Reading between the lines: AI and customer acquisition in professional services

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Abstract

Purpose – Professional service firms face complex challenges in acquiring new clients, owing to the high degree of trust, customization and client involvement these services require. This study aims to explore how large language models (LLMs), such as ChatGPT, can analyze early-stage text-based communications to identify linguistic markers that predict purchase readiness. By focusing on the professional services domain, the study contributes to service marketing theory by introducing a novel method to assess service interest through client-generated text.

Design/methodology/approach – For two years, the authors collected responses submitted through an inquiry form for a home improvement firm. The artificial intelligence (AI) platform ChatGPT was trained to assess the level of specificity in the language used by prospective customers and generated a specificity score for each response. These scores were then used to predict the likelihood of customer purchase over time using an accelerated hazard model.

Findings – The results indicate that the specificity scores generated by ChatGPT effectively predict a customer's position within the sales funnel and likelihood of purchase over time. Customers who provided more detailed information, as measured by AI, exhibited a higher probability of conversion.

Practical implications – This study provides actionable insights for managers aiming to optimize customer acquisition efforts and minimize resource waste. It demonstrates how AI – specifically LLMs – can be leveraged to analyze unstructured text from prospective customers and identify linguistic signals (e.g. specificity) that are predictive of purchase likelihood.

Originality/value – Consumers reveal valuable insights through the language they use. While it has traditionally been difficult to empirically analyze this verbiage, the emergence of LLMs enables the transformation of qualitative text into measurable indicators. These tools allow firms to make data-driven predictions about customer behavior. This study introduces a novel methodological approach to the analysis of customer acquisition.

Keywords Artificial intelligence, Customer acquisition, Sales funnel, Professional services, Temporal construal

Paper type Research paper

Introduction

Professional services pose unique marketing challenges because of their intangible nature, high degree of customization and centrality of the client–provider relationship (Grierson and Brennan, 2017; Lovelock and Gummesson, 2004). Acquisition in these settings often hinges on nuanced, unstructured communication rather than standardized lead funnels. This research demonstrates how artificial intelligence (AI) tools can decode early-stage communications to better qualify and prioritize leads, improving service provider efficiency and client alignment. Thousands of firms, such as home contractors, plumbers and electricians, respond to customer inquiries with proposals that outline the work that they will complete. The firm incurs the cost of meeting with the client and preparing a proposal, but compensation is only provided if the customer accepts it. According to a 2022 survey by Service Direct, 85% of homeowners reach out to three or fewer contractors before selecting one. If customers seek multiple proposals, this means that one firm will receive the revenue, while the others that have made the effort to prepare proposals will only incur the acquisition costs. Conventional wisdom would argue that generating more leads and more activity will ultimately enhance revenue and profit (Kotler *et al.*, 2006). However, unless firms can screen potential customers and focus on those most likely to purchase, they risk wasting valuable resources pursuing prospects that will not convert to customers. In the construction sector, for example, a failed proposal for a routine project can cost $3,000–10,000 (Buckshon, 2013). This dynamic reflects the theory of information asymmetry (Akerlof, 1970; Kirmani and Rao, 2000): where firms must differentiate between potential customers and ascertain which of the prospects will convert to customers. Research has shown that prospective customers in the service sector can be screened to determine who is most likely to purchase (Lagrosen, 2005; Stivaros, 2016; Verhoef and Donkers, 2005). Customers who come from certain channels have demonstrated that they have invested some effort to research the firm, which signals to the firm that they are more likely to purchase than customers who take a more passive approach (Majid, 2021; Verhoef and Donkers, 2005). This work has demonstrated that firms can

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use communication channels to screen customers and reduce asymmetry; however, the words that customers use in their communications could also provide insights into which ones are likely to purchase. With professional services (such as home improvement), customers can communicate what they desire, which gives firms a chance to reply before the purchase decision. Traditionally, a representative of the firm assesses these messages to determine the customer's likelihood of purchase (Bettencourt *et al.*, 2002). However, with most communication occurring through digital channels, an opportunity exists for emerging AI tools to analyze a customer's verbiage before reaching a representative of the firm.

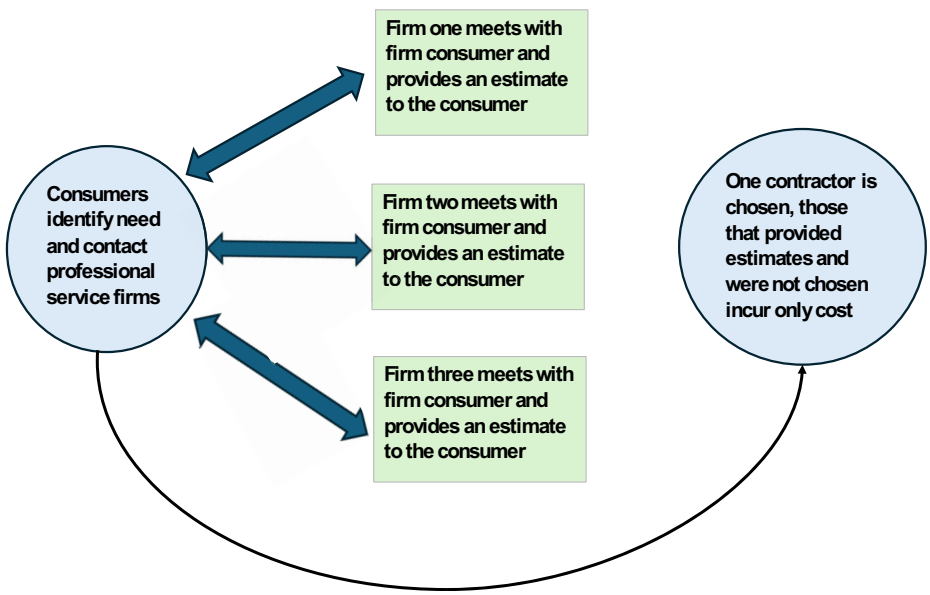
The advancement of technology, in particular the accessibility of AI, offers another screening mechanism that can be used to identify customers with the greatest likelihood of purchase. AI platforms, such as ChatGPT, Gemini, Copilot and a host of others, are natural language processers that review and summarize text. This can be particularly valuable to service firms because customers often communicate the work that they seek to have done when they first initiate contact (Majid, 2021). How customers express themselves in early communications may reveal their stage in the decision journey. Temporal construal theory (Trope and Liberman, 2003, 2010) suggests that people think about distant decisions abstractly but describe near-term decisions more concretely. The process by which firms acquire customers is F1 illustrated in Figure 1. Within it, the prospective customer describes the work and requests an estimate from the service firm. Some prospective customers may be at the top of the sales funnel and are simply seeking an estimate but are unsure if they are ready to purchase. Others may be closer to the bottom of the funnel and ready to purchase. If firms can identify where customers are within the funnel, they can focus their marketing efforts on closing the sale. The capabilities of AI allow it to be deployed to analyze the words that the prospective customer chooses. We use AI to analyze customer requests to a professional service firm and create a measure that helps predict the likelihood of purchase. In professional service contexts – where offerings are intangible, high involvement and relationship driven – customer acquisition depends heavily on trust signals and individualized communication. This study advances service marketing theory by demonstrating how linguistic specificity can serve as a proxy for service readiness and purchase intent (see Table 1 for a summary). T1 We focus on only new customer acquisitions because existing customers are likely to have a different process by which they approach the firm. They may be interested in additional purchases or upgrades and have already developed a rapport with the firm that would affect the level of communication; they may say less because they have already spoken with it. Analyzing only new customers provides the greatest opportunity to study natural communication between the customer and firm without the added element of a previous relationship.

The article proceeds as follows. First, we draw upon the theory of information asymmetry to argue that poor-quality prospects increase sales costs. Second, we discuss the customer journey through the sales funnel from awareness to purchase. We develop hypotheses based on temporal construal theory, which argues that those closer to action are more likely to have specific thoughts – in this case, better-formulated demands – than those at the top of the funnel. We test the hypothesized effects on conversion rates with a hazard modeling approach using data from a home improvement firm. Following the empirical analyses, we discuss the results and present theoretical and managerial implications pertaining to customer acquisition.

Literature background

Research in customer relationship management (CRM) shows that effective customer acquisition and retention are associated with higher financial valuations (Schmitt, Skiera and Van den

Figure 1 Customer acquisition in professional services



Source(s): Authors' own work

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Table 1 Outline of contribution relative to other major work

Study	Screening method (variable of interest)	Summary	Industry
Danatziz *et al.* (2021)	Individual-level readiness	Individual-level readiness impacts the ability of actors within the service ecosystem to engage in different parts of it, including new technologies	Theoretical
Libai *et al.* (2013)	Position within a social network	The authors demonstrate how acceleration and expansion combine to generate value in a word-of-mouth seeding program for a new product	Higher education, technology, entertainment, retail and services
Pham *et al.* (2020)	Technology readiness	The study finds that the perceived value of technology impacts customer satisfaction and purchase intention	Luxury hotels
Majid (2021)	Type of marketing channels (interactive vs. not)	The author demonstrates that customers who approach the firm through an interactive channel are more likely to become customers	Home improvement and real estate
Schmitt *et al.* (2011)	Whether the customer is referred to the firm; existing customers act as gatekeepers	Referred customers have a higher contribution margin and higher retention rate and are more valuable in the short and long run	Financial services
Steffes *et al.* (2011)	Marketing channels (such as direct mail)	Internet and direct mail efforts generate more profitable customers than telemarketing and direct selling	Financial services
Thomas (2001)	Marketing channels (such as direct mail)	Customer acquisition is more costly than customer retention	Membership of trade association
Torkzadeh *et al.* (2022)	Emotional and cognitive connection to the firm	Psychological engagement serves as a mediator, leading to increased goal attainment, satisfaction and retention	Fitness center
This study	The verbiage that customers use in digital channels (specificity and personalization)	Customers who use more specific language when communicating with the firm are more likely to purchase from the firm	Home improvement contractor

Source(s): Authors' own work

Butte, 2011; Schulze *et al.*, 2012; Verhoef and Donkers, 2005). A firm's CRM effectiveness is rooted in its capability to identify, acquire and retain customers, thereby extracting lifetime value from these relationships (Kumar and Reinartz, 2016; Lewis, 2006; Lewis, 2005). Customers are viewed as assets that contribute to varying levels of value. However, when they are attracted mainly through discounts, they might not develop into long-term revenue generators (Lewis, 2006), which underscores the need for companies to target those who value more than occasional promotional deals (Lewis, 2006, 2005). Additionally, at acquisition, customers often represent a net negative value because of the costs incurred to convert prospects; the higher these costs, the longer it takes to break even. Consequently, cost-effective acquisition is fundamental to any CRM strategy, paving the way for successful retention efforts.

Acquisition costs

Achieving cost-effective customer acquisition is especially difficult because firms typically spend far more to gain a new customer than to keep an existing one. For instance, Thomas (2001) found that a professional services organization spent approximately $26.94 to win a new customer compared to only $2.15 annually retaining one. This significant acquisition cost mainly results from the expense of reaching those who ultimately do not convert. Traditional advertising methods – such as signage or television commercials – incur the same cost per prospect, even though only a small fraction will convert. For example, if a company spends $10,000 on a billboard and secures 50 new customers, the effective acquisition cost is $200 per customer, with much of that expense going toward audiences that have no interest in the firm's services.

This situation exemplifies the theory of information asymmetry. The high acquisition cost is driven by an imbalance of information between the firm and its customers (Kirmani and Rao, 2000). Typically, sellers possess more knowledge about the quality of their offerings than buyers, leading to lower prices because buyers demand a discount to offset the risk of subpar service (Akerlof, 1970). Conversely, when buyers have greater insight into their own intentions than sellers do, prices tend to rise. This dynamic is particularly pronounced in the service sector, where time is a limited resource; every moment spent pursuing a lead is not spent on revenue-generating activities. For instance, if a homeowner seeking a remodel

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obtains three estimates and already favors one firm, the other two incur the cost of providing estimates without earning any revenue. This scenario – known as "customer asymmetry" – occurs when firms cannot distinguish between prospects who will yield profits and those who will not, thus incurring higher costs by targeting unprofitable leads (Thomas, 2001). To lower acquisition expenses, firms must enhance their targeting capabilities and focus resources on prospects that are more likely to generate revenue.

This article advances the discussion of acquisition costs with a focused investigation of the language that prospective customers use to communicate to the seller before acquisition. The words that a customer uses for the work they are looking for can provide differing levels of specificity and personalization. If the words are more specific and detailed, then they have likely spent time thinking about the work and are now looking at details of the project, which aligns with being closer to purchase (Zhang and Wang, 2022). Personalizing the communication to the particular seller (e.g. "we like the work you have done on our neighbor's house") indicates that the prospective customer is using language specific to the firm compared to any given firm.

Customer communication with the seller

It is well established that customers move through a sales funnel, progressing from the awareness stage to the purchase stage (Colicev *et al.*, 2019). At the top of the funnel, a firm's primary focus is on generating awareness for its brand and offerings. As prospective customers advance through the funnel, they gain more knowledge about the products or services and may eventually make a purchase decision (Lemon and Verhoef, 2016).

The funnel structure reflects the number of customers at each stage: the top, where awareness is created, consists of a large audience, while the bottom narrows down to a smaller group of customers who ultimately make a purchase. This visual representation underscores the gradual reduction in potential buyers as they move closer to conversion. For firms in the professional services sector, having a relatively large top of the funnel compared with a smaller base can be detrimental to their costs (Majid, 2021). Unlike firms that sell products, attracting many customers comes with the cost of responding to inquiries and developing proposals. If the firm fails to convert many of these potential customers, it must absorb the cost. Therefore, it is in its best interest to keep a narrow funnel between the base and top.

Another key aspect of the sales funnel is the strategic use of different marketing channels at various stages. At the awareness stage, firms often rely on mass marketing techniques, such as television advertisements, billboards and digital display ads, to reach a broad audience (Jansen and Schuster, 2011). As customers move further down the funnel – from awareness to interest and eventually conviction – the approach shifts to more interactive and personalized channels. For instance, they may conduct online research, explore product reviews or compare pricing options to determine their level of interest. Interactive channels where they communicate with the firm allow them to customize the information they receive (Stephen and Galak, 2012). For example, a customer who is primarily interested in costs can research the firm's website and reach out for additional information.

The sales funnel in the professional services industry operates uniquely compared to other sectors, such as leisure or hospitality. Unlike in retail or hospitality, where customers can often make immediate purchasing decisions, those in professional services must actively engage with the firm before deciding. This interaction is necessary for both parties to assess compatibility and define the scope of the project. Clients typically initiate contact by requesting a proposal or estimate. The firm then assesses the work and has its staff and/or subcontractors determine the costs and scope of the project (Wong and Ng, 2023). Completing the work resembles a service process, where the process is co-created between the firm and customer. This illustrates the time and effort that customers must invest before the service is provided.

Potential customers may enter the firm's sales funnel at different levels of purchase intent. Some may be in an exploration phase, assessing feasibility and gathering information, while others may be ready to move forward immediately. A customer may not move from the top to the bottom of the funnel in sequence. In a traditional funnel process, the customer reaches out only at the later stages, when they are close to purchase (Colicev *et al.*, 2019). However, for some professional service firms, it is customary for customers to receive multiple estimates before making a decision. This creates a situation where they approach multiple firms with different levels of sincerity. They form preferences for one or two firms; additional firms are simply used to provide more options, which they are unlikely to accept. Professional services involve trust building and that entails managing customer expectations, as espoused by foundational work on trust in the sector (Parasuraman *et al.*, 1988; Zeithaml *et al.*, 1985). The need to build trust lends itself to a more nuanced reading of client expectations.

Taken together, prior research highlights two consistent themes. First, work on customer acquisition emphasizes the high costs associated with customer acquisition, a problem rooted in information asymmetry between firms and customers (Thomas, 2001; Kirmani and Rao, 2000). Firms must therefore develop screening mechanisms that help them distinguish between prospects likely to convert and those unlikely to do so (Majid, 2021). Second, research on customer journeys and temporal construal theory (Trope and Liberman, 2003, 2010) suggests that individuals signal their proximity to decision-making through the specificity of their language. Customers early in the funnel describe services abstractly, while those closer to purchase provide more concrete details. By integrating these two perspectives, we argue that linguistic cues such as specificity and personalization can serve as observable markers that reduce information asymmetry and indicate a customer's position in the funnel.

Likelihood of customer acquisition based on communication

Temporal construal theory argues that people think about events differently depending on how far off they are in time (Fujita *et al.*, 2006; Trope and Liberman, 2003; Trope and Liberman, 2010). Customers use more abstract, high-level mental representations (construals) for distant events and more

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concrete, detailed construals for near-future events. Initially, customers may visualize long-term abstractions, such as increasing productivity (Dhar and Kim, 2007) or staying healthy (Trope and Liberman, 2010). As the event approaches, the customer focuses on practical details, such as the tools they will use or how much they will need to spend (Dhar and Kim, 2007; Trope and Liberman, 2010). Though not specifically applied in the customer journey from awareness to service acquisition, temporal construal theory can be used to argue that early in the sales funnel, customers may think of the services in abstract terms, such as what the completed project will look like. However, as they are closer to making their purchase, they start to think of more details, such as pricing and time of completion (Guizzardi *et al.*, 2022). Using temporal construal theory, we argue that customers who are close to a purchase decision will focus on the specifics of the work and represent this specificity in the words that they use with the firm. A customer who is far from making a purchase may use language that represents more abstract concepts, such as the finished work they desire (e.g. bathroom, kitchen). These abstract terms provide a starting point but lack details on the materials, timeline for completion or work components. A customer who is closer to purchase may provide more specific details that the firm can implement soon (e.g. crown molding, granite countertops). We propose the following hypothesis to test this argument:

H1. Prospective customers who provide more specific details in their communication with the firm have a higher probability of converting shortly after contacting the firm than potential customers who provide more general details.

We draw upon temporal construal theory to argue that customers further down the funnel will use more specific language. Earlier in the process, the customer creates a consideration set to reach out to, composed of firms that they have researched and decided to contact because they have determined that these could fulfill the work. Research on consideration sets and consumer–brand interactions suggests that personalized messages indicate an early preference for a firm (Labrecque, 2014). However, an additional element also occurs when customers contact a firm that they were referred to; they are likely to personalize the message by mentioning the person who recommended them (Peluso *et al.*, 2021). Personalization describes comments that reference specific elements of the firm – such as past work, referrals, or employee names – rather than generic inquiries. At face value, it appears to signal customer engagement within a consideration set, which may not indicate placement further down the sales funnel. Furthermore, information search behavior research suggests that customers nearing a decision often comparison shop to validate their preferred choice or satisfy due diligence requirements (Bettman *et al.*, 1998). In such cases, personalization may be used broadly across multiple firms rather than indicating strong intent for a specific one. In other words, we expect that when customers personalize their message, they signal that they are in the early stages of the funnel and forming their consideration set. Stated formally, we propose the following:

H2. Personalization in initial customer messages is associated with a longer delay before booking.

Methods

When customers reach out to professional service firms, they often provide information on the work they would like to complete. It is standard practice in the industry for the customer to communicate their needs and information and the firm to engage them in a process that involves additional communication, a proposal (or estimate) and a negotiation on the timeline and parameters for the work. The context for our study is the home improvement sector. Based on industry reports, it was valued at approximately $526.1bn in 2024 and employed approximately 750,000 people across approximately 6,500 firms (IBISWorld, 2024). Marketing efforts are typically conceptualized as inbound as opposed to outbound (where marketing materials are pushed to customers) (Bleoju *et al.*, 2016). Inbound methods involve customers initiating contact with the firm and relying on channels where they can learn more about it, such as word of mouth, its website and/or reviews (Majid, 2021). After a customer identifies the work and potential firms, they reach out with a brief description of their planned project. According to a 2022 survey by Service Direct, 85% of homeowners contact three or fewer contractors before deciding. The first communication involves providing contact information and a description of the work. This is often done through online channels, such as a form on the firm's website. At this point, the customer has provided qualitative information that can be used by the firm to determine whether it is able to complete the requested work. For example, a customer may reach out to a home improvement firm and describe that they want an addition on their home; this may be outside the scope of a firm that will respond appropriately and decline to pursue them any further. Once a potential customer is initially screened for suitability, the firm prepares to meet them and/or prepare an estimate for the work.

The information that customers provide when they describe the work can contain important details that indicate urgency and knowledge of what they want to do. Based on theories of temporal construal, as customers move through the sales funnel and closer to purchase, they are more likely to focus on specific details. This level of specificity can manifest itself in the descriptive words that they use. Interpreting customer comments to determine their stage in the sales funnel has traditionally been challenging due to difficulties in interpretation and standardization. However, the advent of machine learning models, such as ChatGPT, Gemini and Copilot, has made it possible to analyze these communications. Although the use of AI technologies in marketing is still in its infancy, their ability to interpret unstructured text provides a natural advantage in understanding customer language (Kopalle *et al.*, 2022). Large language models (LLMs) can identify keywords and their context, allowing firms to place customers within the appropriate stage of the sales funnel. We use a conversational AI language model to interpret customer comments and link their specificity (*H1*) and personalization (*H2*) to purchase likelihood.

Choice of artificial intelligence to analyze text

The proposed hypotheses both argue that the words customers use can predict the likelihood of purchase. This would support a qualitative study where either the content of words used

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would help gain novel insights or the words would be quantified. Both methodologies have flaws and do not lend themselves to an approach where the results could be generalized to a larger population. The advent of AI LLMs has created a methodology where words can be analyzed and interpreted systematically. LLMs, such as ChatGPT, are based on the Generative Pretrained Transformer (GPT) architecture to read text and interpret it. The power of AI is that it can be trained to interpret the words that people use and then advance upon them. Examples include training AI with content so that it is able to expand on that to write stories, music and create art (Patil *et al.*, 2025). The ability to read and quantify text leverages the unique capabilities of AI and makes it an ideal tool to extract a quantitative measure from qualitative content. Specifically, AI can read communications from the customer and provide a quantitative measure of whether they are early or later in the sales funnel.

We used the machine learning model ChatGPT 4.0 to determine the specificity and personalization (degree to which the message was personalized to the firm) of customer comments. The rationale with specificity is that greater specificity would indicate that the customer is further down the sales funnel and more likely to make a purchase decision soon.

Sample

The sample was drawn from customers of a multimillion-dollar, privately held home improvement firm serving three states and headquartered in a large metropolitan area in the eastern USA. The firm specializes in interior services, such as painting, repairs, cabinetry and flooring and is generally perceived as providing superior service. It consistently receives high ratings (an average of five stars) on online review platforms, such as Angie's List and Yelp, and has an A+ rating from the Better Business Bureau. Its main competitive advantage is its focus on quality rather than price, describing its approach as a "total quality experience" that emphasizes high-quality service and workmanship throughout its dealings with each customer.

When the firm receives an inquiry, an employee is dispatched to assess the work and prepare an estimate for the customer's approval. If the estimate is not approved, the firm does not receive any compensation to offset the cost of preparing it. This highlights the importance of screening prospects, because allocating equal resources to each one can lead to overspending on those who will never buy and underspending on those most likely to become customers.

Over the past three years, customers primarily came from word of mouth or Web searches or were returning clients. Our data collection spanned from August 2023 to May 2025 and included 307 prospective customers. Each time one reached out to the firm, we received the information and compiled it in a spreadsheet. They did so via an online form (see Appendix), where they provided their contact information (name, email address, phone number and street address) and indicated how they found the firm (with options like word of mouth, web search, or previous customer). They were also given space to provide comments about the work. The form recorded the date of initial contact, and a representative followed up to schedule an estimate. Several forms completed by solicitors attempting to sell business services were discarded.

Ethical considerations of research

Information on the firm's potential customers and estimates of the work are the confidential property of the firm. This information is highly sensitive and could cause the firm financial harm if it were revealed to competitors. The firm consented to the use of its data in the hope that results would help it to improve its operations. We signed a nondisclosure agreement with the firm to ensure that none of its data would be given to external parties. All data were either given by the firm or ascertained by us (such as the number of words in the contact form). All the firm's information was kept on one author's personal computer and not shared. AQ: 8

Training artificial intelligence to interpret comments

Potential customers used the online form to describe the desired work. There were no limits on the amount of text they could submit. For example, one customer wrote, "kitchen remodel," while another provided a detailed request: "We are looking to improve our kitchen functionality and storage. Our 100-year-old house has had many hands on it over the years, including some subpar DIY work. We would like design advice and contract work to make the vital part of our house do more for us."

To analyze submitted comments, we followed the procedures outlined by Rai (2020). We first preprocessed the data to remove noise, such as names or bullet points, that might separate requests. We then used ChatGPT 4.0 to analyze the comments. It was selected because it is well-suited to identify patterns in unstructured text. Our goal was to measure the level of specificity and personalization. We hypothesized that customers who provide more specific information are further down the sales funnel and more likely to make a purchase decision soon (*H1*). Additionally, we proposed that a potential customer who crafted a personalized message to the firm was more likely to choose that firm over its competitors (*H2*).

We define specificity as the degree of detail provided by the prospective customer in their initial inquiry. Following temporal construal theory, greater specificity indicates proximity to purchase. Specificity was coded on a four-point scale (1 = very general to 4 = highly detailed) using ChatGPT 4.0.

We input our sample into the model and asked it to rate the specificity of each customer's comments. After receiving the model's scores, we provided feedback by adjusting the scores, if necessary. The rating was done primarily by one of the authors, who relied on his expertise in the home improvement sector, based on both work and academic experience, to determine specificity. For example, in our initial sample, the model rated the following comment as a 3 out of 4, but one of the authors revised it to 4 upon review:

> Small master bath needs remodeling. Only has small shower stall, no tub, toilet, and vanity. Shower needs new pan and drain, retiled, security bars, and showerhead/knobs. Tiles removed from walls (they are halfway up the wall now). New toilet. Vanity is new, never used, would like to keep and get hooked up. New exhaust fan, medicine cabinet. Floor will probably need retiling once wall tiles removed, as there will most likely be a gap. Not sure the outside wall is insulated well, so insulation may need to be applied. It was always cold in shower. Need done ASAP. Hubby has developed mobility issues and needs to use bathroom for more than just a toilet[. . .] only thing working in it at moment.

In contrast, the following comment was rated as 1, and we concurred with this score:

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> We need an estimate for repairs to our house.

To validate coding, an author with domain expertise reviewed initial scores and adjusted them where appropriate during a pretest of 25 cases. Ratings were corrected during our initial pretest to train the data set. After the initial training, the model was trained on the corrected data set and applied to the full sample ($n = 307$).

We define personalization as whether the inquiry contained firm-specific references (e.g. mentioning prior work, referrals or employee names). Personalization was coded as a binary variable (1 = personalized; 0 = not personalized). For instance, the following comment was classified as personalized:

> I received your name from a referral, XXXX. I need a contractor for a quote on fixing or replacing all my hardwood floors in a condo (1100 square feet) due to a water leak from my upstairs neighbor. The remediation is complete, and I just settled the claim with my insurance company. Now, I need to redo/fix my hardwood floors.

In contrast, the following comment was not classified as personalized:

> Need whole house exterior paint, repair any rot or damage, clean, and paint foundation. It is a large 2-story house built in 2013 and hasn't been painted since it was built.

Personalization was treated as a binary variable because only a few of the leads (fewer than 30 of the 307) provided a personalized message. The customers appeared to use language that could have been copied into multiple request forms across firms. The small sample size prevented a more nuanced approach that would allow us to measure personalization on a scale.

For both variables, coding was conducted using ChatGPT 4.0, with human oversight during the pretest to calibrate the model. This hybrid approach ensured consistency across the data set while retaining expert judgment.

Results

Our study generated two sets of outputs, specificity scores on a 1–4 scale (M = 2.84, SD = 0.91) and personalization scores coded dichotomously. After the AI platform provided specificity and personalization scores for each prospective customer, these were added to the final data set, which also included variables such as proposal amount, marketing channel (word of mouth and web search) and contact information. We also controlled for the amount of the contract and number of words in the request. All variables are listed in Table 2. T2

The analysis aimed to determine the likelihood of a customer accepting a proposal based on the specificity and personalization of their comments. Given the complexity of probability over varying times, a survival model was used; estimates were given at different times and using non-survival techniques could produce biased probabilities by counting recent estimates as rejections simply because they were issued shortly before the analysis period ended.

The most appropriate model was the accelerated failure hazard model, which allowed us to determine the impact of multiple covariates while relaxing the assumption that the probability follows a constant hazard. In professional services, the more time that passes after an estimate, the less likely the customer is to accept it. Research shows that the likelihood of acceptance increases for a few days after it is given but then starts to decline (Majid, 2021). If several weeks pass without communication, it is likely they chose another provider or decided not to proceed with the work (Majid, 2021). When the firm did not hear back within a week, it sent a follow-up email. The customer would accept the proposal, decline, say they were still considering, or not reply. If the proposal was accepted or declined, the respective date was recorded. If the customer was still considering or did not reply, the proposal was considered open. When the proposal was declined or another company chosen, the account was considered closed.

Our empirical model is as follows, and descriptive statistics are listed in Table 3: T3

$$H(t) = 1 - \begin{pmatrix} B_0(-1)(t) + B_1(WoM) + B_2(Web) + B_{43}(Specificity) + B_{54}(Personalized) \\ + B_{65}(NumbWords) + B_6(LogContract) + e_i \\ e \end{pmatrix}$$

Using our specificity and personalization scores along with control variables (proposal amount, word count, channel), we generated outputs from an accelerated hazard survival model and found that specificity significantly increased the likelihood of acceptance ($\beta = -0.474$, $p < 0.01$) while personalization was negatively associated with acceptance ($\beta = 0.469$, $p = 0.059$). Larger contract size and higher word counts were both associated with longer acceptance times.

Discussion

The results (listed in Table 4) revealed that our two variables of interest – specificity and personalization – had a significant impact on the likelihood of customer acceptance but in opposite directions. Specificity increased the likelihood of acceptance the day after receiving the estimate; with the expected time to acceptance being 1.42 days, *H1* was supported. In contrast, personalized comments were associated with a decreased likelihood of acceptance, with an expected time to acceptance of 3.66 days. *H2*, which argued that personalization in initial messages is associated with a longer delay before booking and decreases the probability of purchase, was also supported. The finding that personalization decreased customer acquisition supported our argument that those who use it are higher up in the sales funnel. They may reach out to the firm first due to recommendations from others and then add firms as they progress through the funnel. The firm in our study is known for its high-quality services but also charges higher-than-average prices, which may dissuade customers as they move down the funnel. T4

The estimated time for acceptance based on the marketing channel was 4.67–8.32 days. The contract amount also negatively impacted acceptance probability after the first day. This is unsurprising given that the larger the project, the more time the customer needs to consider the purchase. These results suggest that specificity increases short-term acceptance probability.

We conducted multiple robustness checks to confirm our results. Multicollinearity was tested; the VIF for all variables was below 5, which indicates no significant issues with multicollinearity. We also performed a logistic regression to predict customer acceptance and found that our main variables of interest had a significant impact on it: specificity increased it ($B_5 = 0.71$, $p < 0.01$), while personalization had a negative impact ($B_4 = -0.49$, $p = 0.059$).

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Table 2 Variable key

Abbreviation	Variable explanation	Source
WoM	If the primary sales channel was word of mouth; a binary variable, 1 or 0	Customer input on form
Web	If the primary sales channel was an internet search; a binary variable, 1 or 0	Customer input on form
NumbWords	A count of the variables that the prospective customer used to describe the work that they wanted the firm to do	Customer input on form
Personalized	A binary variable, 1 or 0, based on if the comments were deemed to contain information that was specific to the firm (For example, the following customer was determined to have submitted a personalized message: "You did some work for the owners here a few years ago, and they recommended you to me. I am their tenant, and we are preparing to move out on July 5th. We need to do some repair work on the house before the move-out inspection by the owners - mostly drywall work and painting. Can we set up an appointment for you to come to the house and give us an estimate? Thanks")	AI-trained machine learning algorithm
Specificity	If the comments provided to the firm were deemed to contain specific information; scaled on a score of 1–4, with 4 being the greatest degree of specificity. The following comment was given a score of 4: "Hi, we spoke with company a couple years ago for a project, but we weren't ready to pull the trigger then. We're ready to move forward now and want to get an estimate. We also have two additional projects that we'd like to throw in. A description of all 3 projects are as follows: 1. Wainscotting for our stairwell and adjacent wall. (Your team did a great job for one of our neighbors which you feature on your website and we're looking to do something very similar). 2. Custom built-in bookshelves for the living room. 3. Interior sliding glass doors and glass wall panels for two area ways into the living room. Thanks" The following comments were given a score of 1: "Kitchen and bathroom remodels")	AI-trained machine learning algorithm
LogContract	The natural logarithm of the contract (proposed amount for the requested services) so that the range of values could be condensed for interpretation (The lowest proposed amount was $445; the highest was $161,100. The average was $32,627.)	Home improvement firm, usually a single estimator employed by the firm

Source(s): Authors' own work

Table 3 Descriptive statistics and Pearson correlation coefficients for analysis of customer acquisition

					($n = 307$, level of significance below correlation coefficient)							
Variable	**Mean**	**SD**	**Min.**	**Max.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. WoM	0.887	0.051	0.726	0.943		−0.201	−0.161	−0.264	−0.232	−0.118	0.127	−0.305
						<0.001	*<0.001*	*<0.001*	*<0.001*	*<0.05*	*<0.01*	*<0.001*
2. Website	3.841	0.161	3.546	4.317			0.232	0.849	0.671	0.228	0.483	0.601
							<0.001	*<0.001*	*<0.001*	*<0.001*	*<0.001*	*<0.001*
3. Specificity	0.514	0.266	0	1				0.313	0.195	−0.040	−0.232	0.315
								<0.001	*<0.001*	0.347	*<0.001*	*<0.001*
4. Personalized	4.602	0.228	4.190	5.077					0.883	0.261	0.425	0.666
									<0.001	*<0.001*	*<0.001*	*<0.001*
5. Number of Words	4.133	0.413	2.954	4.816						0.448	0.883	0.195
										<0.001	*<0.001*	<0.001
6. LogContract	3.693	1.656	0	5.802							0.303	0.109
											<0.001	*<0.01*

Source(s): Authors' own work

Table 4 Likelihood of customer acceptance of proposal over time

Parameter	Estimate	Std error	LL95%	UL95%	Increase in Probability Above Baseline at Time (1)	Expected time to accept proposal based on covariate (in days)
Intercept	0.828	0.089	0.670	1.023		2.29
WoM	1.130	0.370	0.404	1.855	−67.7%	7.09
Website	0.713	0.448	−0.165	1.591	−51.0%	4.67
Specificity	−0.474	0.188	−0.842	−0.106	60.6%	1.42
Personalized	0.469	0.253	−0.027	0.965	−37.4%	3.66
Number of words	1.291	0.429	0.449	2.132	−72.5%	8.32
LogContract	0.905	0.263	0.390	1.420	−59.6%	5.66
Scale	1					

Note(s): Log-Likelihood = −172.8019, df = 8, AIC = 361.6039
Source(s): Authors' own work

Theoretical contribution

While temporal construal theory has been widely used to explain how customers perceive events at varying temporal distances (Fujita *et al.*, 2006; Trope and Liberman, 2003), its application has been largely confined to domains such as health behavior, goal pursuit and advertising framing. This article extends the theory into the domain of professional services and customer acquisition by suggesting that the level of specificity in customer communication reflects temporal proximity to the purchase decision. Specifically, as customers move closer to the point of purchase, they tend to describe their needs with greater specificity – consistent with a low-level construal of imminent decisions. This novel application provides theoretical evidence that language can serve as a behavioral cue for temporal distance in the service purchase context.

Models of the customer journey recognize that individuals move from awareness to purchase through a funnel-like process (Tueanrat *et al.*, 2021). However, few studies have proposed observable, scalable indicators of a customer's position within that funnel based on their *own language*. This research contributes to theory by demonstrating that linguistic cues – specificity – can function as reliable markers of a customer's stage in the funnel. The use of AI to extract these cues from unstructured communication introduces a methodological innovation that bridges text analysis and customer behavior theory.

Additionally, the explanation for why the cost of customer acquisition is higher than retention is rooted in the theory of asymmetry. Potential customers know their true likelihood of purchasing from the firm, while the firm must do its best to identify them and appeal to them appropriately. In the realm of professional services, potential customers may contact three firms but only choose one; each firm treats each one equally, which causes at least two of those firms to incur costs without any corresponding revenue. To reduce this asymmetry, firms can rely on marketing channels (such as word of mouth or online reviews) as signals that indicate the likelihood of purchase (Lemon and Verhoef, 2016). If a potential customer invests time and effort by learning more about the firm, then they signal a greater purchase likelihood. The results of our study indicate that specificity can also act as a relevant signal. If a customer is willing to explain the specifics of what they are looking for, then this level of effort can be used to reduce the asymmetry between firms (who have less information) and customers (who have more).

Managerial implications

Professional service firms often face high customer acquisition costs due to the need to generate personalized proposals without any guarantee of conversion. This challenge is amplified because customers often solicit estimates from multiple firms, even when they may have already formed preferences. Our study offers several actionable insights for managers seeking to optimize acquisition efforts and reduce resource waste.

It is well established that consumers move through a sales funnel from awareness to purchase. This research demonstrates how AI – specifically LLMs, such as ChatGPT – can be used to analyze unstructured text from prospective customers and identify linguistic signals (e.g. specificity) that correlate with stage of the funnel. Our findings suggest that AI-enabled linguistic analysis can help managers quantify stages of the marketing funnel, moving beyond intuition-driven lead management. By scoring customer inquiries on specificity, firms can assign prospects to earlier or later funnel stages and adjust their resource allocation accordingly. This allows firms to reduce sunk costs on low-probability leads and potentially reallocate those resources to higher-value opportunities. Quantification of the sales funnel enables managers to monitor funnel health using specificity-weighted metrics, such as conversion rates by funnel stage, thus providing a more precise basis for decision-making and resourced organization.

Traditionally, many service firms rely on a "more leads equal more sales" mindset. However, the findings suggest that not all leads are equal. Specificity in customer inquiries served as a strong predictor of short-term acceptance, reinforcing the idea that *quality of intent* matters more than quantity of contacts. Managers should be encouraged to shift from viewing acquisition as a volume-driven process to managing it as a quality and stage-based pipeline.

Interestingly, the study found that personalization – although often assumed to signal customer intent – did not predict higher conversion and, in fact, corresponded with a longer time to acceptance. This counterintuitive finding highlights the importance of data-driven insight over intuition. Managers should be cautious about over-indexing on personalization

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without supporting indicators of purchase intent (e.g. project detail, timing, budget). Instead, personalization might indicate broader exploration rather than imminent commitment.

Firms with digital inquiry forms and CRM can integrate AI scoring tools into their workflows. For example, when a new inquiry is submitted, a backend AI system could assign a specificity score and flag high-priority prospects for expedited follow-up. Over time, firms could train their models further by using historical conversion data to refine these scores and potentially predict not only likelihood but also time to conversion or project value.

Limitations and future research

While this study offers promising insights into the use of AI for predicting customer acquisition in professional services, several limitations should be acknowledged, which in turn offer avenues for future research. The study was conducted in the home improvement sector, where it is common for prospective clients to submit detailed, unstructured text outlining their service needs. This setting lends itself well to AI-based text analysis. However, the findings may not be generalizable to other professional service industries where customer interaction is more structured, transactional or real time (e.g. legal consultations, transportation or health services); communication may not be initiated in writing or may occur too late in the customer journey to be useful for predictive modeling. Research should examine whether similar models can be developed for sectors with more limited or differently structured pre-purchase communication.

Another weakness was our inability to measure personalization at a more granular level. We had fewer than 30 customers provide a personalized request. This is not unexpected, as tools that allow consumers are readily available to reduce the time required to complete a form. For example, they can copy their requests and auto-populate their address and contact information. The ease of communication may limit how many take the time to personalize their messages.

The AI platform (ChatGPT 4.0) provides powerful text interpretation capabilities, but AI models themselves are evolving rapidly. Newer models may offer greater interpretability or alternative approaches to measuring customer intent that are more nuanced or domain-specific. Research should consider how different AI architectures (e.g. fine-tuned or industry-specific models) compare in their ability to detect signals of intent and how explainability frameworks (e.g. SHAP or LIME) can be used to build managerial trust in AI-driven predictions.

This study primarily focused on short-term acquisition – specifically, whether a customer accepted a proposal shortly after receiving it. However, some customers with low specificity or delayed responses may convert later. Our survival analysis accounts for variable timing, but follow-up beyond the study's time horizon may reveal delayed purchases or secondary factors (e.g. seasonal trends or budget cycles). Longitudinal studies could provide insight into whether linguistic cues also predict longer-term conversion or customer lifetime value.

Conclusion

Customers respond differently to marketing appeals depending on their stage in the sales funnel. At the top, appeals that help customers identify a need may be particularly impactful. As customers move closer to a purchase decision, they may be more influenced by details such as seller ratings, promotional offers, or the speed of service delivery. Understanding where customers are in the sales funnel allows firms to optimize their marketing efforts. For instance, customers further from purchasing may be more interested in learning about service quality, while those closer to purchasing may prioritize delivery speed.

This study provides insights into how an LLM based on GPT architecture, such as ChatGPT, can be used to analyze customers' comments to assess their position in the sales funnel. The language model can identify keywords or phrases associated with each stage, such as "I'm curious about [. . .]" Moreover, ChatGPT can analyze the broader context of comments, including budgetary constraints or timing. By using an LLM, firms – especially service firms – can personalize their marketing strategies and ultimately increase conversions by addressing customer needs at each stage of their journey.

Theoretically, this work extends temporal construal theory into the domain of customer acquisition, showing that linguistic concreteness can reflect purchase readiness. Managerially, it offers a scalable and data-driven approach to qualifying leads, moving firms beyond intuition and toward evidence-based customer engagement. While personalization was not predictive of short-term conversion as hypothesized, this unexpected result suggests further complexity in how customers interact with service providers – and invites deeper investigation into the role of messaging nuance. As AI models evolve, their potential to support service-based firms in decision-making will only expand. Future work should test these findings across diverse sectors, refine the interpretation of personalization and explore long-term outcomes, allowing researchers and practitioners alike to harness AI to not only predict customer behavior but also better understand the intent behind customers' words. AQ: 9

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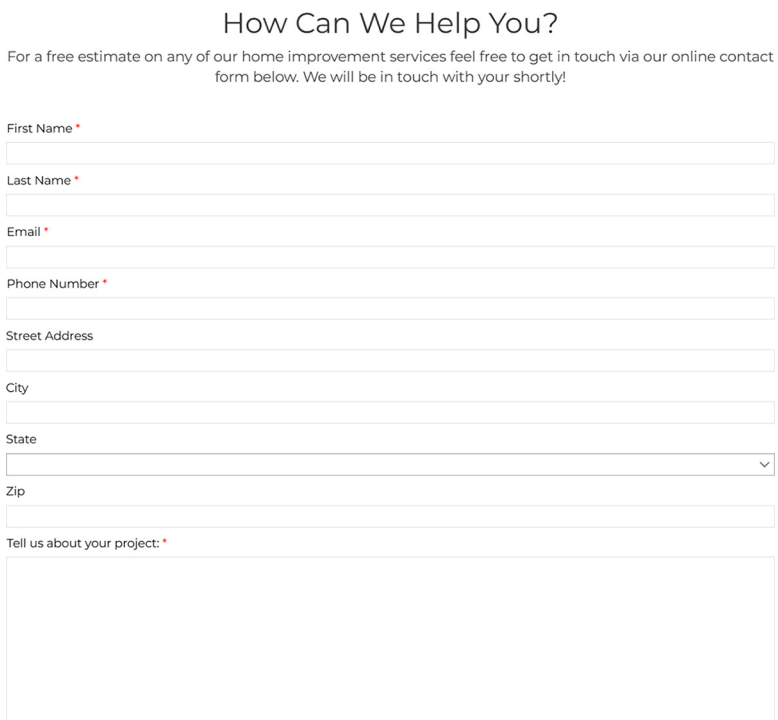
Fa1 **Appendix. Customer form**



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