

When Language Matters

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Text analysis is increasingly used for consumer and marketing insight. But while work has shed light on *what* firms should say to customers, *when* to say those things (e.g., within an advertisement or sales interaction) is less clear. Service employees, for example, could adopt a certain speaking style at a conversation's start, end, or throughout. *When* might specific language features be beneficial? This article introduces a novel approach to address this question. To demonstrate its potential, we apply it to warm and competent language. Prior research suggests that an affective (i.e., warm) speaking approach leads customers to think employees are less competent, so a cognitive (competent) style should be prioritized. In contrast, our theorizing, analysis of hundreds of real service conversations from two firms across thousands of conversational moments ($N = 23,958$), and four experiments (total $N = 1,589$) offer a more nuanced perspective. Customers are more satisfied when employees use *both* cognitive and affective language but at separate, specific times. Ancillary analyses show how this method can be applied to other language features. Taken together, this work offers a method to explore *when* language matters, sheds new light on the warmth/competence trade-off, and highlights ways to improve the customer experience.

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Language is an integral part of communication. Advertising copy shapes purchase, service language shapes customer retention, and the words in word of mouth shape consumer behavior (McGuire 2000; Ordenes et al. 2014; Pogacar, Shrum, and Lowrey 2018; Schellekens,

Verlegh, and Smidts 2010). Consistent with language's importance, decades of research have considered how employees should speak to customers (Parasuraman, Zeithaml, and Berry 1985) and natural language processing tools are shedding new light on language that increases communication's impact (Berger et al. 2020; Humphreys and Wang 2018).

But while it is clear that *what* companies, employees, and consumers say matters, might *when* they say it within a given communication also play an important role?

Calling customer service, for example, or speaking with a salesperson usually involves a conversation. Customers say something, employees respond, and the two go back and forth. While research suggests that asking questions, using first-person pronouns, or speaking in a rational, competence-oriented way can improve customer satisfaction (Drollinger, Comer, and Warrington 2006; Marinova, Singh, and Singh 2018; Packard, Moore, and McFerran 2018), should employees do these things throughout an interaction? Or might doing so at certain conversational points be more beneficial?

Take greetings. Call center agents could say "Who do I have the pleasure of speaking with?" or "How may I assist

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you?” Both are common openings, but the first is warmer while the latter focuses on competence. The same goes for conversation endings such as “It was my pleasure. Take care now” or “I’m glad I could solve that for you. Bye now.” The former uses warmer, more affective language and the latter a more cognitive, competence-oriented approach. While a great deal of research suggests prioritizing competence in consumer communications (e.g., Gunturkun, Haumann, and Mikolon 2020; Kirmani et al. 2017; Li, Chan, and Kim 2019), is that actually the best course of action in these conversational moments?

This article moves beyond asking *whether* particular language features matter, to introducing an approach for studying *when*. Conversations are a key part of social interaction (Huang et al. 2017), but their moment-to-moment content variation makes them difficult to analyze (Reece et al. 2022; Zhang, Wang, and Chen 2020b). To address these challenges, we use functional data analysis (FDA; Foutz and Jank 2010), recovering time-based sensitivity trajectories and documenting the dynamic relationship between language and important marketing outcomes.

To demonstrate the approach, and its potential, we apply it to language linked to the two central dimensions of person perception—warmth and competence (Fiske, Cuddy, and Glick 2007). A multimethod investigation, including analysis of thousands of moments across hundreds of service conversations at two firms, and four experiments, suggests that customers are more satisfied (and spend more) when employees use *both* cognitive and affective language but at separate, specific times. Ancillary analyses apply our approach to other language features.

This article makes three main contributions. First, most narrowly, we deepen insight into the so-called warmth/competence trade-off. While research suggests emphasizing only one of these in a given interaction (i.e., prioritize warmth or competence but not both; Dubois, Rucker and Galinsky 2016; Fiske et al. 2007; Holoien and Fiske 2013), we find this “trade off” may not be so stark. Results reveal that service employees should prioritize *both* cognitive and affective language but at different points in time. Each is beneficial (or costly) at different, specific moments.

Second, we demonstrate that understanding when different language features matter improves marketing outcomes. While one might wonder whether employees are already sufficiently warm at the start and end, for example, two field data sets suggest that this is not the case. Results reveal that employees may benefit from using warmer language than they currently do at the start of interactions. Ancillary analyses reveal when other language features (e.g., question asking and first-person pronouns) matter as well. Our approach can help improve customer service, aid employee assessment and development, and fine-tune artificial intelligence chatbots’ effectiveness. It can also be used to shed light on word of mouth, sales interactions, and marketing communications more broadly.

Third, we introduce a novel modeling approach using FDA and Group-Lasso to tackle the high dimensionality, irregularity, and sparsity inherent in conversational data. An emerging stream of work has begun to study conversations (Boghrati and Berger 2024; Ordenes et al. 2019; Yeomans, Schweitzer, and Brooks 2022), advertising, word of mouth, and other marketing interactions involving conversational language. Across these and other contexts, our method can help researchers better understand not only what language matters, but *when*. This approach provides a framework for understanding language dynamics, and their impact, within consumer research, and beyond. To help other researchers leverage this approach, we created a free user-friendly web application.¹

TALKING TO CUSTOMERS

Talking to customers is important. Companies spend over a trillion dollars a year on sales and service alone, making it the single largest strategic investment for most firms, and nearly tripling what they spend on other marketing communications (Cespedes and Wallace 2017; Morgan 2017). Furthermore, these costs are rising as channel complexity and technology make it harder to deliver great service (McBain 2020).

Consistent with its importance, a great deal of research has tried to understand and improve these interactions. Thousands of articles have studied service quality (Parasuraman and Zeithaml 2002; Snyder et al. 2016), examining how consumers evaluate salespeople (Zeithaml, Berry, and Parasuraman 1996), service initiatives shape customer attitudes (Bolton and Drew 1991), and service quality impacts firms (Rust and Chung 2006).

Along these lines, research has explored the role of language in marketing communications, sales, and service (cf. Kronrod 2022; Packard and Berger 2024 reviews). Experienced salespeople are more likely to use questions like “Could you tell me more?” (Castleberry, Shepherd, and Ridnour 1999), for example, and asking such questions can signal attention and empathy, fostering effective conversations (Brody 1994; Brooks and John 2018). Similarly, concrete language (e.g., “jeans” instead of “clothes”) encourages purchase because it suggests that service agents are listening (Packard and Berger 2021) and first-person singular (“I”) pronouns enhance customer satisfaction because it makes employees seem more agentic and empathetic (Packard et al. 2018).

But while a growing body of research demonstrates language’s importance, less is known about *when* particular language features should be used. Should such language

¹ Non-technical users can upload a text file and perform dynamic “when” analysis on their own datasets without the use of programming language at whenlanguagematters.net. Customizable R code is also available at the same website.

features be used throughout a conversation, for example, or might they be more beneficial at certain moments? And might they backfire in others?

WHEN LANGUAGE MATTERS

To illustrate the value of *when*, we examine the “warmth/competence trade-off” (Durante, Tablante, and Fiske 2017). Warmth and competence are central dimensions of social cognition, accounting for almost all person perception (Fiske et al. 2007). Warmth captures affective expression and attention to emotions while competence focuses on agency, rationality, and cognitive efficiency (Abele and Wojciszke 2007). Above all else, people evaluate others on these fundamental dimensions (Judd et al. 2005).

Importantly, however, a great deal of research suggests that these two dimensions are inversely related. Being affectively engaged makes people seem less competent, while being cognitively oriented makes people seem less warm (Fiske et al. 2007). This has led researchers to suggest that people should try to be warm or competent, but not both (Dubois et al. 2016; Fiske et al. 2007; Holoiën and Fiske 2013; Wojciszke, Bazinska, and Jaworski 1998).

Many marketing researchers have suggested that a competence-oriented approach is best (e.g., cf. Gunturkun et al. 2020 review; Marinova et al. 2018). Solution-oriented service advisors reportedly enhance customer satisfaction more than socially oriented agents (van Dolen, Dabholkar, and de Ruyter 2007) and service employees who use emotions are seen as warmer, but less competent, leaving customers less satisfied (Li et al. 2019). Competence is said to be prized over warmth in service interactions (Kirmani et al. 2017) because consumers are goal-oriented and cannot achieve their goals if a service provider is not sufficiently skilled (Kirmani and Campbell 2004).

Consistent with this, when engaging customers, firms tend to prioritize competent problem solving rather than relational warmth (Dixon, Freeman, and Toman 2010; Jasmand, Blazevic, and de Ruyter 2012). When we asked 160 customer service managers and workers about the most important service priority, 80.8% indicated “competently addressing the customer’s needs” (vs. “warmly relating to the customer”), and 76.1% indicated their company training prioritizes competence. Only 21.3% indicated their firm trains employees to be both competent and warm.

But should service agents necessarily prioritize a competence-oriented, cognitive manner of speaking throughout an interaction? And how does this fit with older work encouraging employees to speak affectively to show customers they care (de Ruyter and Wetzels 2000; Parasuraman et al. 1985; Spiro and Weitz 1990)?

THE CURRENT RESEARCH

We propose that, rather than asking *whether* employees should speak cognitively or affectively, it is important to consider *when*. Rather than only considering whether one type of language is better, overall, we suggest that analyzing more granular conversational moments will show that what language is effective depends on when in a conversation it occurs.

Research on conversational analysis and implicature supports this suggestion. Each turn contributes to a conversation’s ultimate meaning and outcome (Goffman 1981; Schegloff 1999). A conversational dialogue that “works” is one in which each meaningful statement is satisfied by a relevant and meaningful response (Grice 1991). Indeed, Grice’s famous conversational principles (e.g., relation and manner) are explicitly conceptualized as localized, turn-by-turn exchanges rather than at an aggregate level.

Building on this work, we suggest that a given language feature’s importance should be moderated by conversational moment. Early in service interactions, we suggest that affective language will be more effective than task-oriented, cognitive language. While the norms of conversational openings demand a sequence of pleasantries (Schegloff 1999), these turns can vary in the extent to which they focus on warmth or competence. Agents could start with more cognitive, competence-oriented language (e.g., “How may I assist you?”) or more affective, warm language (e.g., “How are you today?”). Social norms suggest that warm behaviors such as relationship-building, empathy, or apology can be useful before turning to the speakers’ specific goals (Clark et al. 2013; Gabor 2011; Kaski, Niemi, and Pullins 2018). Consequently, while “How may I assist you?” is a common opening, it jumps straight into problem solving rather than establishing a warm, relational base (Placencia 2004), which should make it less effective in early conversational moments.

But while starting with more affective language may be important, it should only go so far. Eventually, employees must competently address the customer’s goals and needs. Conversation analysis notes the importance of shifting discourse from greetings and preliminaries to “getting down to business” (Bolden 2008; Pallotti and Varcasia 2008). Consequently, in conversation’s middle moments, a more analytic, cognitive communication style (e.g., “I’m going to resolve this” rather than “I’m happy to help with this”) should be beneficial.

Finally, more affective language may be beneficial at a conversation’s close. Consistent with our suggestion, wrapping up an interaction in a considerate or empathetic manner is thought to be a key feature of successful conversations (Schegloff and Sacks 1973) and may help align participants’ conceptions of the interaction (Aston 1995; Frank 1982).

Again, we are not just suggesting that it is good to be polite and positive at the beginning and end of conversations. Instead, we propose prioritizing different *kinds* of language at such conversational moments. Both “My pleasure. Take care now” and “I’m glad we could solve that for you. Bye now” signal the conversation’s end in a polite and positive way. But because the former involves warmer, more affective language, we suggest that it will be more beneficial.

To test these predictions, we analyze linguistic (verbal) features over conversational time to examine *when* employee language has a positive, null, or negative relationship with customer satisfaction. A multimethod approach, including two field data sets and four experiments, tests this perspective. To examine these relationships in the field, we devise a novel empirical approach and analyze two large turn-level data sets of customer service conversations from companies in different market sectors. To assess our approach’s contribution, we compare it to (1) traditional static approaches, (2) simpler, more discrete (rather than continuous) dynamics considered in prior literature, and (3) other simplified or restricted models. We demonstrate its robustness not only for customer satisfaction but also for purchase behavior and willingness to recommend. Four experiments then directly test causality and validity of the model results, consider alternative dynamics, and explore robustness across various naturalistic and carefully controlled stimuli (studies 3, 4A, 4B, and 5).

Finally, we demonstrate how our approach can offer new insight into other language features and discuss its potential for understanding and optimizing communication more broadly.

STUDY 1: RETAILER FIELD DATA

As an initial test of our theorizing, we collected a random sample of 200 customer service calls from a large online retailer. A professional transcription company converted the recordings to text, separating each conversational turn (e.g., turn 1 (agent): “How can I help you?,” turn 2 (customer): “I can’t find . . .”). Part of the conversation was inaudible for 15 recordings provided, leaving 12,410 turns from 185 conversations (handled by a total of 130 agents).² The average conversation lasted 6.19 minutes (SD = 3.97) and included 66.75 turns (SD = 44.49). See [web appendix A](#) for additional conversation descriptive statistics.

2 While the number of conversations analyzed may seem smaller than contexts like online reviews, it is quite large when it comes to the dynamics of marketing conversations ([web appendix table A1](#)). This is in part because the unit of analysis in such research entails modeling a time series of units within each conversation, described as slices, stages, segments, or turns ([Marinova et al. 2018](#); [Singh et al. 2018](#)).

Independent Measures: Agent Affective and Cognitive Language

Following prior work ([Berry et al. 1997](#); [Marinova et al. 2018](#); [Singh et al. 2018](#)), we measure affective and cognitive language through Linguistic Inquiry and Word Count’s (LIWC; [Pennebaker et al. 2015](#)) affective processes module. Warmth is conveyed through emotional expression. Using affective words like *happy* (e.g., “I’m happy you like the pants”) or *horrible* (“That’s horrible”) signals that an employee is attending to a customer’s emotional state or expressing their own.

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. Following prior work, cognitive language is measured through LIWC’s cognitive processes module.

[Figure 1](#) illustrates what agents do currently (i.e., their average affective and cognitive language over the course of conversations). Affective language, for example, makes up roughly 13–24% of words in opening turns. Notably, while conversations often start with pleasantries or greetings, affective language is not particularly high at the outset, indicating that agents do not use especially warm language at this time. Similarly, agent use of cognitive language does not peak in the middle, “business” portion of the conversation where we suggest it may be important. Finally, as indicated by the 95% confidence dotted lines, there is considerable variation across agents in the language used over the course of conversation.³

Dependent Measure

Study 1 focuses on perceived helpfulness, a key measure of customer satisfaction ([Cronin and Taylor 1992](#); [Parasuraman, Berry, and Zeithaml 1991](#)). We collected the firm’s measure of this for each call (1 = not at all helpful, 4 = very helpful, measured at the end of the call). For robustness, we also later consider a behavioral measure—the number of purchases made in the 30 days following the call.

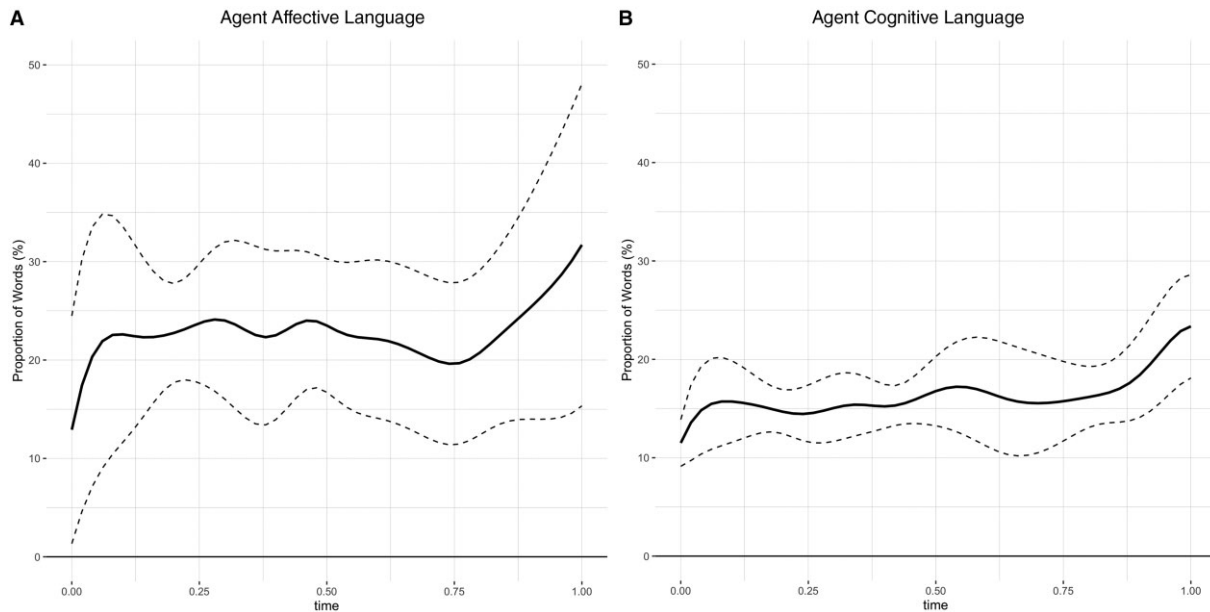
Controls

While our interest is in warm and competent language, one could wonder whether any relationship between these features and customer satisfaction is driven by other factors. Consequently, we control for a range of control variables pertaining to the call, agent, or customer that are

3 The ratio of the two language types over time ([web appendix A figure A1](#)) also suggests that agents do not prioritize warm, affective language over competence oriented, cognitive language at the start or end of conversations.

FIGURE 1

FOCAL FEATURES OVER CONVERSATIONAL TIME



NOTE.— The y-axis depicts conversational turn-level measurement of a focal language feature across non-zero turns (i.e., the percentage of words in a turn corresponding to affective and cognitive language respectively). Conversation length (time) in all figures is standardized to a range of 0–1.

conceptually or substantively related to the focal predictors and outcome.

Call. First, the particular issue customers are calling about could impact agent language and customer satisfaction, so we include dummies to control for the four call categories captured by the firm (*Order, Shipping, Return, and Product*).

Second, the complexity of the call could shape agent language, and their ability to satisfy the customer, so we control for that as well. We take the average of two judges who listened to each call and indicated perceived difficulty or severity of the call on a 5-point scale ($r = 0.72$; *Severity*). In addition, given that complex issues may require more discussion, we control for call length using the total number of words spoken (*Length*).

Third, whether the agent was able to resolve the customer’s issue during the call likely impacts how the agent and customer speak, as well as customer satisfaction. To account for this, two judges read each call transcript and indicated whether the customer’s main issue had been resolved (1 or 0; *Resolved*). Judge disagreements were settled via discussion.

Fourth, rather than the dynamic timing of agent warm and competent language (i.e., *when* language matters), it could be just the overall conversation-level presence of such language that drives any results (i.e., *what* language

matters). To account for this, we include controls for agent affective and cognitive language at the conversation level.

Agent. An employee’s experience could shape how they speak and conversation outcomes, so we control for agent characteristics in two ways. First, to capture organizational experience, we include how many days agents have been with the firm (*Agent Tenure*). Second, to account for direct customer experience, we consider the number of calls they have handled (*Agent Calls*), which is only moderately correlated with tenure ($r = 0.38, p < .05$). These measures help capture unobservable aspects of agent quality or performance (Ng and Feldman 2010). The firm also provided agent gender, which we include as a dummy variable (*Agent Female*).

Customer. Customer attributes can also impact satisfaction and purchase, so we control for the demographic variables provided by the firm, using dummies for which geographic regions a customer resides in (*Customer Region*) and customer gender (*Customer Female*).

Experience with a firm can affect customer satisfaction and behavior, 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*). Customer attitudes about other aspects of the firm could impact how they interact with the agent and their

satisfaction. To control for this possibility, we also include measures of attitudes toward the website (*Attitude Web*) and shopping experience (*Attitude Shop*), which were captured after the customer satisfaction measure at the end of the call.⁴

Modeling Approach

Functional Data Analysis. To characterize the relationship between the focal dynamic conversational features (e.g., affective and cognitive language) and static conversational outcome (i.e., customer satisfaction), we use semi-parametric tools from FDA (Ramsay and Silverman 1997). Functional data have seen growing applications in marketing to help address dynamic modeling challenges such as predicting motion picture demand (Foutz and Jank 2010) or relating moment-to-moment consumer attitudes to TV show judgments (Hui, Meyvis, and Assael 2014).

We extend FDA to conversations. We consider time-varying measurement of a conversation feature (e.g., affective or cognitive language) within the n th conversation as a trajectory $X_n(t)$, $n = 1, \dots, N$, 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 $X_n(t)$,

$$y_n = \alpha + \int_0^1 \beta(t)[X_n(t) - \mu(t)]dt + e_n \quad (1)$$

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 interest that characterizes the dynamic impact of a linguistic feature at different moments during a conversation. To meet the requirement that the units of functional analysis have the same duration, we standardize the varied conversation lengths to a common interval $[0, 1]$ (Ramsay and Silverman 1997). Therefore, any conclusions should be viewed against the relative progress of a conversation rather than the absolute time passed. To account for the potential impact on model estimates due to standardization, we include conversational length in seconds and word count as controls in the main model.⁵

There are also some challenges specific to conversational data (i.e., irregularity and sparsity) that need to be addressed. 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 tends to be irregularly spaced across time. Further, not every conversational feature (e.g., cognitive words) appears in every turn, resulting in sparse measurement. Except for a handful of calls that contain close to 100 measures of some language features, most interactions have 10–30 turn-level measurements. Consequently, functional regression for conversation must be able to handle the irregular and sparse presence of language features (web appendix figures A3 and A4).

Our dynamic modeling approach addresses these challenges. We consider a dynamic unstructured 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 assumed to be independently drawn from an underlying stochastic function, with unknown mean function $\mu(t) = \mathbb{E}[Z_n(t)]$ and 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, $m = 1, \dots, M_n$, of the n th conversation is given by

$$X_n(t_m) = Z_n(t_m) + \varepsilon_n(t_m) \quad (2)$$

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 that M_n is exogenous and control for its effect in our model.

For the focal functional predictors (agent affective and cognitive language), we apply scatterplot and surface smoothing, both via local linear regression, to estimate mean and covariance functions, respectively (Chen et al. 2016; Wang, Chiou, and Muller 2016; Yao, Muller, and Wang 2005).⁶ We use the entire sample simultaneously in the smoothing procedure to allow information shrinkage across observations to accommodate the sparseness discussed above.

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

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

and so

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

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.

4 See web appendix tables A2–A4 for summary statistics and variance inflation factors (VIFs) for the focal predictors and controls. All VIFs fall under the conservative cut-off of 5.

5 Alternatively, one could standardize by conversational turn rather than by time. Compared with the average call length of 371.40 (SD = 238.22) seconds, the mean inter-turn interval of 0.26 (SD = 0.53) seconds is negligible and so standardization by time is preferred.

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

If we expand the unknown $\beta(t)$ curve onto the same eigen bases,⁷

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

thanks to orthogonality, the functional regression in equation 1 can be simplified to

$$y_n = \alpha + \sum_{i=1}^{\infty} b_i \omega_{ni} \approx \alpha + \sum_{i=1}^I b_i \omega_{ni} \quad (6)$$

In the above, the truncation I , or the actual number of eigen components to appear in the regression, is determined using AIC. We also tested metrics such as BIC and leave-one-out cross-validation and saw almost identical truncations across language features.

The above approach allows us to examine the relationship between the dynamic moments (turns) of our focal dynamic predictors (agent affective and cognitive language) and the static outcome (customer satisfaction). When there are multiple functional predictors and scalar controls, we can describe a generalized functional regression as follows:

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

where L and J denote the number of functional predictors and scalar controls 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 a nonlinear dependent variable. Besides using agent observables as controls, we capture unobserved agent heterogeneity with a random intercept α_a for every agent.

Applying the smoothing procedure and Karhunen–Loève expansion to the data, we obtain a simplified generalized regression as follows,

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

where I_l for functional variable $X_l(t)$ is determined by the truncation criterion discussed above.

⁷ Alternatively, one could use Riemann sum to remove the integral without assuming identical bases for $\beta(t)$. But doing so would introduce numerical errors into the estimation and burden the subsequent model regularization with many additional variables.

Main Results

Figure 2 presents the key results. Functional regression results are depicted as a sensitivity curve $\beta_l(t)$, plotting the moment-to-moment beta coefficients for the focal affective and cognitive language predictors over conversational time. Model 1 shows the relationship between affective and cognitive language and customer satisfaction, and model 2 presents the same results after adding the controls. When the pointwise 95% confidence interval (dotted line) is above (below) zero for one of these language features, that feature has a positive (negative) relationship with the customer satisfaction outcome at that particular point in conversational time, allowing one to interpret *when* affective and cognitive language matter. For example, model results reveal that approximately 12.5% into a service conversation, affective language (red line) has a positive and significant beta coefficient of 0.5, and cognitive language (blue line) has a negative and significant beta coefficient of 0.3. The relative scale of the coefficients signals their relative importance across both predictors and moments.

As predicted, customers are more satisfied when agents use more affective language at the beginning and end of conversations. But affective language is not beneficial during the middle of the call.

Cognitive language results are quite different. Speaking more rationally at the beginning of conversations appears to be costly, but customers are more satisfied when agents use more cognitive language in the middle of the conversation.

Taken together, these findings suggest that affective and cognitive language are *both* linked to positive satisfaction outcomes, but at *different times* during an interaction.⁸ Customers were more satisfied when agents use warm language at the start and end, but cognitive language primarily in the middle. Further, a comparison of the optimal dynamics of agent language (figure 2) to actual language use (figure 1) shows that agents are not using language this way currently, casting doubt on the notion that these patterns are somehow already known and in use.

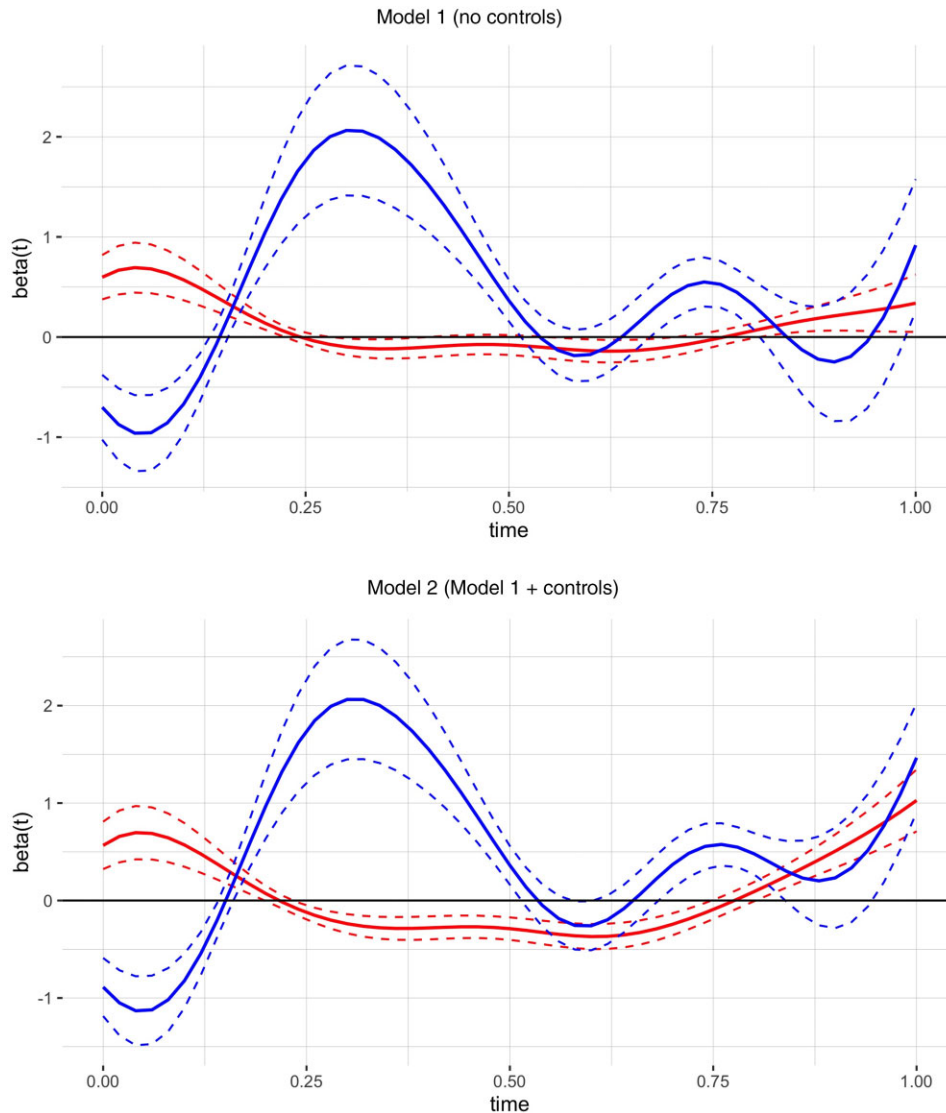
Additional Unstructured Controls

While the 22 factors controlled for are more than prior conversation dynamics research in marketing (Marinova et al. 2018; Singh et al. 2018), one can always wonder about additional possible sources of endogeneity. We test causality through four experiments, but to further explore the field data, we also consider unstructured text and voice controls.

⁸ Corroborating prior research (Marinova et al. 2018; Singh et al. 2018), the size of cognitive language’s positive coefficient supports the importance of a competence-oriented approach. That said, the present study reveals *when* in conversation conveying competence is important (e.g., middle), and that its use can be detrimental if used at the wrong conversational moments (e.g., start).

FIGURE 2

AGENT LANGUAGE AND CUSTOMER SATISFACTION



NOTE.— Red lines: affective language; blue lines: cognitive language; and dotted lines: pointwise 95% confidence intervals.

One of the benefits of unstructured data is the ability to control for a wide range of features. Aspects of language, vocal features (e.g., pitch), and images that vary across conversational moments (e.g., turns) can now be measured. As such, one can consider myriad factors that might help explain a focal relationship, and by including them in the model, test potential alternative explanations (Berger, van Osselaer, and Janiszewski 2024).

That said, this benefit comes with a downside. There are hundreds, if not thousands of potential unstructured data

dimensions researchers could include, and as more variables are considered, *overfitting* becomes a problem. Further, it is problematic to include controls due only to their availability (Clarke 2006; Spector and Brannick 2011).

Nonetheless, to further control for possible sources of endogeneity, we apply Group-Lasso (Meier, Van De Geer, and Bühlmann 2008; Yang and Zou 2015; Yuan and Lin 2006), a machine-learning method that attempts to incorporate as many of the unstructured controls as

appropriate while preventing overfitting. The Group-Lasso regularization helps avoid the path-dependency problem in conventional stepwise regression (Foutz and Jank 2010), and allows for *group-wise* variable selection as the selection of functional variables corresponds to selecting from the L groups of eigen scores in equation 8 (see web appendix B for more details).

For this wide data exercise, we consider an additional 28 text and voice controls (see below), which equal up to 111 potential additional control parameters after calculating their eigen components to account for moment-to-moment dynamics.

Dynamics of Other Major Agent Language Features.

First, beyond affective and cognitive language, other moment-to-moment features of employee language may shape how customers perceive or speak to them. To control for this, we include dynamic, turn-level measures of LIWC's other main psychological process dictionaries (e.g., *Social processes*, *Perceptual processes*, *Drives*, *Temporal perspective*, and *Informality*; Pennebaker et al. 2015).

Dynamics of Agent Paralanguage. In addition to what was said, one could wonder whether how things were said (i.e., paralanguage) might drive the effects. We control for dynamic acoustic features linked to persuasion (Van Zant and Berger 2020) at the turn level using phonetics software (*Pitch* and *Intensity*; Boersma and van Heuven 2001) applied to the original audio call recordings.

Dynamics of Customer Affective and Cognitive Language. Agents might mimic or repeat recent customer language, which could shape agents' affective and cognitive language (the focal IVs). To account for this possibility, we include the customer's own affective and cognitive language over the course of the conversation as dynamic controls.

Dynamics of Other Major Customer Language Features. Beyond affective and cognitive language, other moment-to-moment aspects of customer language may shape how employees speak, so we control for these using turn-level measurement of the same psychological process dictionaries used for employee language (e.g., *Social processes*, *Drives*, and *Informality*).

LDA Topics. To account for a more fine-grained mixture of topics than the five call categories provided by the firm, we use customer language to uncover the hidden mixture of topics via topic modeling (i.e., latent Dirichlet allocation; Blei, Ng, and Jordan 2003). Standard pre-processing included stemming related words (e.g., walk, walked, or walking = walk) and removing punctuation and numbers. Results were robust to the inclusion or exclusion of infrequent words and stop words. We followed suggested practices and prior research (Chang et al. 2009) in

determining the number of topics. We examined 5–15 topic solutions, and perplexity fit measures revealed a peak (lower perplexity) at 13 topics, so we attempted to include the 13 topic model results as additional controls.

Moment-to-Moment Linguistic Synchronicity. To further isolate the dynamic impact of agent language, we further consider how it may be shaped by customer language over the conversation. How someone speaks can impact their conversation partner but also can reflect what the conversation partner said previously (Goffman 1981; Grice 1991; Zhang, Mullainathan, and Danescu-Niculescu-Mizil 2020a; Zhang et al. 2020b). To control for these aspects, we use a moment-to-moment measure of linguistic synchronicity (*Synchronicity*). Specifically, following Zhang et al. (2020b), we create a synchronicity measure using the R^2 of the moment-to-moment regression from customer language on agent language. See web appendix figure A2 for details.

Model. As discussed, while these additional unstructured text and voice controls help further assess robustness to omitted control endogeneity, given the large number of unstructured controls and their moments (N = up to 111 additional control parameters), one could worry about overfitting. Consequently, we use Group-Lasso machine learning to penalize out unstructured controls that impede model fit and inference (see web appendix B for method details). The method selected 23 additional unstructured control parameters in this extended model (model 3), in addition to the 22 controls considered in model 2.

Results. Results of model 3 (figure 3) are highly similar to the functional forms observed in models 1 and 2. Specifically, affective language is beneficial at the start (25%) and end (25%), but not in the middle (50%) of these conversations. In contrast, cognitive language is costly at the start, beneficial in the middle, and null for most of the conversation's end.⁹

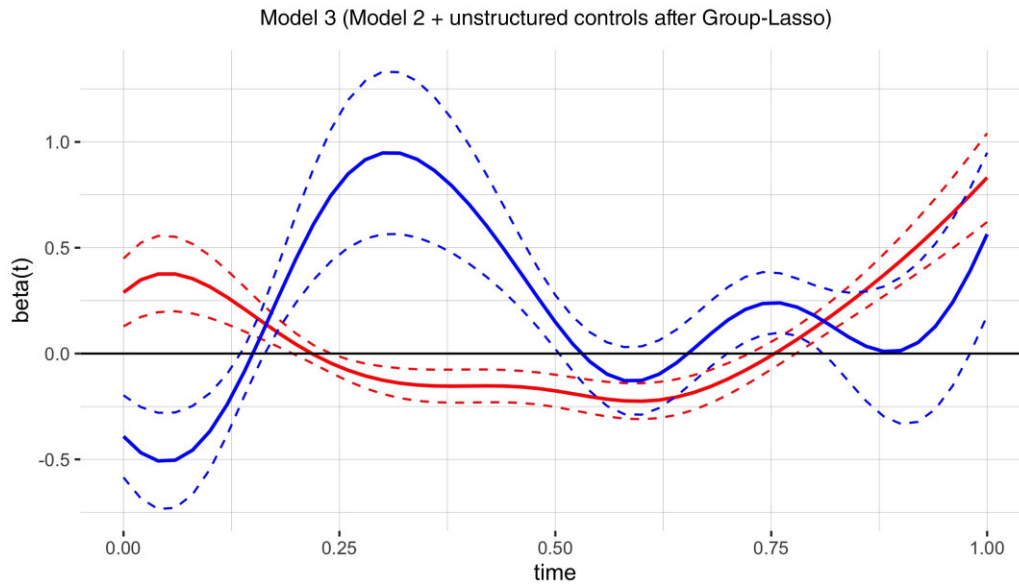
Discussion

Overall, results suggest that the relationship between agent language and customer satisfaction depends on *when* in the conversation it occurs. Consistent with our theorizing, rather than a more cognitive, competence-related language style being beneficial throughout, it is mainly helpful in the middle of conversations. Warmer, more affective language is beneficial at the conversation's start and end. Results are robust to the inclusion of over 40 traditional and unstructured (text and voice) control variables. While it is difficult to rule out omitted variable endogeneity in conversational data (Reece et al. 2022; Zhang et al.

⁹ Table A7 in the web appendix presents parameter estimates for the focal predictors, structured controls, and additional wide data unstructured controls across all three study 1 models.

FIGURE 3

AGENT LANGUAGE AND CUSTOMER SATISFACTION



NOTE.— Red lines: affective language; blue lines: cognitive language; and dotted lines: pointwise 95% confidence intervals.

2020a, 2020b), considering a wide variety of factors potentially linked to our focal IVs and customer satisfaction helps mitigate such concerns.

Robustness. We also performed several additional robustness tests (web appendix B). First, we tested robustness to a different outcome variable: purchases. Results follow similar functional forms (e.g., affective language beneficial at the start, cognitive language in the middle), suggesting that the benefit of our dynamic approach may extend to important downstream behaviors.

Second, results are robust to using other relevant language dictionaries from prior research (e.g., “relating” vs. “resolving” from Marinova et al. 2018; Singh et al. 2018).

Third, the link between affective language and customer satisfaction is robust to considering only positive or negative language but is more strongly driven by positive language.

Fourth, while results suggest conversational moments when affective and cognitive language are each beneficial, one might wonder which language is more important “overall.” Results suggest that if the timing of both affective and cognitive language is optimized, cognitive language makes a somewhat greater overall contribution.

Benchmarks and Simulations. We also investigated whether our approach performs better than competing benchmarks (web appendix B). Our dynamic model yields stronger in-sample and out-of-sample predictions than

(1) traditional “what” analysis that does not account for dynamics at all, (2) a “what” analysis that includes the “sensing, seeking, and settling” conversational stages offered in Marinova et al. (2018), (3) our functional model including all additional unstructured text and voice controls without consideration of model overfitting, and (4) a model ignoring the agent heterogeneous effect. Taken together, this comparison suggests that our approach offers superior predictive performance relative to previous models.

To further test these ideas, we performed a series of simulations comparing our model with various alternatives in when affective and cognitive language should be used. Results underscore 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 beyond merely *what* language is used overall. See web appendix B for details.

STUDY 2: AIRLINE FIELD DATA

While the initial results are intriguing, one might wonder whether they are driven by the specific firm, industry, or customer satisfaction measure used. To test generalizability, we worked with a major U.S. airline to acquire an additional randomly selected (by the firm) dataset of 204 customer service calls (11,548 conversational turns). The airline captured willingness to recommend at the end of the

call, a measure widely used to assess customer satisfaction (Keiningham et al. 2007).

Model 1 examines this outcome as a function of agent affective and cognitive language dynamics, and model 2 used a similar set of structured controls as in study 1. As in study 1, we created a control for *Call Complexity* (length in words). The airline was not able to provide customer or agent observables but provided their measure of *Call Category* (which of four *Departments* the calls were routed to), and whether customers received an *Exchange* or *Refund*.¹⁰ Model 3 includes additional unstructured controls that further add to model fit and inference.

Results

Even exploring a different company, in a different industry, results are similar (figure 4). Customers were more willing to recommend the airline when agents used more affective language at the start and end of the conversation, but more cognitive language in the middle. Further, as shown in the retailer data, airline agents do not already follow the estimated sensitivity curves (figure 4 vs. web appendix figure C1), casting additional doubt on the notion that these patterns are somehow already known and practiced. Regression coefficients for predictors and controls for all three models are presented in web appendix table C1.¹¹

STUDY 3: EXPERIMENT USING NATURALISTIC STIMULI

Finding the same results across two different field datasets underscores their validity and generalizability. That said, one could wonder whether the effects are causal. Including a large number of control variables helps cast doubt on many alternative explanations, but it is still possible some unobserved factor could explain the results. Alternatively, perhaps agents infer the customer's satisfaction early on in the conversation, and this shapes their subsequent language (i.e., reverse causality).

To more directly test when language matters, study 3 manipulates it. We vary agent language to test whether, compared to the strategy recommended in prior research (i.e., emphasizing competence throughout; Kirmani et al. 2017), the dynamic strategy recommended by our conceptualization (and supported by studies 1 and 2, i.e., using more affective language at the beginning and end) boosts customer satisfaction.

To maximize external validity, we use five different conversations from the study 1 field data to assess robustness

to stimulus sampling. This study was preregistered (https://aspredicted.org/M1K_4VC). All experiments used the same exclusion criteria and replicated without the exclusion (web appendix D). Achieved power after exclusion was greater than 85% ($\alpha = 5\%$) for all experiments.

Method

Participants ($N = 686$, Prolific) were randomly presented with the full transcript of a version of one of five real service conversations sampled from study 1. To approximate the topic distribution in the field data, we sampled across all of the firm's call topics and included calls related to returns, orders, shipping, and product (web appendix table A3).

The only difference between conditions was agent language. In the control condition, participants saw the original conversation transcript, edited to remove personally identifiable information (e.g., customer's address). In the dynamic treatment condition, employee language was adjusted based on the dynamic findings of studies 1 and 2. Specifically, agents used warmer, more affective language (e.g., words and phrases like "feel" and "no worries," adapted from the LIWC affective dictionary) in the first and last 25% of each conversation. See web appendix D for full stimuli and affective language LIWC scores by condition.

After reading one of the 10 conditions (2 [language: control vs. treatment] \times 5 [conversational variant: return 1, return 2, order, shipping, product]), participants were asked "How satisfied would you be with the employee?" (1 = not at all, 7 = very much).

Results

As predicted, across a range of real customer service conversations, using our dynamic language recommendation boosts customer satisfaction ($M_{\text{treatment}} = 5.10$, $SD = 1.81$ vs. $M_{\text{control}} = 4.61$, $SD = 1.86$; $F(1, 684) = 12.45$, $p < .001$, $\eta^2_p = 0.02$).

Results remain the same controlling for conversation variant and its interaction with language condition ($F(1, 676) = 17.21$, $p < .001$, $\eta^2_p = 0.03$). Further, the benefit of adding more affective language to the start and end did not vary across the five conversations (interaction $F(4, 676) = 0.62$, $p = .645$). See web appendix D for condition means for all five stimuli.

Discussion

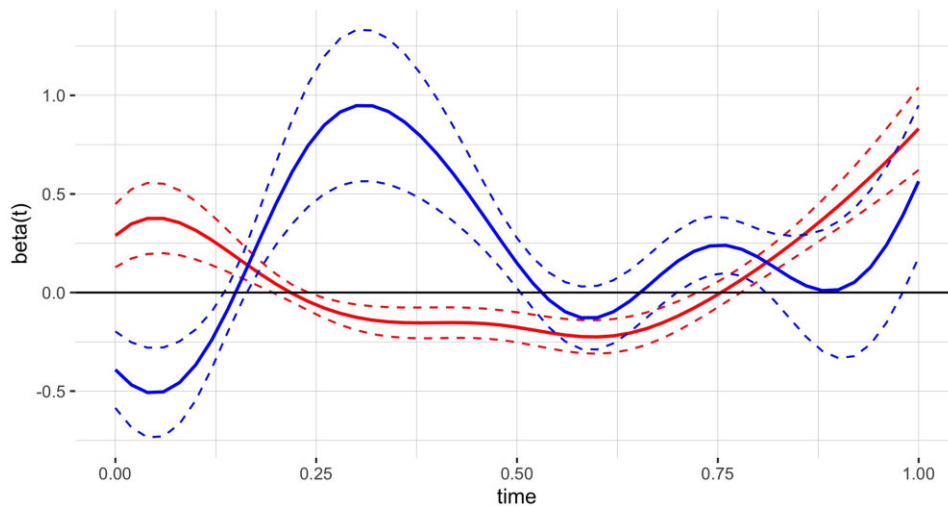
An externally valid experiment, sampling a variety of real customer service interactions, provides direct causal support for our theorizing. Consistent with our suggestion, and with studies 1 and 2, using more affective language at the start and end boosted customer satisfaction.

10 The firm blinded the researchers to the Category and Department names. They are represented only as numbers.

11 Following a reviewer's suggestion, we also present the results of an analysis that attempts to pool the study 1 and study 2 data in web appendix A.

FIGURE 4

STUDY 2 AGENT LANGUAGE AND WILLINGNESS TO RECOMMEND



NOTE.— Red lines: affective language; blue lines: cognitive language; and dotted lines: pointwise 95% confidence intervals. Model 3 with all controls after Group-Lasso shown here. Results without controls (Model 1) and with only static controls (Model 2) are presented in [web appendix figure C2](#).

Ancillary analyses also cast doubt on the notion that the effects could be driven by *what* rather than *when*. If the condition that used more affective language at the start and end also used more affective language overall, maybe it is the greater amount of affective language used, rather than when it occurred, that is increasing customer satisfaction. To test whether this alternative can explain the results, we control for the proportion of affective (and cognitive) language in each stimuli variant as covariates. Results remain the same ($F(1, 682) = 124.04, p < .001, \eta^2_p = 0.15$).¹²

STUDY 4A: CONTROLLED STIMULI

While study 3 provides direct causal evidence using a range of real conversations, the idiosyncratic and complex nature of natural conversation makes it difficult to maintain strong experimental control (Reece et al. 2022). Consequently, study 4 provides a simpler, more controlled language manipulation.

Method

Participants ($N = 146$, Amazon Mechanical Turk) were randomly assigned to one of two versions of a simple scenario based on the field data conversations. Shipping-related issues were common in study 1 and perceived to be

approximately average in severity ($M_{\text{shipping}} = 2.84$ vs. $M_{\text{all}} = 2.61$), so participants imagined calling an online retailer, and read a conversation in which they asked the customer service agent for shipping help.

The only difference between conditions was the agent's language. As recommended by prior research, in the all-cognitive condition, the agent used cognitive language throughout (i.e., a "competent-competent-competent" sequence). In the dynamic condition, agent language followed the findings of studies 1 and 2. Specifically, in the first and last 25% of the conversation, cognitive language was replaced with more affective language from the LIWC affective dictionary (i.e., a "warm-competent-warm" sequence). In the all-cognitive condition, for example, the agent started by saying "Hello. How might I assist you today?," while in the dynamic condition, they used the warmer "Hello. I hope you're enjoying this fine day?"¹³ See [web appendix D](#) for full stimuli.

Then, participants completed the dependent variable (i.e., customer satisfaction, "How satisfied are you with the agent?"; 1 = not at all, 7 = very much). To replicate the study 1 satisfaction measure, we also asked "How helpful was the agent?" (1 = not at all, 7 = very).

12 Note that our modeling results (studies 1 and 2) already account for, and our simulations ([web appendix B](#)) directly test, the effects of overall agent use of affective language, and thus cast doubt on this alternative.

13 While one might wonder whether the dynamic language condition recommended by our model seemed less typical, expected, or standard, this was not the case. There was no difference in perceived language typicality across conditions ($F < 1$ using the three-item measure from Kronrod, Grinstein, and Wathieu 2012), casting doubt on this alternative.

Results

As predicted, changing agent language based on our dynamic recommendation (i.e., more affective language at the start and end) improved customer satisfaction ($M_{\text{dynamic}} = 6.30$, $SD_{\text{dynamic}} = .73$ vs. $M_{\text{all cognitive}} = 5.87$, $SD_{\text{all cognitive}} = 0.89$; $F(1, 144) = 10.25$, $p = .002$, $\eta^2_p = 0.07$). It also led agents to be perceived as more helpful ($M_{\text{dynamic}} = 6.14$, $SD_{\text{dynamic}} = 0.88$ vs. $M_{\text{all cognitive}} = 5.84$, $SD_{\text{all cognitive}} = 0.93$; $F(1, 142) = 4.07$, $p = .046$, $\eta^2_p = 0.03$).

Discussion

Controlled manipulation of the language used at different conversational stages provides further causal support. Consistent with our theorizing, and with the results of the first three studies, dynamic “warm–competent–warm” language boosted customer satisfaction over previously recommended approaches prioritizing competence throughout (i.e., “competent–competent–competent”).

STUDY 4B: COMPARISON TO OTHER LANGUAGE SEQUENCES

While the results of study 4A are supportive, one could wonder whether other sequences of affective and cognitive language might be more beneficial. To test this possibility, study 4B adds all other permutations (i.e., “competent–competent–warm,” “warm–competent–competent,” “warm–warm–warm,” “competent–warm–competent,” “competent–warm–warm,” and “warm–warm–competent”); total $N = 603$, Amazon Mechanical Turk; see [web appendix D](#) for stimuli). This study was preregistered (https://aspredicted.org/Y2Y_SZC).

Results indicate that language based on the dynamic model’s recommendation improved customer satisfaction relative to all other conditions (all $ps < .05$, [figure 5](#)).¹⁴ This underscores the notion that the specific dynamic sequence from our theorizing is superior to a variety of alternative sequences. Notably, the fully reversed condition (i.e., competent–warm–competent) uses the same total amount of agent warm and competent language, ruling against the possibility that this can drive the effect.¹⁵

14 Pairwise tests of our dynamic sequence versus all other conditions are reported in [web appendix D](#). As in study 4, results also replicate using the study 1 retailer’s satisfaction measure “How helpful was the agent?” Our dynamic treatment condition again outperformed the recommendation of prior research ($M_{\text{dynamic}} = 5.54$, $SD_{\text{dynamic}} = 1.58$ vs. $M_{\text{all cognitive}} = 4.87$, $SD_{\text{all cognitive}} = 2.02$; $F(1, 146) = 5.07$, $p = .026$, $\eta^2_p = 0.03$) and all six other conditions (all $ps < .02$; all $\eta^2_p > 0.03$) in perceived helpfulness.

15 The proportion of overall agent words in the fully reversed “competent–warm–competent” condition is the same as in our dynamic treatment condition (“warm–competent–warm”) for both affective (8.9% vs. 10.6%; $\chi^2 = 0.005$, $p = .778$) and cognitive language (22.2% vs. 21.3%; $\chi^2_{\text{cognitive}} = 0.040$, $p = .841$).

STUDY 5: REPLICATION AND ROBUSTNESS

Studies 1, 2, 3, 4A, and 4B offer evidence that, beyond *what* language agents use overall (i.e., conversation-level use of warm language), *when* agents use it matters (i.e., at the start and end). Study 5 extends this approach further, testing our dynamic treatment using a “competent–warm–competent” control that uses exactly the same number and proportion of warm words.

We randomly assigned participants ($N = 154$, Prolific) to one of two versions of a simple airline service scenario based on the study 2 field data conversations. To fully control for the overall count and proportion of affective and cognitive language that agents used, we made sure they were identical across the conditions. See [web appendix D](#) for full stimuli. Participants completed the same customer satisfaction-dependent measure as all prior experiments. This study was preregistered (https://aspredicted.org/YL7_9LY).

As predicted, even though it used the exact same number and proportion of warm and competent agent words overall, agent language based on our dynamic recommendation (i.e., warmth–competence–warmth) improved customer satisfaction ($M_{\text{dynamic}} = 5.74$, $SD_{\text{dynamic}} = 1.26$ vs. $M_{\text{fully reversed}} = 5.06$, $SD_{\text{fully reversed}} = 1.38$; $F(1, 152) = 9.98$, $p = .002$, $\eta^2_p = 0.06$).

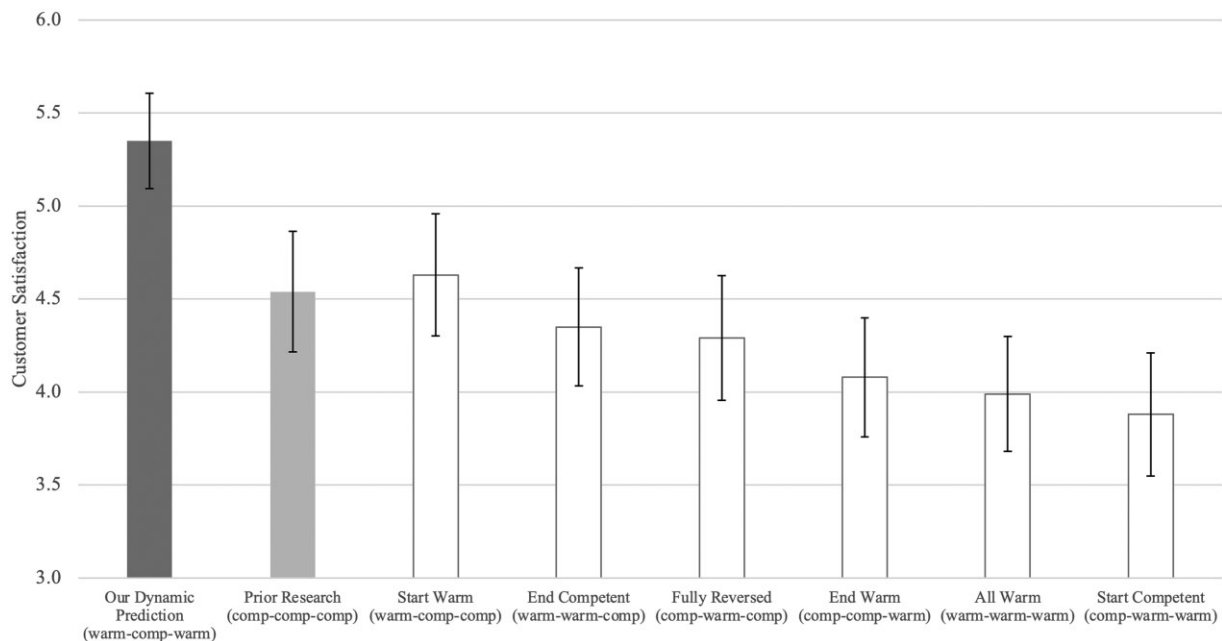
GENERAL DISCUSSION

Language impacts a range of consumer interactions. But while a great deal of research has examined customer service and other marketing dialogues (e.g., social media conversations; [Berger and Schwartz 2011](#)), *when* different language features matter has received less attention.

To address this gap, we offer an approach that examines how language at different moments of an interaction relates to important outcomes. As an initial demonstration, we applied it to the two most important dimensions of person perception: warmth and competence. While existing research suggests that either competence (in customer service) or warmth (in everyday interpersonal relations) should take primacy, our approach suggests that a more dynamic perspective may be beneficial. Consistent with this, six studies find that “bookending” the efficient, competent addressing of customer needs with warmer, more affective rapport building at the start and end of service interactions increases customer satisfaction. Finding the same results in the lab and two field settings, across a range of naturalistic and controlled stimuli, using different topical contexts and words, and different dependent measures (i.e., customer satisfaction, helpfulness, purchase behavior, word of mouth intentions) speaks to their generalizability. Simulations ([web appendix B](#)) speak to the ceiling of the potential impact of these effects.

Importantly, these results go beyond existing research and practice. Launching straight into the competence-

FIGURE 5
COMPARISON AGAINST VARIOUS ALTERNATIVES



NOTE.— Error bars represent 95% confidence intervals. Text between parentheses describes the manipulated sequence of more affective (warm) or more cognitive (comp) agent language for each condition.

oriented language endorsed by prior research may hurt customer satisfaction and purchase, as may using only a warmth-oriented approach. Instead, results suggest that agents should use warmer language at the start and end of conversations than they do currently, and generally avoid more cognitive, competence-oriented approaches during these periods. Language like “My pleasure. Take care now,” should be used at the end of conversations, for example, rather than language such as “I’m glad we could solve that for you. Bye now.”

Our modeling approach also helps address three major challenges in examining moment-to-moment dynamics in communications—irregularity, sparsity, and high dimensionality (e.g., wide data unstructured text and voice controls). Language measurement is often irregular and sparse, so we modeled the time-varying data as random trajectories realized from smooth underlying functions. We used Group-Lasso machine learning to select additional unstructured controls that enhanced, rather than impeded, model fit and inference.

Applications to Other Linguistic Features

We focused on affective and cognitive language, but our method can be applied to any language (or paralinguistic) feature. Take questions. Prior research suggests that asking

questions can be beneficial (Huang et al. 2017) because it signals interest (Drollinger and Comer 1999). Consumers also believe that asking questions is important, making it a common feature of scales used to evaluate employee performance (Drollinger et al. 2006).

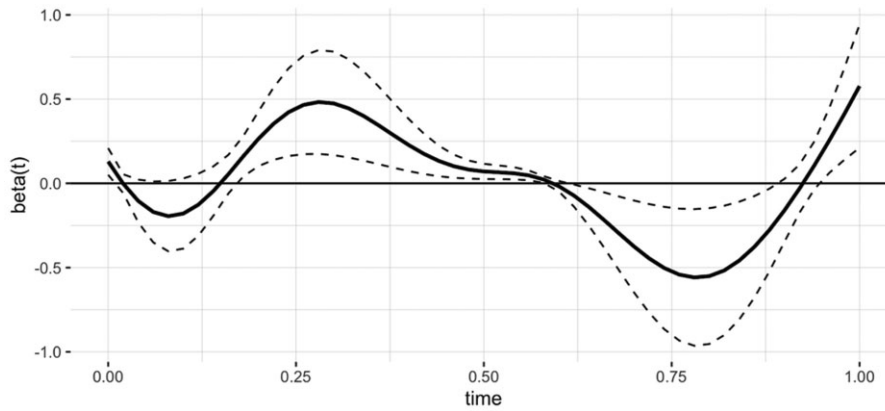
But while our main dataset (study 1) replicates prior findings that customers are indeed more satisfied when agents ask more questions overall ($b = 0.13$, $p = .010$), is asking questions good at any point in the conversation? Or might it be more beneficial in certain parts?

To illustrate how our method can test such ideas, we run our functional model with agent question asking as the focal dynamic predictor of customer satisfaction. Results indicate that the positive relationship between customer satisfaction and question asking depends on *when* agents do so (figure 6). While asking questions is not helpful in the first 15%, doing so is beneficial when used between 15% and 57% of the interaction, and can even be costly at 60–85% of the way through. This suggests that agents might best emphasize questions after the customer has a chance to describe their needs.

To further explore the method’s value, we also looked at pronouns. Research suggests that first-person singular (“I”) pronouns make agents seem more agentic and empathetic (Packard et al. 2018), and a traditional conversation-level

FIGURE 6

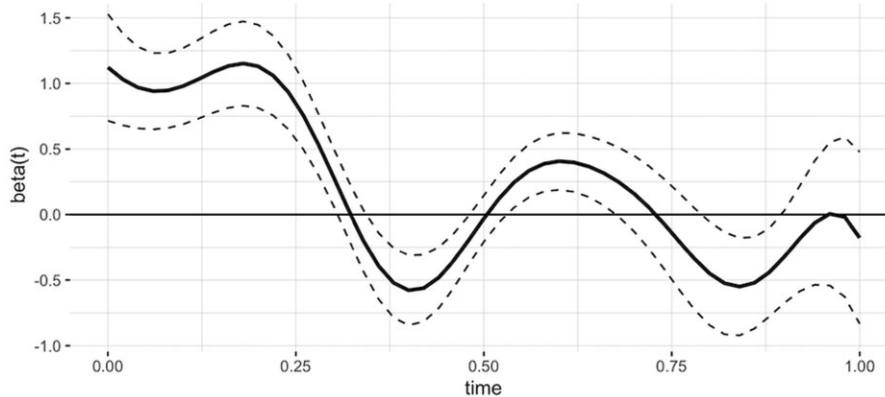
AGENT QUESTION ASKING AND CUSTOMER SATISFACTION



NOTE.— Dotted lines: pointwise 95% confidence intervals.

FIGURE 7

AGENT FIRST PERSON SINGULAR PRONOUNS AND CUSTOMER SATISFACTION



NOTE.— Dotted lines: pointwise 95% confidence intervals.

analysis of the study 1 field data replicates the finding that first-person singular pronouns are positively related to customer satisfaction overall ($b = 0.051$, $p = .040$). But are these pronouns necessarily important throughout a conversation?

Running the same model with agent first person singular pronouns as the main dynamic predictor finds that their benefit mostly occurs at the beginning of conversations (figure 7). This is the same period when warm, affective language is beneficial. In contrast, first-person singular

pronouns may be costly for a brief period when cognitive language matters (i.e., the middle of the conversation). This pattern suggests that first-person perspective may be more important when conveying warm empathy (“I’m sorry”) than signaling competent agency (“I’ll fix it”). Competence might be better achieved by using more objective voice (e.g., third person).

Overall, these examples further underscore the potential value of examining language dynamics, demonstrating not only whether the words we use matter, but *when*.

TABLE 1
MANAGERIAL TRAINING EXAMPLES OF BENEFICIAL SERVICE AGENT LANGUAGE

Conversation stage	Recommended language style	Service agent language example
Opening	More affective/warm	Who do I have the pleasure of speaking with? (less effective: How might I assist you?)
Middle	More cognitive/competent	Could you verify your address again? (less effective: I'm sorry, could you share your address again?)
Closing	More affective/warm	Glad I could help. Call us back and we'll take care of you. (less effective: No problem. Call us back if you need anything else.)

Substantive Implications, Limitations, and Future Research

Our findings have clear implications for researchers and managers. For researchers, our approach offers a way to move beyond just *whether* certain language features matter to *when*. This method expands the toolkit available to researchers who use text analysis to understand consumer behavior (Berger et al. 2020; Humphreys and Wang 2018). It could easily be applied to paralanguage (Luangrath, Peck, and Barger 2017) or non-verbal communications, and other long-form language contexts (e.g., advertising copy, movie scripts, or online reviews).

Managers can use the approach to understand not only what language to use but also when to use it (see table 1 for examples). When trying to design more effective chatbots, for example, understanding when to prioritize different language features and non-verbal cues (e.g., tone, pitch, pauses) should make these conversational technologies more effective.

We accounted for agent, customer, and firm-level factors, but as with most field data, our estimates remain subject to potential endogeneities due to unobserved factors. The temporal sequence of our language predictors and outcomes makes reverse causality seem unlikely, and four experiments using both naturalistic and controlled stimuli support causality. But future research could use field experiments to further test external validity.

We focused on effects of language over time, but future work could delve more deeply into the mechanisms behind these effects. We theorized, for example, that warmer, more affective language should be beneficial at the start because it helps establish a warm, relational base before competently addressing the customer's needs. Consistent with this, exploratory measures of perceived warmth captured at the end of studies 4A and 5 suggest that using affective language at the start and end made the agent seem warmer. Both warmth and competence perceptions were supported as mediators for our primary customer satisfaction outcome, and competence perceptions were supported for the secondary helpfulness outcome used by the firm in study 1. See web appendix F for details.

That said, measuring overall perceptions at the end of the interaction may not be the best approach. Temporal language effects may simply mean shifting the same amount of a feature (e.g., warmth) to a different moment, meaning that overall perceptions of warmth or competence might not always change. Consequently, future studies could use moment-to-moment measures (Ramanathan and McGill 2007), to better investigate the mechanisms that underlie these temporal shifts. Future research could also consider more detailed measures of different dimensions of warmth (e.g., rapport-building vs. empathetic).

Moderators also deserve further attention. To illustrate how one might approach such opportunities, ancillary analyses explored whether issue severity moderates the benefit of affective or cognitive language at particular conversational moments (web appendix E, study 6). Other situated aspects may also shape the effects. The best time to use affective language may be different in initial sales calls, for example, than when resolving existing customer issues. A single-speaker monologue (e.g., voice actor in a radio ad) likely entails different temporal dynamics than two actors in dialogue. Results may also vary outside of traditional marketing contexts (e.g., doctor-patient conversations; Berger and Packard 2023). The importance of affective language may also be diminished when employees can build rapport using other means (e.g., facial expression).

Work could also explore conversational norms. While preferences for warmth and competence likely drive the observed effects, norms may also play a role. Customer service is a relatively constrained process (Marinova et al. 2018), which can lead to structured, ritualistic conversational norms (Goffman 1981) or expectations of how dialogues evolve. Future work should consider such possibilities, and whether the impact of violating conversational norms (e.g., turn-taking, maxim violations; Grice 1975; Seedhouse 2005) may vary over conversational time.

Future work might also examine the role of culture. While warmth and competence are key dimensions across cultures, different cultures may have different values or baseline expectations around how much of each is desired. Spanish, Portuguese, and Italian people are seen as warmer,

for example, while German and English people are seen as more competent (but less warm; Cuddy et al., 2009). Consequently, if they internalize these stereotypes, German and English consumers may prefer relatively more competence, for example, and less warmth.

The dynamic value of warmth and competence might also vary cross-culturally. Conversational norms differ across cultures (Kim 2017), so warmth may be less important at the beginning or end in some contexts. Even outside of culture, languages have different norms about when and how to express warmth and competence. Korean, for example, has a linguistic device that conveys warmth-related information at the end of most sentences (Lee and Ramsey 2000). In this language, limiting warmth to a conversation's start and end may be less beneficial, or difficult to achieve. Even within the same cultural context or language, variations in norms and expectations may shape what dynamic patterns are preferred. A conversation among Americans will often entail dyads from sub-cultures with different warmth and competence norms or stereotypes (e.g., southern vs. northeastern or Italian vs. Asian Americans; Fiske 2017). Such cultural features, context (e.g., professional vs. personal), relative power, in- or out-group status, gender, and other factors likely shape conversation dynamics in complex ways. We hope future research may consider such potentially important variation.

Conclusion

This research begins to quantify when language matters. Beyond warmth and competence, the approach presented (and accessible at whenlanguagematters.net) should also be useful in studying advertising language, word of mouth, negotiation, message recall, and various other topics. We hope this work provides a useful framework for those examining conversations and other facets of human interactions.

DATA COLLECTION STATEMENT

The third author collected the data for study 1 (online retailer) in the fall of 2016 and study 2 (airline) in the summer of 2017. The first author collected the data for study 3 in the spring of 2023, study 4A in the summer of 2021, and studies 4B and 5 in the fall of 2023. All experimental data were collected via Prolific or Amazon Mechanical Turk as detailed in the article. The second author analyzed the two field data sets (studies 1 and 2). The first author analyzed the data for the four experiments (studies 3, 4A, 4B, and 5). The experiment data are stored in a project directory on the Open Science Framework. The field data are stored on the authors' computers and are under non-disclosure agreement but are available to the journal editors for review on request.

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