address this question, we compare the proportions of positive versus negative areas of the beta curve for each functional feature.

Table 1: Relative Contributions of Agent Affective and Cognitive Language

	Customer Satisfaction		Customer Purchases	
Agent Language	Positive Proportion	Negative Proportion	Positive Proportion	Negative Proportion
Affective	51.25%	48.75%	53.79%	46.21%
Cognitive	83.02%	16.98%	80.51%	19.49%

For both customer satisfaction and purchase, the majority of both affective and cognitive language contributions are positive (Table 1). However, the relatively larger negative area for employee affective language suggests it is particularly important to know when to speak to customers more affectively (i.e., start and end, but not middle).

[8]The beta curve for agent affective language is highly similar when we exclude the control variables, as is the beta curve for cognitive language, but with larger confidence bands (see Web Appendix Figure A3).

[9]To account for the possibility of an interactive effect between agent's use of affective and cognitive language, we also considered models including a functional interaction term for affective and cognitive language. Three of the four resulting beta curves replicate the main results when we include this additional variable. The beta curve of agent affective language on purchases changed such that affective language remains important at the end of the conversation, but not at the start (see Web Appendix Figures A4 and A5).

5.4 Simulations for "What" versus "When" Approaches

Results suggest that affective and cognitive language can productively co-exist within a single interaction, but one could still wonder whether speaking exclusively in a cognitive or affective style, as suggested by prior work, may be better. To consider this question, we perform a series of simulations. They compare the customer satisfaction and purchase resulted from the current approach (i.e., accounting for when affective and cognitive language matter) to those suggested by (a) alternatives that recommend only affective *or* cognitive language but not both, and (b) alternatives that support both, but do not account for when a given style should be used.

Because our model identifies when affective and cognitive language should be used, but not the optimal level of these features at a given moment, the simulations utilize the average observed levels of affective and/or cognitive language at each conversational moment, and then turn that language feature "on" or "off" at different moments based on the simulation condition. We caution that these simulations compare alternative approaches to the dynamic language use suggested by our modeling estimates. Consequently, the simulated improvements in customer satisfaction and purchase should be considered ceilings rather than expected outcomes.

First, we compare the current approach to the marketing literature's recommendation to be competence-oriented throughout the interaction. The simulation suggests that employees who follow the timing of affective and cognitive language suggested in the current approach (Figures 3 and 4) would see a 2.50 point increase in customer satisfaction ($p < 0.01$) and 3.42 more purchases in the 30 days following the call ($p < 0.01$). For a more conservative test, we also compare our approach to a competence-only approach that uses cognitive language at the "right times" (per Figures 3 and 4). Results further the notion that using both affective and cognitive language at the right times, rather than only cognitive language at the right times, should have beneficial effects, i.e., difference in customer satisfaction = 2.06 ($p < 0.01$)

and in purchases = 2.84 ($p < 0.01$).

Results are similar when we compare the current approach to the psychology literature's suggestion to be affective (or warm) throughout the interaction, i.e., difference in customer satisfaction = 2.42 ($p < 0.01$) and in purchases = 3.69 ($p < 0.01$). A comparison to being affective only but at the "right" times shows similar results, i.e., difference in customer satisfaction = 1.36 ($p < 0.01$) and in purchases = 1.87 ($p < 0.01$).

Second, we consider a comparison which acknowledges that affective and cognitive language can fruitfully co-exist in a single interaction but ignores the possibility that *when* these speaking styles are used matters. To do so, we simulate a scenario in which the two speaking styles are turned on at the mean observed level at each point in conversational time. Speaking both affective and cognitively *at the right times* rather than at all times results in a simulated improvement of 1.49 points in customer satisfaction ($p < 0.05$) and an incremental 2.39 purchases in the 30 days after the call ($p < 0.05$).

Taken together, while the size of the results are likely influenced by our modeling approach, they support the benefits of using *both* affective and cognitive language rather than only one, and of considering *when* to use each of these approaches over the course of a conversation.

5.5 Results of Traditional Call Level "What" Analysis Approach

Rather than modeling dynamically, one might wonder what the results would look like if each language feature was simply examined at the call level (i.e., the traditional *what* approach). To test this, we assessed call level agent use of affective and cognitive language as predictors of customer satisfaction including all static controls from the dynamic models, as well as the means of the agent and customer language and paralanguage features using a straightforward multivariate Lasso regression.

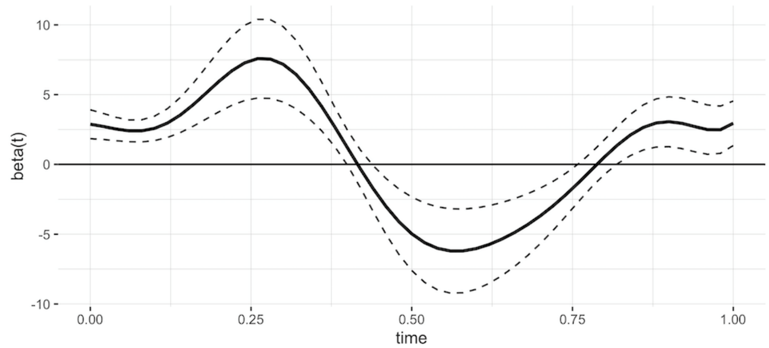
Results suggest that if we had only analyzed these language features at call level, consistent with prior research (e.g., Marinova et al. 2018; Singh et al. 2018), we would have concluded that agents should use only one of either affective or cognitive language. Call level model results indicate that customer satisfaction has a positive relationship with agent affective language ($b = 0.05$, $p < 0.05$), and a negative, but non-significant relationship with agent cognitive language ($b = -0.04$, $p > 0.1$). Results for the Poisson model examining post interaction orders similarly suggest agent affective language matters more than cognitive language (Web Appendix Tables A4 and A5).

These analyses highlight the value of considering conversational dynamics, and how doing so may provide new insights.

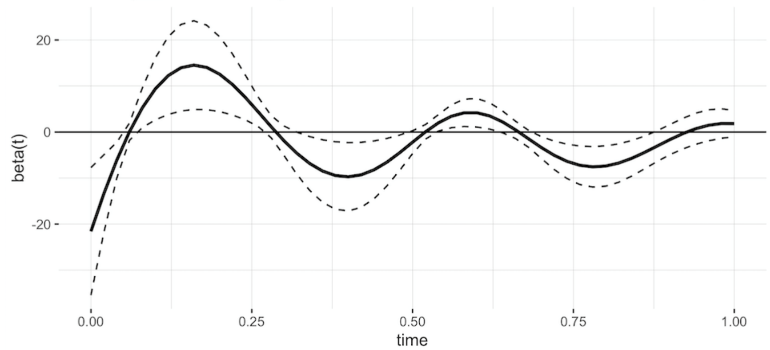
5.6 Alternative Measures of Affective and Cognitive Language Styles

These analyses leveraged affective and cognitive language measures extensively validated and applied in prior work (cf. reviews by Kahn et al. 2007 and Tausczik and Pennebaker 2010), but one could wonder whether they might somehow miss certain idiosyncratic linguistic feature of these speaking styles in customer service conversation. To address this possibility, we borrow custom dictionaries used to approximate affective and cognitive language in prior customer service research (Marinova et al. 2018; Singh et al. 2018). This work combined established dictionaries (LIWC) and human judging to develop custom lists of service-oriented "relating" (i.e., affective) words (N = 247) and "resolving" (i.e., cognitive) words (N = 649). We scored all agent and customer conversational turns using this approach, added them to the model instead of the LIWC measures, and estimated the model for our main analysis to test robustness.

As shown in Figure 5, beta curve estimates remain similar. The alternative affective language measure ("relating") has a positive relationship with customer satisfaction during the start and end of the conversation, but a negative relationship in the middle. Like our



(a) Agent "Relating" Language

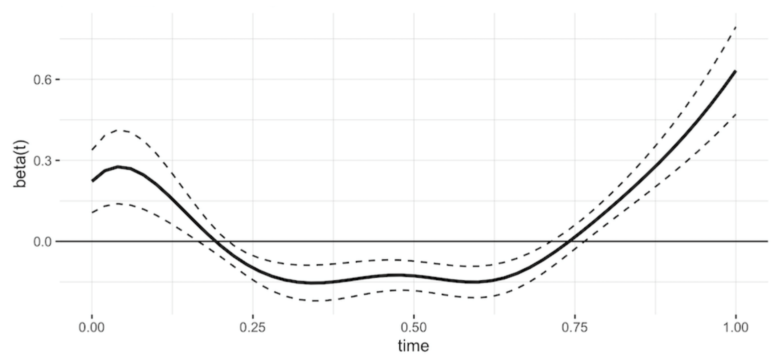


(b) Agent "Resolving" Language

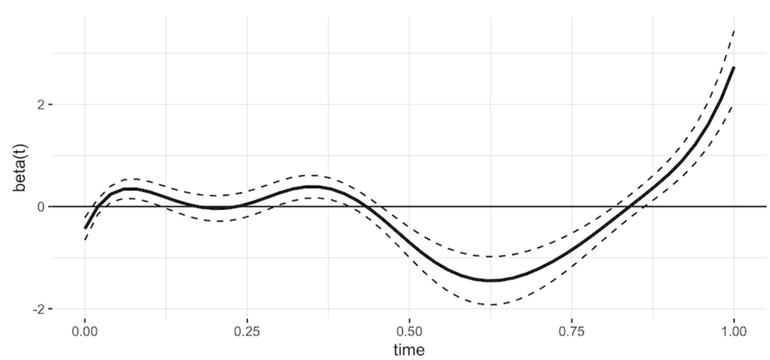
Figure 5: Beta Curves for Agent "Relating" (a) and "Resolving" (b) Language in Relation to Customer Satisfaction

cognitive language measure (Figure 3b), the "resolving" language measure (Figure 5b) has a negative relationship with customer satisfaction at the start of the call, but then turns positive in most of the middle region. While the overall shapes are comparable, the beta curve with the Marinova et al. (2018) measure of cognitive language dips into negative significance (i.e., suggesting cognitive language is costly) at two points for which the LIWC cognitive language measure result does not cross zero. The outputs for the functional Poisson model using the purchase count dependent variable remain similar (see Web Appendix Figure A6).

Overall, results are robust to the use of these alternative language dictionaries. Notably, the research that developed these dictionaries (Marinova et al. 2018) found that only agent cognitive language had a positive effect on their dependent measure — human judgement of customer emotion. The same study found that agent's affective language impeded the benefit of cognitive language when both were included in the model, supporting the warmth/competence trade-off and a recommendation to focus exclusively on cognitive language (which is linked to competence). We expect these differences are due to the dynamic modeling approach introduced here, but may also be due in part to differences in the specific customer service context (airline counter service vs. online retailing), or the different dependent measure used (e.g., third-party judgment of displayed affect vs. customer satisfaction self-reports).



(a) Agent Positive Affective Language



(b) Agent Negative Affective Language

Figure 6: Beta Curves for Agent Positive Affective (a) and Negative Affective (b) Language in Relation to Customer Satisfaction

5.7 Valenced Subsets of Affective Language

While LIWC's affective process dictionary is often used to capture warmth in language, one could argue that "warm" affective language should contain only positive emotional words (e.g., happy and wonderful) and exclude negative ones (e.g., sad and disappointed). Agents often use negative affective language in a warm manner to convey empathy (e.g., "I'm disappointed we didn't deliver your order on time"), but to test the contribution of each valence, we repeat the main analysis incorporating agents' positive and negative affective words as separate predictors.

Results are again similar. The beta curve for positive affective language (Figure 6a) is close to that of the full affective language dictionary, while negative affective language also appears to contribute positively, albeit only at the end time period (Figure 6b). A review of the negative affect words used in the last 12.5% of conversations reveals that the presence of words like "sorry," "problem," and "wrong" are positively correlated with customer satisfaction, which appear in phrases such as "Again, sorry about that" or "Glad we could fix the problem." Our functional approach appears to capture such subtle conversational language features well. The beta curves for the Poisson model for the purchase count dependent measure are replicated for positive affective language, but reduced for negative affective language (see Web Appendix Figure A7).

6 General Discussion

6.1 Intended Contributions

This research helps shed light on a richer theory of conversational dynamics. While a great deal of work has looked at customer service language and other consumer dialogues (e.g., social media conversations; Berger and Schwartz 2011; Ordenes et al. 2017), *when* different linguistic styles are most useful in conversation has received little attention.

To address this gap, we developed an empirical modeling approach examining how the conversational timing of language relates to important customer service outcomes. This approach helps address two major challenges in modeling conversational dynamics — sparsity and high dimensionality. Linguistic measurement of human language is inevitably irregular and sparse, therefore we modeled the sparse time-varying data as random trajectories realized from underlying smooth functions. Human conversation also often yields wide data situation in which a large number of verbal and vocal features need to be accommodated to strengthen inference (Zhang et al. 2020). To achieve model regularization within the functional analysis framework, we incorporated Group-Lasso from the machine learning literature to automatically select functional and scalar variables to enter the functional regression and avoid overfitting the noise from the data. The flexibility inherent in the Group-Lasso method allows us to retain the focal predictors of interest (e.g., affective and cognitive language) while penalizing other variables to find the most statistically meaningful set of available controls.

We apply this method to language features related to the two most important dimensions of person perception — warmth and competence. Results indicate that customer service employees should try to speak in both an affective and cognitive manner, but at different times in the conversation. Speaking affectively at the beginning and end should enhance customer satisfaction and purchase, but may have negative effects in the middle. The opposite pattern holds for competence-related language. Ancillary analyses further suggest that, compared with competence-related language, it is particularly important to understand the right time to speak affectively. In addition, results reveal that had conversational dynamics not been considered, conclusions similar to prior research (prioritize only one of the two language features) would have been made, which would likely lead to reduced customer satisfaction and purchase. This further highlights the value of considering dynamics.

6.2 Applications to Prior Theorizing and in The Field

While affective and cognitive language are important given they capture the two most important dimensions of person perception, they are just one example of the potential importance of conversational dynamics. The same modeling approach can be applied to examine other linguistic features thought to be beneficial, such as concreteness, asking questions, and using long sentences (Castleberry et al. 1999; de Ruyter and Wetzels 2000; Packard and Berger 2020).

Take asking questions. Prior research suggests asking questions is beneficial because it signals interest in the customer's issue (Brody 1994; Drollinger and Comer 1997). Consumers also believe that asking questions is an important attribute of agent behavior, making it a common feature of scales used to evaluate agent performance (Drollinger et al. 2006; Ramsey and Sohi 1997).

But *when* should agents ask questions? One possibility is that asking questions is particularly beneficial after customers have explained their needs. Agents might ask clarifying or information-gathering questions to make sure they are adequately informed before proceeding to address the customer's issue. In this context, agents that ask questions early in the conversation might be sending a positive signal of their motivation to understand and help the customer. Asking questions later in the call, however, might suggest the agent never understood what was needed.

To illustrate our method's potential to test such ideas, we run the same main model described in Section 4, but with agent question-asking as the dynamic predictor of customer satisfaction. Results indicate that *when* agents ask questions is indeed linked to customer satisfaction (Figure 7). Agent question asking has a positive relationship with satisfaction when used approximately 15-50% into the service interaction, but has a negative relationship after that point. This shape is consistent with the notion that, ideally, agents should ask questions after the customer attempts to describe their needs, but not throughout the entire conversation. The curve also suggests it is beneficial to ask questions at the very end of the conversation. Review of call transcripts indicates this may be suggesting the importance of the "Is there anything else I can help with?" question that agents often ask shortly before the conversation ends.[10] This example further underscores the potential of examining temporal dynamics of language features, demonstrating not only whether they matter, but *when*.

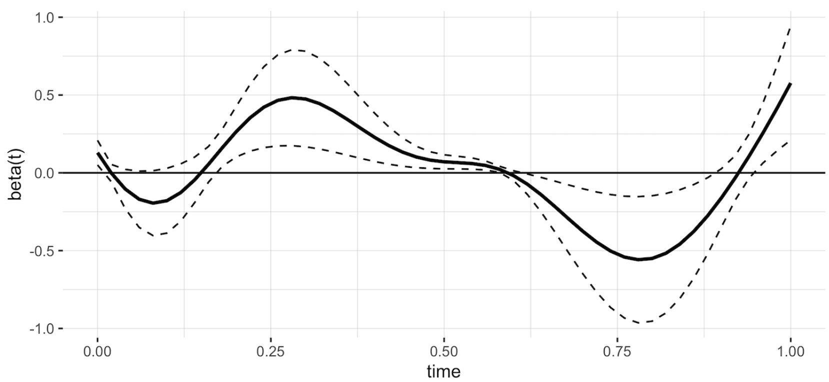


Figure 7: Beta Curve for Agent Question Asking in Relation to Customer Satisfaction

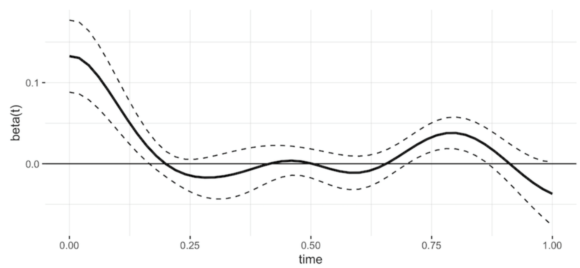
Insights from conversational dynamics have clear practical implications. In addition to instructing service employees on *what* to say, or types of language to use, our approach offers model-based suggestions on *when* to say it. Moreover, as many organizations look to integrate automated chatbots and other forms of verbal artificial intelligence into their customer service experience, a better understanding of the optimal temporal application of language features may help make these conversational technologies more effective.

6.3 Limitations and Future Research

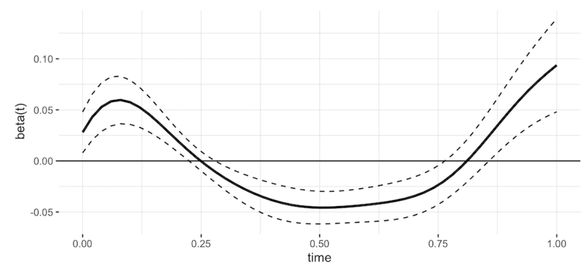
Future work might build on these findings in a number of ways. The functional regression framework takes the dynamic language features as given, for example, without looking into the underlying mechanisms of how a particular feature emerges in conversation, or how

[10]We also ran the main model for affective and cognitive language adding question asking as a dynamic control. Results remain similar.

different features may enhance or diminish each other. Future research could conduct a "cost assessment" of a language feature, thereby allowing for the determination of an "optimal" level of that feature at a particular conversational time. Future work could also study conversational dynamics across domains. When certain linguistic features are beneficial in doctor-patient conversations, for example, may differ from what was observed in customer service.

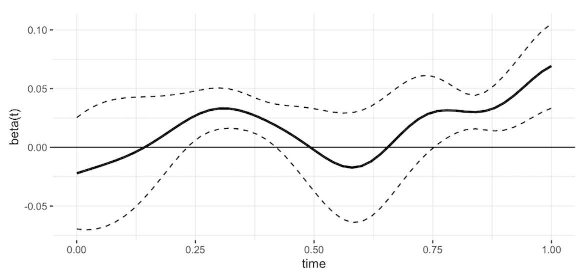


Low Severity



High Severity

(a) Agent Affective Language



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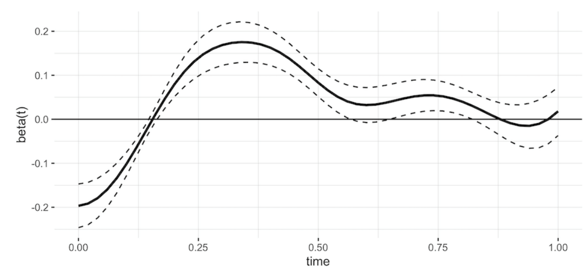

High Severity

(b) Agent Cognitive Language

Figure 8: Beta Curves for Agent (a) Affective and (b) Cognitive Language in Relation to Customer Satisfaction Moderated by Call Severity

Future research might also explore how situated features moderate the temporal importance of language features (Zhang et al. 2020). While our results accounted for over 50 such features, including both dynamic and static controls, to uncover the main relationship, the dynamics of language features could shift due to other situated factors. For instance, our model accounts for the severity of the customer's issue and features that might be linked to this (i.e., pitch and intensity of customer's voice), but agent affective or cognitive language may become particularly important when customers seek resolution of a more severe, difficult issue. Exploratory analyses using a median split on judged severity suggests that for difficult issues, cognitive language is more important overall, while affective language becomes particularly important at the end of the call (Figure 8). Competently solving difficult issues may be more important than rapport building in this case. In contrast, more mundane service interactions may benefit most from a more personable, affective engagement approach, primarily at the conversation's start. While these are just exploratory analyses, they speak to the value of conversational dynamics in future work.

While we controlled for numerous call-, agent-, customer- and firm-level factors, as well as a range of dynamic language and paralanguage features, as with most analyses of field data, our estimates remain subject to endogenous sources of variation due to the interactional nature of these dynamics and missing variables. Although the temporal sequence of our language predictors and outcomes do not support reverse causality, future research could pursue field experiment or datasets in which causality could be assessed with greater certainty.

This research takes an important step toward quantifying the dynamic role of language in conversation. While we focused on customer service language, the modeling approach may also be valuable for studying word of mouth, negotiations, message recall, or other important marketing topics. We hope this work provides a useful approach for those examining conversations in the marketing domain, and beyond.

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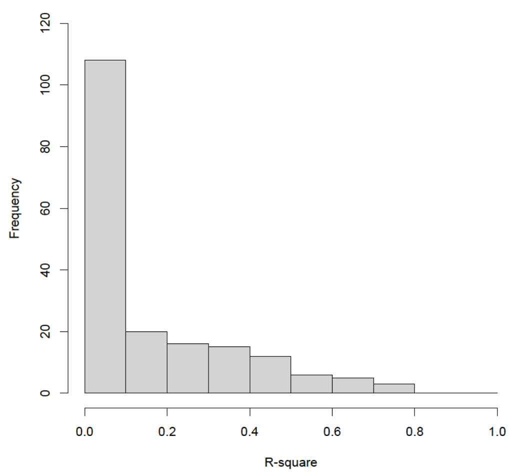
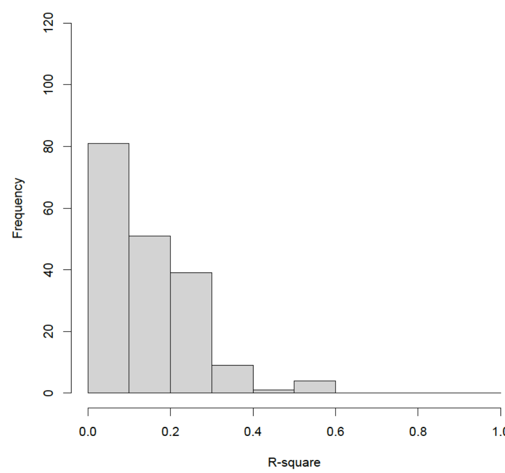
WEB APPENDIX



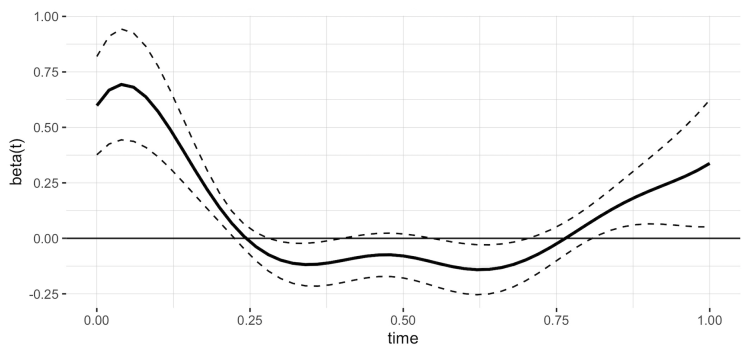
(a) Agent Affective Language



(b) Agent Cognitive Language

Figure A1: Variance in Agent Language Explained by Customer Language (R^2)

Note: The histograms summarize the linguistic synchronicity of agent's and customer's affective and cognitive language across the 185 conversations. Overall, some level of conversational synchronicity occurs more frequently for cognitive language, but synchronicity occurs more deeply for affective language in the fewer conversations in which it occurs. From the figure we can also discern that the moment-to-moment collinearity between affective and cognitive variables is less of a concern in the functional regression analysis.



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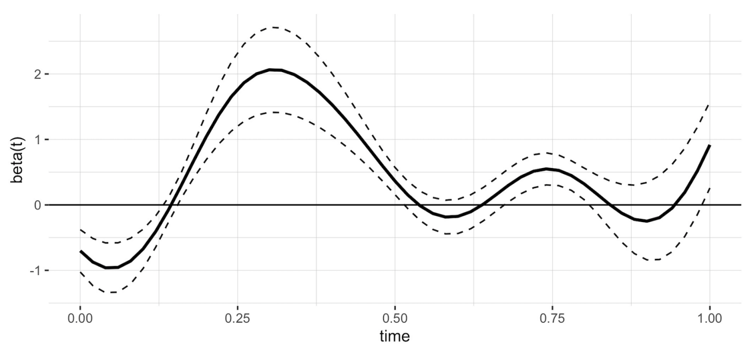
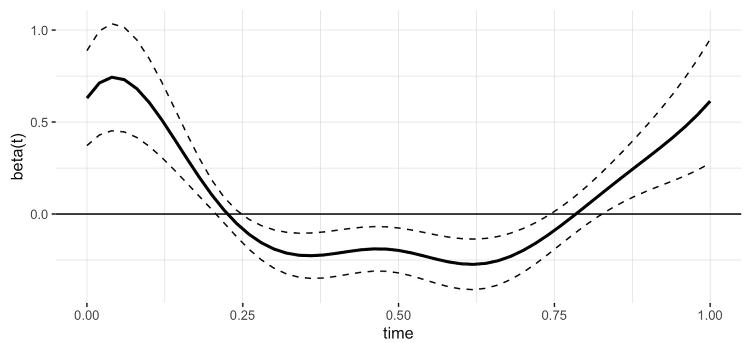
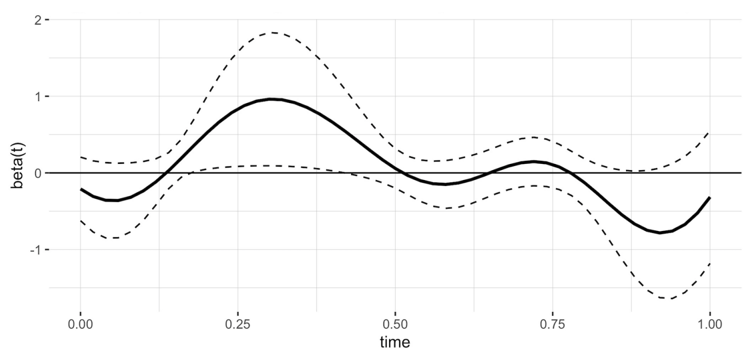


(b) Agent Cognitive Language

Figure A2: Beta Curves for Agent Affective (a) and Cognitive (b) Language in Relation to Customer Satisfaction without Controls

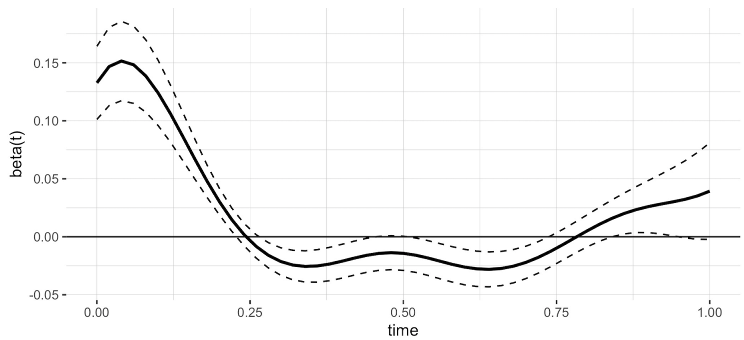


(a) Agent Affective Language

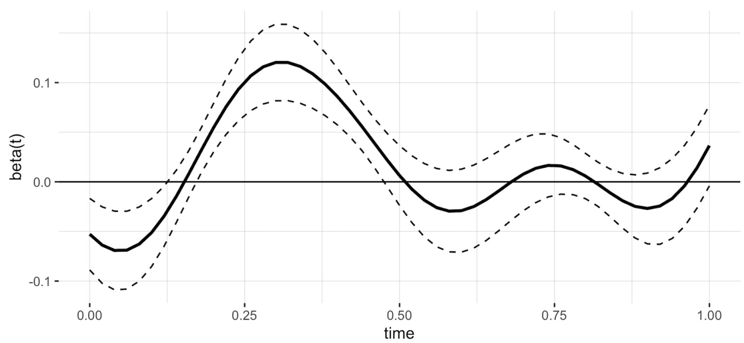


(b) Agent Cognitive Language

Figure A3: Beta Curves for Agent Affective (a) and Cognitive (b) Language in Relation to Order Count within 30 Days Post Interaction without Controls

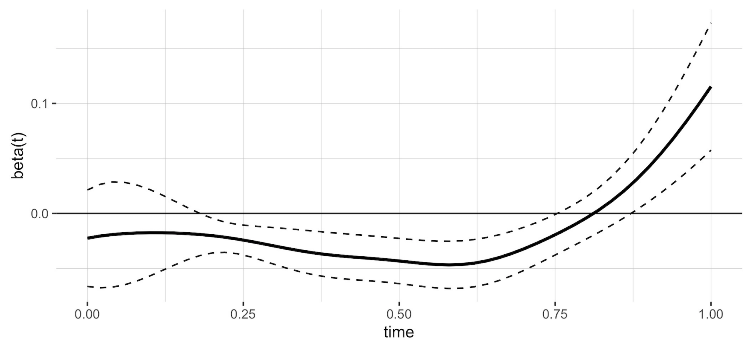


(a) Agent Affective Language

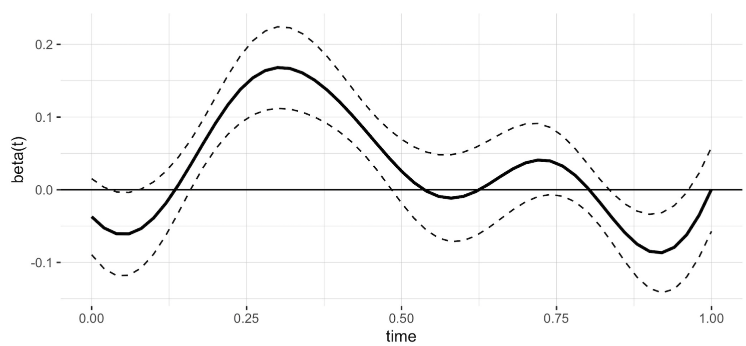


(b) Agent Cognitive Language

Figure A4: Beta Curves for Agent Affective (a) and Cognitive (b) Language in Relation to Customer Satisfaction, Including an Interactive Term on Agent Affective and Cognitive Language

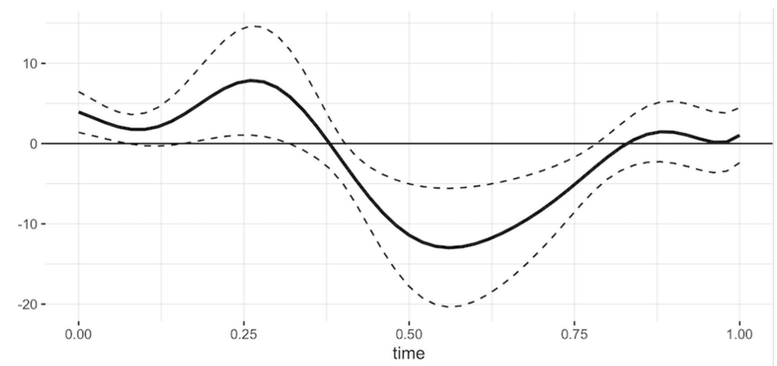


(a) Agent Affective Language

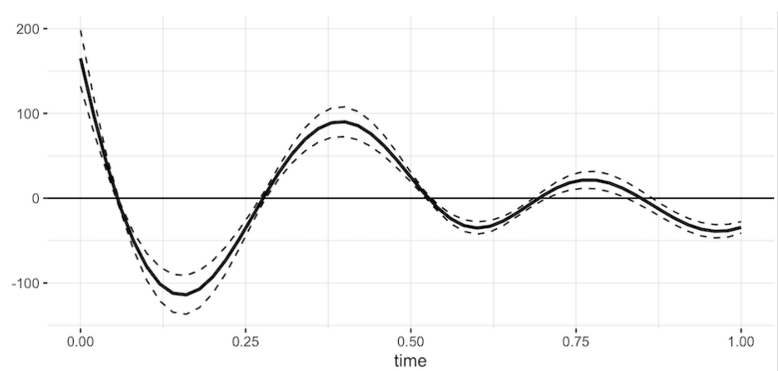


(b) Agent Cognitive Language

Figure A5: Beta Curves for Agent Affective (a) and Cognitive (b) Language in Relation to Order Count within 30 Days Post Interaction, Including an Interactive Term on Agent Affective and Cognitive Language

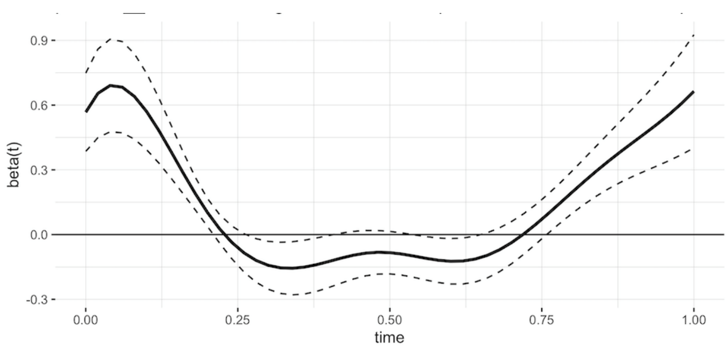


(a) Agent Affective Language

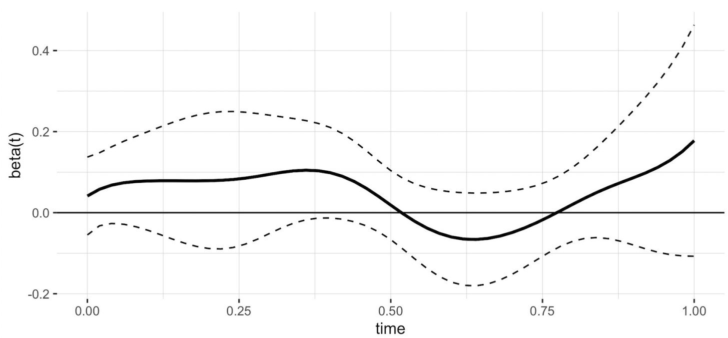


(b) Agent Cognitive Language

Figure A6: Beta Curves for Agent "Relating" (a) and "Resolving" (b) Language in Relation to Order Count within 30 Days Post Interaction



(a) Agent Positive Affective Language



(b) Agent Negative Affective Language

Figure A7: Beta Curves for Agent Positive Affective (a) and Negative Affective (b) Language in Relation to Order Count within 30 Days post Interaction

Table A1: Summary Statistics

	Mean	SD	Min	Median	Max
Independent Measures					
Agent Affective Language	22.74	27.42	0.00	11.11	100.00
Agent Cognitive Language	16.03	14.79	0.00	12.50	100.00
Dependent Measures					
Customer Satisfaction	3.34	1.61	1.00	3.00	4.00
Orders 30 Days Post	0.76	1.76	0.00	0.00	23.00
Controls					
Order	0.27	0.44	0.00	0.00	1.00
Shipping	0.27	0.45	0.00	0.00	1.00
Return	0.38	0.49	0.00	0.00	1.00
Product	0.05	0.22	0.00	0.00	1.00
Topic 1	0.09	0.06	0.02	0.07	0.41
Topic 2	0.07	0.06	0.01	0.04	0.35
Topic 3	0.08	0.05	0.02	0.07	0.45
Topic 4	0.08	0.07	0.02	0.07	0.60
Topic 5	0.07	0.06	0.01	0.05	0.45
Topic 6	0.09	0.10	0.02	0.06	0.61
Topic 7	0.07	0.06	0.01	0.05	0.44
Topic 8	0.08	0.05	0.01	0.07	0.28
Topic 9	0.07	0.05	0.01	0.06	0.30
Topic 10	0.07	0.04	0.01	0.06	0.38
Topic 11	0.08	0.05	0.02	0.06	0.28
Topic 12	0.08	0.07	0.02	0.06	0.58
Topic 13	0.09	0.05	0.01	0.07	0.29
Severity	2.61	0.94	1.00	2.50	5.00
Length	1082.03	853.54	112.00	854.00	4385.00
Resolved	0.80	0.40	0.00	1.00	1.00
Agent Tenure	412.38	650.85	0.00	216.00	3880.00
Agent Calls	4160.34	2456.80	37.00	4072.00	15010.00
Agent Female	0.61	0.49	0.00	1.00	1.00
Agent Social	12.35	16.85	0.00	8.57	100.00
Agent Perception	2.07	6.30	0.00	0.00	100.00
Agent Drive	6.48	10.73	0.00	0.00	100.00
Agent Time	17.10	15.06	0.00	17.39	100.00
Agent Informal	18.58	31.67	0.00	5.56	100.00
Agent Pitch	89.00	5.80	0.00	89.22	115.42
Agent Intensity	65.35	6.73	0.00	66.25	80.72
Customer Tenure	2177.19	1172.09	0.00	2123.00	4718.00
Customer LTV	6433.80	14600.02	68.00	2177.33	119762.85
Customer Region S	0.13	0.34	0.00	0.00	1.00
Customer Region E	0.36	0.48	0.00	0.00	1.00
Customer Region W	0.28	0.45	0.00	0.00	1.00
Customer Region MW	0.13	0.33	0.00	0.00	1.00
Customer Region OTHR	0.10	0.30	0.00	0.00	1.00
Customer Female	0.81	0.39	0.00	1.00	1.00
Att_Web	3.67	1.58	1.00	4.00	5.00
Att_Shop	3.47	1.71	1.00	4.00	5.00
Customer Affective Language	22.96	27.61	0.00	18.57	100.00
Customer Cognitive Language	21.51	19.79	0.00	16.67	100.00
Customer Social	7.88	16.00	0.00	0.00	100.00
Customer Perception	1.39	6.40	0.00	0.00	100.00
Customer Drive	4.85	13.28	0.00	0.00	100.00
Customer Time	14.79	17.16	0.00	12.50	100.00
Customer Informal	27.89	39.30	0.00	5.56	100.00
Customer Pitch	90.58	6.79	0.00	90.81	112.31
Customer Intensity	64.94	11.02	0.00	66.91	84.96
Orders 30 Days Pre	1.30	1.71	0.00	1.00	18.00

Table A2: Parameter Estimates for Customer Satisfaction after Group-Lasso

	Estimate	SE	p
(Intercept)	1.18	0.39	0.003
affect_A_1	0.02	0.01	0.028
affect_A_2	-0.01	0.04	0.721
affect_A_3	0.15	0.07	0.031
affect_A_4	0.06	0.16	0.691
affect_A_5	1.42	3.28	0.666
affect_A_6	0.65	1.17	0.579
cognition_A_1	0.11	0.05	0.025
cognition_A_2	0.21	0.15	0.176
cognition_A_3	0.65	0.22	0.004
cognition_A_4	-1.29	0.99	0.197
cognition_A_5	7.19	7.45	0.336
cognition_A_6	2.64	3.70	0.476
cognition_C_1	0.01	0.03	0.753
cognition_C_2	0.03	0.05	0.488
cognition_C_3	-0.20	0.16	0.218
cognition_C_4	0.20	0.25	0.413
cognition_C_5	0.34	0.81	0.678
pitch_A_1	0.01	0.02	0.649
pitch_A_2	0.25	0.23	0.276
pitch_A_3	-0.73	0.45	0.104
pitch_A_4	-2.03	0.92	0.029
pitch_A_5	0.74	1.75	0.674
percept_C_1	0.00	0.03	0.940
percept_C_2	-0.08	0.10	0.435
percept_C_3	0.01	0.15	0.964
percept_C_4	2.83	2.57	0.274
percept_C_5	0.92	11.90	0.939
percept_C_6	-6.94	3.89	0.076
time_C_1	0.10	0.05	0.043
time_C_2	0.25	0.10	0.009
time_C_3	0.25	0.32	0.430
time_C_4	0.11	0.72	0.876
time_C_5	0.09	1.51	0.951
pitch_C_1	-0.04	0.02	0.057
pitch_C_2	-0.05	0.28	0.874
pitch_C_3	0.16	0.85	0.849
pitch_C_4	-1.29	1.61	0.423
pitch_C_5	-1.63	0.81	0.046
intensity_C_1	-0.04	0.02	0.008
intensity_C_2	0.07	0.05	0.205
intensity_C_3	0.21	0.14	0.124
intensity_C_4	-0.07	0.38	0.850
intensity_C_5	0.14	0.48	0.770
intensity_C_6	4.83	2.25	0.033
intensity_C_7	6.20	5.93	0.297
Topic1	2.97	1.42	0.039
Topic2	-4.53	1.13	0.000
Topic4	-1.04	1.26	0.414
Topic7	-4.11	1.13	0.000
Topic9	2.43	1.41	0.086
Topic11	1.43	1.38	0.301
Agent Tenure	0.00	0.00	0.233
Att_Web	0.19	0.06	0.001
Att_Shopping	0.46	0.05	0.000

Note: Functional components in Tables A2 and A3 are described by the language or paralanguage variable name (e.g., affect, pitch), then by a letter representing the speaker (A = agent; C = customer), and then by the eigen component number. For example, "affect_A_1" indicates the coefficient estimate of the first eigen score of agent's affective language.

Table A3: Parameter Estimates for Customer Purchase after Group-Lasso

	Estimate	SE	p
(Intercept)	-0.97	0.13	0.000
affect_A_1	0.08	0.04	0.042
affect_A_2	0.01	0.05	0.845
affect_A_3	0.24	0.10	0.019
affect_A_4	-0.41	0.27	0.140
affect_A_5	-0.98	4.90	0.841
affect_A_6	-2.40	1.94	0.215
cognition_A_1	0.17	0.08	0.037
cognition_A_2	-0.18	0.26	0.490
cognition_A_3	0.59	0.36	0.105
cognition_A_4	-1.53	1.58	0.335
cognition_A_5	-2.49	1.26	0.049
cognition_A_6	-0.29	6.11	0.961
Orders 30 Pre	0.24	0.02	0.000

Table A4: Call-Level Linear Regression for Customer Satisfaction after Lasso

	Estimate	SE	p
(Intercept)	0.50	0.47	0.29
Agent Affective Language	0.05	0.03	0.04
Agent Cognitive Language	-0.04	0.03	0.15
Topic 1	2.67	1.34	0.05
Topic 2	-3.99	1.17	0.00
Topic 7	-2.40	1.08	0.03
Cust. Region MW	-0.37	0.18	0.04
Att_Web	0.24	0.06	0.00
Att_Shop	0.46	0.05	0.00
Cust. Perception	0.12	0.05	0.01
Cust. Informal	0.03	0.01	0.05

Table A5: Call Level Poisson Regression for Customer Purchases after Lasso

	Estimate	SE	p
(Intercept)	-0.07	0.47	0.89
Agent Affective Language	-0.08	0.04	0.05
Agent Cognitive Language	-0.02	0.04	0.54
Orders 30 Pre	0.21	0.01	0.00