Decoding Sales Success:

Language, Hiring, and Key Performance Categories

Inauguraldissertation
zur
Erlangung des Doktorgrades
der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der
Universität zu Köln

2025

vorgelegt
von

M. Sc. Robert Alexej Münster
aus
Köln

Referent:	Prof. Dr. Werner Reinartz
Korreferent:	Prof. Dr. Hernan Bruno
Tag der Promotion:	03.06.2025

Table of Contents

List of Figures

Synopsis

Paper I: Analyzing Successful Language Styles in Inside Sales Calls

Paper II: Automated Pre-Selection of Sales Job Candidates

Paper III: Success Factors of Salespeople: A Topic Modeling Approach

List of Tables

Synopsis

Paper I: Analyzing Successful Language Styles in Inside Sales Calls

Paper II: Automated Pre-Selection of Sales Job Candidates

Paper III: Success Factors of Salespeople: A Topic Modeling Approach

List of Abbreviations

AI	Artificial Intelligence
AIC	Akaike Information Criterion
AM	Ante Meridiem
API	Application Programming Interface
B2B	Business to Business
BERT	Bidirectional Encoder Representations from Transformers
BI	Business Insider
BIC	Bayesian Information Criterion
BPM	Beats per Minute
CA	Communication Apprehension
CI	Corporate Identity
CRM	Customer Relationship Management
CV	Curriculum Vitae
DV	Dependent Variable
GPT	Generative Pre-Trained Transformer
HBR	Harvard Business Review
II	Interaction Involvement
kNN	k-Nearest Neighbors
LASSO	Least Absolute Shrinkage and Selection Operator
LDA	Latent Dirichlet Allocation
LIWC	Linguistic Inquiry and Word Count
M	Mean
NLP	Natural Language Processing
n.s.	Not Significant
PCA	Principal Component Analysis
PM	Post Meridiem
SD	Standard Deviation
SPS	Sales Performance Score

SVM	Support Vector Machine
UMAP	Uniform Manifold Approximation and Projection
US	United States
VIF	Variance Inflation Factor
WoS	Web of Science

Synopsis

1 Overview

The central objective of this cumulative dissertation is to generate novel insights on drivers of sales success. The first paper investigates the effect of unique language styles that inside sales agents apply in customer conversations. The second paper develops a multidimensional sales performance score to test the suitability of sales job candidates during the hiring process. The third paper divides key success drivers of salespeople into three major categories and identifies a gap between theoretical and practical relevance of core categories. The three papers of this dissertation make significant contributions to the field of sales and marketing research by offering novel insights on the factors that influence sales success.

Firstly, an existing body of research has examined the impact of language on sales success, focusing on both the content of what is said and the manner in which it is conveyed (e.g., Packard et al. 2018; Singh et al. 2018). However, there is a paucity of research on how the combination of these elements, that is, the concrete language style encompassing both the content and the perception of sales, affects performance outcomes [Paper I]. Secondly, sales success is frequently measured within the job by taking actual performance outcomes into account (e.g., Claro et al. 2024). An objective evaluation of sales performance prior to employment, especially for novice candidates, is imperative to substantiate a valid statement about whether a sales job candidate is suited for a sales position [Paper II]. Thirdly, an examination of sales and marketing literature reveals numerous factors that contribute to sales success. Studies and meta-analyses have conceptualized complex frameworks of these factors (e.g., Churchill et al. 1985; Rapp et al. 2006). It is imperative to categorize core success drivers into a clearly arranged number of categories and assess the theoretical relevance of certain categories in relation to the focus of practical-oriented sales managers [Paper III]. Table 1 shows an overview of the papers including the key objectives, data, and applied methods.

Table 1: Overview of Dissertation Papers

Paper	Title	Publication status	Key objectives	Data	Method
I	"Analyzing Successful Language Styles in Inside Sales Calls" *Authors:* *Robert A. Muenster* *Thomas P. Scholdra* *Werner J. Reinartz*	2nd round: *Journal of the Academy of Marketing Science*	• Investigate how different language styles used by agents in customer calls influence sales success	*Type:* • Agent-customer-call transcripts *Source:* • German insurance company	• AI-based text analysis • PCA • Binary logit regression
II	"Automated Pre-Selection of Sales Job Candidates" *Authors:* *Robert A. Muenster* *Thomas P. Scholdra* *Werner J. Reinartz*	In preparation to submit to: *Journal of Marketing*	• Develop a multidimensional score to determine sales performance before a new sales job; measuring sales performance within a chatbot • Predict suitability of sales job candidates using personal characteristics drawn from audio, video, and text data	*Type:* • Survey • Video interviews • Chatbot transcripts *Source:* • Experiment • Experiment • Chatbot application	• AI-based face emotion detection • Text mining • Audio analyses • Chatbot application • SVM classifier
III	"Success Factors of Salespeople: A Topic Modeling Approach" *Author:* *Robert A. Muenster*	Working Paper	• Classify key sales success factors into three major categories using four text classification approaches • Uncover differences in the prioritization of topics between academics and practitioners	*Type:* • Academic and practitioner articles *Source:* • Academic and practitioner journals	• Human classification • AI-based text classification • BERT Topic modeling • LDA

Notes: PCA = Principal Component Analysis; SVM = Support Vector Machine; BERT: Bidirectional Encoder Representations from Transformers; LDA = Latent Dirichlet Allocation. Robert A. Muenster made a major and substantial contribution to all three papers of this dissertation, including idea development, development of the empirical design, data collection (Paper II and III as Paper I uses a company data set), data analyses, and writing up the manuscripts.

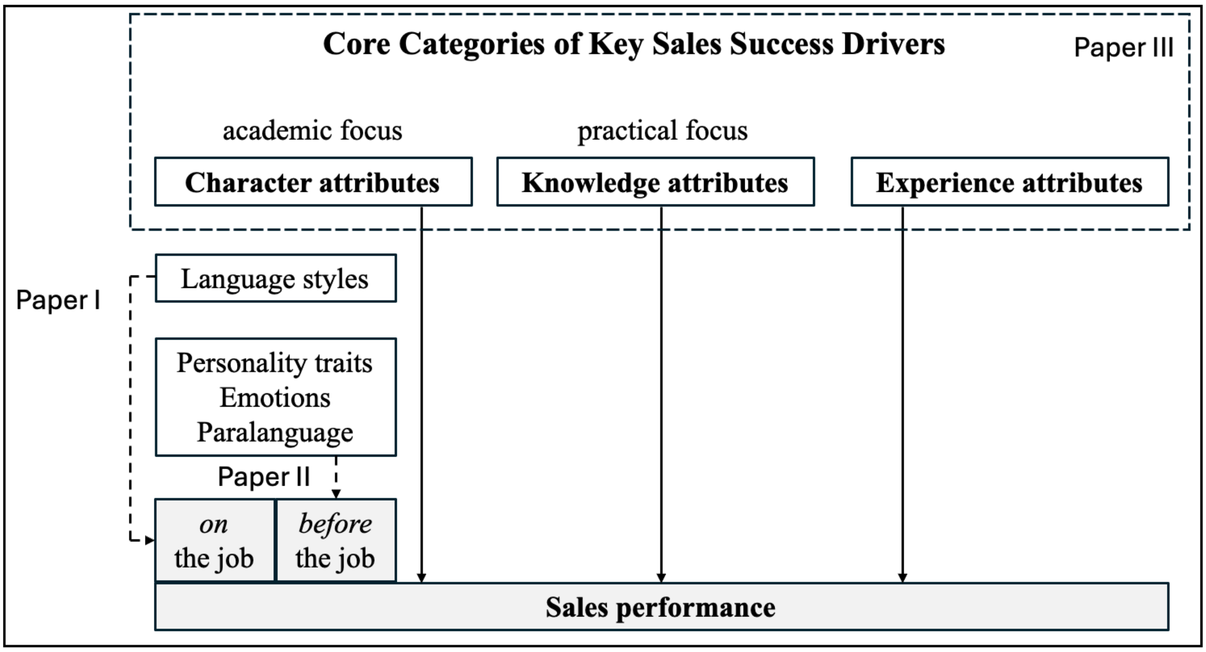
2 Introduction

Sales are irreplaceable in any company. They are responsible for selling products and services, thereby generating revenue and contributing directly to the company's success. Sales are an incremental part of the marketing mix and act as a direct interface between the company and its customers. As stated by Vinchur et al. (1998, p. 586): "Improvements in productivity, personnel, product quality, and efficiency would be pointless if the product or service could not be placed in the hands of the customer". Personal selling, whether face-to-face, hybrid, on the phone or virtually, are therefore an important pillar of the company's revenue generation and depends to a large extent on the appropriate communication of the agent (Packard and Berger 2021; 2024; Williams and Spiro 1985).

Furthermore, an efficient selection of suitable and high-performing sales personnel through the utilization of artificial intelligence (AI) and automated methods during the hiring process is a crucial concern for both recruiters and sales managers, as it is instrumental in establishing and maintaining a competitive advantage in sales (Chakraborty et al. 2024). Consequently, researchers, companies, and managers have a genuine interest in the factors that contribute to the success of salespeople, the methods for identifying them prior to employment, and the factors that enhance their performance, as they directly lead to an increase in sales and to an increase of the company's financial performance (Churchill et al. 1985; Claro et al. 2024; Verbeke et al. 2011; Vinchur et al. 1998). Figure 1 illustrates the interconnection of the three papers comprising this cumulative dissertation and how each paper will contribute to the decoding of sales success: The initial two papers consider character attributes, encompassing language styles, personality traits, emotions, and paralanguage. The third paper categorizes key salespeople's success drivers as either character-related or knowledge- and experience-related.

Paper I develops unique language styles exhibited by inside sales agents during customer interactions and examines its impact on job performance. In contrast, Paper II uncovers the performance of salespeople before the job in developing a sales performance score and using AI and automated methods for predicting the suitability of sales job candidates. Paper III uses diverse topic modeling approaches to group key sales success factors into three core categories (character, knowledge, and experience) and provides insights on which of these categories is of primary importance by either academics or practitioners.

Figure 1: Interdependencies of the Dissertation Papers



The first paper, titled "Analyzing Successful Language Styles in Inside Sales Calls," is co-authored by Robert A. Muenster, Thomas P. Scholdra, and Werner J. Reinartz. It employs a company data set comprising over 43,000 customer call transcripts and utilizes artificial intelligence (AI)-driven text analyses and the employee voice behavior framework developed by Maynes and Podsakoff (2014) to identify six distinct language styles present within these transcripts. Employing a binary logit model, the study identifies three (two) language styles that exhibit significant positive (negative) effects on the completion of contracts, contingent on the specific call. The call intent functioned as a moderator and is capable of attenuating the negative impacts of two language styles in purchase-intended (vs. inquiry-intended) calls. The study underscored the significance of language utilization in sales interactions and its impact on performance.

The second paper, titled "Automated Pre-Selection of Sales Job Candidates," is also co-authored by Robert A. Muenster, Thomas P. Scholdra, and Werner J. Reinartz. This paper proposes a multidimensional sales performance score (SPS) that is measured within an independently programmed chatbot assignment. The study's participants are 208 student sales job candidates who submitted video applications for a framed sales vacancy. These applications are analyzed with AI to extract personality traits, emotions, and paralanguage from text, audio, and video data drawn from the application videos. A Support Vector Machine (SVM) classifier model is then applied that is able to predict suitable sales job candidates with 95% accuracy. The model uses the participants' SPS and the SPS from a professional and experienced salesforce sample as a reference. This approach offers sales recruiters and managers a sophisticated solution for efficiently identifying suitable candidates during the hiring process, thereby underscoring the potential of AI in the realm of sales recruiting.

The third paper, titled "Success Factors of Salespeople: A Topic Modeling Approach" (by Robert A. Muenster), methodically groups several key success drivers that are identified in a data set of n = 224 academic publications into three core categories using four different topic modeling approaches (human, AI-based, BERT, and LDA). The same classification is conducted for a data set of n = 139 practitioner publications, observing that the priorities of academic and practitioner articles do not totally match. While academics have published the most articles on character-related topics, practitioners have published the most articles on knowledge-related topics. The study provides sales researchers with an important insight on rethinking their research priorities to better align with managerial interest regarding the success factors of salespeople and offers both researchers and practitioners a valuable overview of the most important key success drivers of salespeople.

3 Summary of Dissertation Papers

The following section summarizes the three papers of this dissertation. Each summary includes the motivation and relevance of the topic, the contribution, the main method, the key findings and the main managerial implication.

3.1 Paper I: **Analyzing Successful Language Styles in Inside Sales Calls**

Authors: Robert A. Muenster, Thomas P. Scholdra, & Werner J. Reinartz

Successful communication between sales agents and customers is fundamental for inside sales interactions. The generation of contracts via telephone is of particular importance, as the agent's language and communication style serve as the sole and primary medium of transmission. For instance, 30% of all contract completions occur via the phone in the insurance sector (Invoca 2022). Concurrently, customers exhibit a high rate of dissatisfaction with telephone calls (Moyse 2018), compelling companies to allocate billions of dollars annually to the training of their internal sales forces (Cespedes and Wallace 2017).

Given the pivotal role of language in sales, the sales and marketing literature has already explored the relationship between language and sales performance. Specifically, the content (i.e., the *what*) of language has been analyzed, including how the use of certain pronouns or words influences the performance of inside sales agents (Packard and Berger 2021; Packard et al. 2018; You et al. 2020). Conversely, the perception of language, defined as the manner in which language is expressed (i.e., the *how*), has been examined. Specifically, the extent to which positive, warm, or competent language can be employed to attain specific performance outcomes has been investigated (Li et al. 2023; Singh et al. 2018). However, there is a scantiness of research on how specific language styles, that is, the manner in which sales agents communicate, encompassing both the content of what is said and how it is said, affect the performance of inside sales agents.

Furthermore, language styles can be utilized in a highly idiosyncratic manner, exhibiting varied effects on sales success depending on the customer's call intent. Customer call occasions are not exclusively sales-driven; they can also be service-seeking (Aksin and Harker 1999; CX Today 2021; Jasmand et al. 2012). Also, daytime might be an important moderator (Crandell 2014; Park and Yi 2023) as language styles might work differently at certain times of the day. The objective of this study is to address the following three research questions: Which language styles do sales agents use in inside sales calls? Which language styles are more likely to generate sales success in inside sales calls? How does the call intent (purchase vs. inquiry) and the time of the day moderate the effect of sales agent language styles on sales success?

To address these research questions, we have examined a data set comprising more than 43,000 call transcripts from an inside sales department of a big German insurance company. The identification of unique language styles in the context of sales and marketing literature is predicated on the employee voice behavior framework developed by Maynes and Podsakoff (2014). This framework categorizes language into four distinct quadrants, contingent on the positive or negative intent underlying the language. The model is then adapted for application in the sales domain, wherein a systematic review of the extant sales and marketing literature, as well as practitioner articles, is undertaken to identify specific language dimensions employed by inside sales agents in customer interactions and their impact on sales success. This analysis yielded the identification of nearly two dozen language dimensions, which are then transformed into six distinct language styles. These styles consist of multiple language dimensions and are created using a Principal Component Analysis (PCA) (Becker et al. 2023).

The six language styles are labeled "Endorser" (e.g., empathic and helpful language dimensions), "Adviser" (e.g., friendly and positive language dimensions), "Boss" (e.g., visionary and optimistic language dimensions), "Freethinker" (e.g., intellectual and unconventional language dimensions), "Educator" (e.g., structured and philosophical language dimensions), and "Diva" (e.g., dramatic and authoritative language dimensions). To ascertain the impact of these language styles on performance, a binary logit model is specified, linking these six distinct language styles to a sales success measure. This measure is used to determine the completion of a new insurance contract in relation to a specific call (1 = yes; 0 = no). The call intent (i.e., product or inquiry) is considered an important contingency factor.

The results indicate that the language styles of the Adviser, Boss, and Educator are positively associated with sales success, while the Freethinker and Diva styles are negatively associated with sales success. Adding the call intent as a moderator to the model reveals that the negative effects on sales success of the Freethinker and the Diva can be diminished in purchase-intended calls. The Diva style has also a less-negative (more-negative) likelihood on sales success in the morning (afternoon, evening). A set of robustness checks is also conducted to substantiate these results. We also provide specific words and patterns to use or not to use within the respective language styles.

The present study makes a significant contribution to both academic literature and managerial practice by providing empirical evidence on the influence of language styles applied by inside sales agents. It offers practical recommendations for optimizing sales training, agent allocation, and hiring strategies based on communication effectiveness. Future research could expand on these findings by examining AI-based text analyses for the detection of patterns in sales language to uncover further drivers that might affect performance. Additionally, the findings could be expanded by investigating additional industries and incorporating audio-based analyses to explore the role of vocal characteristics in sales performance.

3.2 Paper II: **Automated Pre-Selection of Sales Job Candidates**

Authors: Robert A. Muenster, Thomas P. Scholdra, & Werner J. Reinartz

The identification of the most suitable candidates for sales jobs represents a pivotal challenge for sales recruiters and is of crucial importance for sales managers. The process of hiring new salespeople and their subsequent training and integration into the team can be time-consuming and a protracted and costly endeavor (LinkedIn 2024). Furthermore, sales job candidates often prioritize a seamless hiring process when making their final employment decision, and numerous sales positions remain unfilled for extended periods (Cronofy 2023; Sampat 2023). The identification of the most suitable candidates for sales jobs is a challenging, subjective process, as evidenced by expert interviews. The assessment of performance, particularly for salespeople with limited experience, poses significant challenges, and the identification of the most suitable candidates remains a substantial hurdle for both recruiters and managers. To address these challenges, this study proposes a four-stage, AI-driven framework and a Sales Performance Score (SPS) that measures multiple dimensions of sales performance to automatically pre-select sales job candidates with greater accuracy and efficiency. The overarching research question guiding this study is: How to efficiently detect a suitable salesperson during the hiring process?

A substantial amount of research has been dedicated to investigating the factors that contribute to the success of salespeople. According to the extant literature, these key success drivers encompass engagement and empathy (e.g., Mayer and Greenberg 2006; Verbeke et al. 2011), selling skills (e.g., Churchill et al. 1985; Claro et al. 2024), product knowledge (e.g., Verbeke et al. 2011), competitiveness (e.g., Plotkin 1987; Shannahan et al. 2013), persuasiveness and drive (e.g., Mayer and Greenberg 2006; Pöyry et al. 2017), communication skills and motivation (e.g., Williams and Spiro 1985; Good et al. 2022), and self-confidence (e.g., Bande et al. 2015).

Furthermore, the extant literature has identified a set of influence and selling tactics that salespeople employ in customer conversations, which also drive performance outcomes (McFarland et al. 2006; Plouffe et al. 2014; Singh et al. 2020). Next to these drivers, a strong emphasis was given to the character identification of salespeople. Among the most discussed character factors, personality traits (e.g., Barrick and Mount 1991; Hurtz and Donovan 2000, Mayer and Greenberg 2006; Satornino et al. 2023; Vinchur et al. 1998), emotions (e.g., Bande et al. 2015; Brown et al. 1997; Kidwell et al. 2021; Wang et al. 2022) and paralanguage (e.g., Downing 2011; Hecht and LaFrance 1995; Van Zant and Berger 2020) show significant correlations with sales performance outcomes.

In the four-stage AI-driven framework, a Sales Performance Score (SPS) is developed, comprising the key success factors and influence tactics of salespeople. The suitability of sales job candidates is predicted using personality traits, emotions, and paralanguage extracted from video job application videos of n = 208 student sales job candidates. The utilization of AI and automated methods enables the analysis of the Big 5 personality traits within the text, Ekman's (1999) seven basic emotions through AI face recognition within the videos, and paralanguage from audio parameters of the job application videos. The SPS is determined through an independently programmed chatbot assignment that frames a customer conversation in which the sales job candidate is tasked with selling a generic product to the bot-framed customer. The occurrence of key success drivers and influence tactics is measured by automated extraction of information and through a comparison with individually created dictionaries. A validation of the bot and a reference SPS for being a suitable sales job candidate was obtained by a sample of n = 30 professional salespeople who also conducted the assignment.

The results show that the SPS of the professional salespeople is 21.05% higher compared to the student sales job candidate sample. Using their SPS as a reference score for being suitable, a Support Vector Machine (SVM) classifier is trained using the collected character identification variables and some control variables as predictors. The model achieves an accuracy of 95%, demonstrating its effectiveness in automatically pre-select sales job candidates in either suitable or non-suitable. The study further conducts robustness checks, including logistic regression and k-Nearest Neighbors (kNN) models, confirming that the SVM classifier outperforms alternative methods.

The findings yield significant managerial and theoretical implications. Firstly, the SPS provides a comprehensive assessment of sales performance and a quantifiable metric for evaluating candidates prior to hiring, thereby reducing reliance on subjective assessments. Secondly, the incorporation of AI-driven classification models into the hiring process enables recruiters and sales managers to make data-informed decisions, ultimately reducing the time-to-hire and minimizing recruitment costs. Thirdly, the study underscores the potential for further refinement through machine learning enhancements, such as adaptive AI-driven chatbot interactions tailored to candidate responses.

3.3 Paper III: **Success Factors of Salespeople: A Topic Modeling Approach**

Author: Robert A. Muenster

Sales has the main responsibility for generating revenue in any company. Consequently, firms often employ their sales force to execute personal selling operations, leveraging the competitive advantage resulting from their salespeople's success (Claro et al. 2024). This phenomenon has prompted a sustained focus in academic sales and marketing literature on the core success factors of salespeople, as displayed in several meta-analyses (e.g., Churchill et al. 1985; Claro et al. 2024; Verbeke et al. 2011). Additionally, the Big 5 personality model has been a subject of academic discourse, with studies examining the relationship between personality traits and sales performance (e.g., Barrick and Mount 1991; Hurtz and Donovan 2000; Vinchur et al. 1998).

In addition to the noteworthy findings and success drivers identified by the articles over time, two managerial problems have been identified as contributing factors to the motivation of this paper. First, the intricacy of the drivers that are uncovered and discussed in all the articles and meta-analyses may result in ambiguity and inconsistencies in terminology and specification. This challenge is further compounded by the intricate frameworks employed in numerous studies, which seek to establish complex relationships between the numerous key success drivers and sales performance (e.g., Claro et al. 2024; Rapp et al. 2006; Szymanski 1988; Weitz et al. 1986). Secondly, a challenge emerges from the ambiguity surrounding the correspondence between the priorities derived from academic articles and those originating from practical literature streams. Given that the fundamental motivation of marketing and sales research lies in its potential to inform substantial managerial implications, it is imperative to ascertain whether the key success drivers of salespeople in academic research align with practical interests. The subsequent research questions, therefore, guide the present study: What are the core categories of sales success drivers? Do the priorities of sales success drivers match between academic and practitioner literature?

This study utilizes an extant literature review to categorize the key success drivers of salespeople into three core categories: knowledge, experience, and character. Knowledge encompasses product expertise, market awareness, and customer understanding. Experience is defined as the practical application of knowledge over time, enhancing a salesperson's ability to navigate complex sales environments. Character includes intrinsic traits, behaviors, and soft skills such as motivation, adaptability, and persuasion techniques, which influence interpersonal interactions and sales performance.

The three core categories are confirmed through the implementation of a topic modeling approach, which utilizes a combination of human and AI-based classification techniques. The integration of human and AI-assisted classification with two distinct topic modeling approaches, the Bidirectional Encoder Representations from Transformers (BERT) and Latent Dirichlet Allocation (LDA), facilitates a comprehensive analysis of a data set comprising 224 academic research articles. This analysis aims to elucidate the core categories of sales success drivers that the data set addresses.

The results indicate that, on average, 74.78% of the articles were classified into the character dimension of sales success drivers, 37.5% into the knowledge dimension, and 12.06% into the experience dimension. Furthermore, the relative shares of articles belonging to these dimensions are consistent across most methods, with the exception of the LDA classification, which yielded the most divergent results.

In a subsequent step, the same four topic modeling approaches are implemented for a data set of 139 practitioner articles dealing with key success drivers of salespeople. The results reveal a different distribution, with an average of 65.29% of the practitioner articles classified into the character dimension, 77.34% into the knowledge dimension, and 24.46% into the experience dimension. Of the methods, BERT topic modeling yielded the least accurate results compared to the overall averages. These analyses explore differences in emphasis between academic and practitioner literature. Academic research tends to prioritize character-related attributes, focusing on personality traits, behavioral tendencies, and psychological aspects of sales performance. In contrast, practitioner literature, in which character-related articles are also commonly addressed, predominantly highlights knowledge-related factors, particularly sales techniques, product expertise, and strategic information transfer. Experience, while recognized as a key component of sales effectiveness, receives comparatively less attention in both academic and practitioner domains.

In addition to classification, the study examines publication trends over time. The findings indicate that character-related research has grown significantly in academia, while knowledge-focused articles have gained traction in practitioner literature. Experience-related research remains the least explored dimension across both domains.

A thorough sentiment and citation analysis further accentuates the divergence between academic and practical domains. Academic articles addressing character-related factors exhibit higher average citation counts, signifying robust scholarly interest in the psychological and behavioral facets of sales performance. In contrast, knowledge-based practitioner articles garner greater averaged readership and social media engagement, reflecting managerial priorities in skill development and training. The study's semantic similarity analysis reveals that the alignment between academic and practitioner texts is limited, suggesting a gap between theoretical research and practical application in sales management.

The present study makes notable contributions to the extant literature. Firstly, it offers a systematic classification of sales success factors, thereby demonstrating the divergence between academic and practitioner priorities. Secondly, it highlights the need for future research to bridge this gap by integrating knowledge- and character-related insights into holistic sales training frameworks. From a managerial perspective, the findings emphasize the importance of balancing technical skills with behavioral competencies in hiring and training salespeople. Furthermore, the study proposes that artificial intelligence (AI)-driven text analysis methods, such as BERT and LDA, can serve as valuable tools for deriving actionable insights from extensive text corpora in sales research.

4 References Synopsis

Aksin, O. Z., & Harker, P. T. (1999). To Sell or Not to Sell: Determining the Trade-offs Between Service and Sales in Retail Banking Phone Centers. Journal of Service Research, 2 (1), 19–33.

Bande, B., Pilar, F.-F., Varela, J. A., & Jaramillo, F. (2015). Emotions and salesperson propensity to leave: The effects of emotional intelligence and resilience. Industrial Marketing Management, 44, 142–153.

Barrick, M. R., & Mount, M. K. (1991). The Big Five Personality Dimensions and Job Performance: A Meta-Analysis. Personnel Psychology, 44, 1–26.

Becker, M., Scholdra, T. P., Berkmann, M., & Reinartz, W. J. (2022). The Effect of Content on Zapping in TV Advertising. Journal of Marketing, 87 (2), 275–297.

Brown, S. P., Cron, W. L., & Slocum Jr., J. W. (1997). Effects of Goal-Directed Emotions on Salesperson Volitions, Behavior, and Performance: A Longitudinal Study. Journal of Marketing, 61, 39–50.

Cespedes, F. V., & Wallace, C. (2017). Executives and Salespeople Are Misaligned - and the Effects are Costly. Retrieved August 15, 2023 from https://hbr.org/2017/01/executives-and-salespeople-are-misaligned-and-the-effects-are-costly

Chakraborty, I., Chiong, K., Dover, H., & Sudhir, K. (2024). Can AI and AI-Hybrids Detect Persuasion Skills? Salesforce Hiring with Conversational Video Interviews. Marketing Science, 44 (1), 30–53.

Churchill, G. A., Ford, N. M., Hartley, S. W., & Walker, O. C. (1985). The Determinants of Salesperson Performance: A Meta-Analysis. Journal of Marketing Research, 22, 103–118.

Claro, D. P., Ramos, C., & Palmatier, R. W. (2024). Dynamic and global drivers of salesperson effectiveness. Journal of the Academy of Marketing Science, 52, 399–425.

Crandell, C. (2014). Wednesday At Lunch Time Is Best Time for Prospecting Calls. Retrieved March 20, 2025 from https://www.forbes.com/sites/christinecrandell/2014/01/18/wednesday-at-lunch-time-is-best-time-for-prospecting-calls/

Cronofy (2023). Interview Scheduling: Candidate expectations, frustrations, and preferences. Retrieved July 12, 2024 from https://www.cronofy.com/reports/candidate-expectations-report-2023

CX Today (2021). What is the Difference between Sales and Service Call Durations. Retrieved July 17, 2024 from https://www.cxtoday.com/contact-centre/what-is-the-difference-between-sales-and-service-call-durations/

Downing, J. R. (2011). Linking Communication Competence with Call Center Agents' Sales Effectiveness. Journal of Business Communication, 48 (4), 409–425.

Ekman, P. (1999). Basic Emotions. In T. Dalgleish & M. J. Power (Eds.), Handbook of cognition and emotion (pp. 45-60). Hoboken, NJ: John Wiley & Sons.

Good, V., Hughes, D. E., Kirca, A. H., & McGrath, S. (2022). A self-determination theory-based meta-analysis on the differential effects of intrinsic and extrinsic motivation on salesperson performance. Journal of the Academy of Marketing Science, 50, 586–614.

Hecht, M. A., & LaFrance, M. (1995). How (Fast) Can I Help You? Tone of Voice and Telephone Operator Efficiency in Interactions. Journal of Applied Social Psychology, 23 (23), 2086–2098.

Hurtz, G. M., & Donovan, J. J. (2000). Personality and Job Performance: The Big Five Revisited. Journal of Applied Psychology, 85 (6), 869–879.

Invoca (2022). Customer Experience Expectations In the Face of Inflation, Retrieved November 4, 2022 from https://experience.invoca.com/2022-invoca-buyer-experience-report/p/1

Jasmand, C., Blazevic, V., & de Ruyter, K. (2012). Generating Sales While Providing Service: A Study of Customer Service Representatives' Ambidextrous Behavior. Journal of Marketing, 76, 20–37.

Kidwell, B., Hasford, J., Turner, B., Hardesty, D. M., & Zablah, A. R. (2021). Emotional Calibration and Salesperson Performance. Journal of Marketing, 85 (6), 141–161.

Li, X., Hsee, C. K., & O'Brien, E. (2023). "It Could Be Better" Can Make It Worse: When and Why People Mistakenly Communicate Upward Counterfactual Information. Journal of Marketing Research, 60 (2), 1–18.

LinkedIn (2024). The Costs and Challenges of Recruiting Sales Professionals. Retrieved from July 9, 2024 from https://www.linkedin.com/pulse/costs-challenges-recruiting-sales-professionals-neal-tricarico-22v7c/

Mayer, D., & Greenberg, H. M. (2006). What makes a good salesman. Harvard Business Review, 84, 164–171.

Maynes, T. D., & Podsakoff, P. M. (2014). Speaking More Broadly: An Examination of the Nature, Antecedents, and Consequences of an Expanded Set of Employee Voice Behaviors. Journal of Applied Psychology, 99 (1), 87–112.

McFarland, R. G., Challagalla, G. N., & Shervani, T. A. (2006). Influence Tactics for Effective Adaptive Selling. Journal of Marketing, 70, 103–117.

Moyse, I. (2018). The Phone is Dead, Long Live the Phone. Retrieved July 1, 2024 from https://www.uctoday.com/meeting-rooms-and-devices/the-phone-is-dead-long-live-the-phone/

Packard, G., Moore, S. G., & McFerran, B. (2018). (I'm) Happy to Help (You): The Impact of Personal Pronoun Use in Customer–Firm Interactions. Journal of Marketing Research, 55 (4), 541–555.

Packard, G., & Berger, J. (2021). How Concrete Language Shapes Customer Satisfaction. Journal of Consumer Research, 47 (5), 787–806.

Packard, G., Li, Y., & Berger, J. (2024). When Language Matters. Journal of Consumer Research, 51 (3), 634–653.

Park, Y., & Yi, Y. (2023). Morning deals make me feel smart: Consumer evaluations of online sales promotions differ by time of day. Journal of Retailing and Consumer Services, 73, 1–8.

Plotkin, H. M. (1987). What makes a successful salesperson? Training and Development Journal, 54–56.

Plouffe, C. R., Bolander, W., & Cote, J. A. (2014). Which influence tactics lead to sales performance? It is a matter of style. Journal of Personal Selling and Sales Management, 34 (2), 141–159.

Pöyry, E., Parvinen, P., & McFarland, R. G. (2017). Generating leads with sequential persuasion. Journal of Personal Selling and Sales Management, 37 (2), 89–99.

Rapp, A., Ahearne, M., Mathieu, J., & Schillewaert, N. (2006). The impact of knowledge and empowerment on working smart and working hard: The moderating role of experience. International Journal of Research in Marketing, 23, 279–293.

Sampat, S. (2023). 20 Statistics You Need to Know Before Hiring Your First Salesperson. Retrieved July 9, 2024 from https://smith.ai/blog/20-statistics-you-need-to-know-before-hiring-your-first-salesperson

Satornino, C. B., Allen, A., & Bolander, W. (2023). Understanding the Performance Effects of "Dark" Salesperson Traits: Machiavellianism, Narcissism, and Psychopathy. Journal of Marketing, 87 (2), 298–318.

Shannahan, K. L. J., Bush, A. J., & Shannahan, R. J. (2013). Are your salespeople coachable? How salesperson coachability, trait competitiveness, and transformational leadership enhance sales performance. Journal of the Academy of Marketing Science, 41, 40–54.

Singh, S., Marinova, D., Singh, J., & Evans, K. R. (2018). Customer query handling in sales interactions. Journal of the Academy of Marketing Science, 46, 837–856.

Singh, S. K., Marinova, D., & Singh, J. (2020). Business-to-Business E-Negotiations and Influence Tactics. Journal of Marketing, 84 (2), 47-68.

Szymanski, D. M. (1988). Determinants of Seling Effectiveness: The Importance of Declarative Knowledge to the Personal Selling Concept. Journal of Marketing, 52, 64–77.

Van Zant, A. B., & Berger, J. (2020). How the Voice Persuades. Journal of Personality and Social Psychology: Interpersonal Relations and Group Processes, 118 (4), 661–682.

Verbeke, W., Dietz, B., & Verwaal, E. (2011). Drivers of sales performance: a contemporary meta-analysis. Have salespeople become knowledge brokers? Journal of the Academy of Marketing Science, 39, 407–428.

Vinchur, A. J., Schippmann, J. S., Switzer, III, F. S., & Roth, P. L. (1998). A Meta-Analytic Review of Predictors of Job Performance for Salespeople. Journal of Applied Psychology, 83 (4), 586–597.

Wang, X., Jiang, M., Han, W., & Qiu, L. (2022). Do Emotions Sell? The Impact of Emotional Expressions on Sales in the Space-Sharing Economy. Production and Operations Management, 31 (1), 65–82.

Weitz, B. A., Sujan, H., & Sujan, M. (1986). Knowledge, Motivation, and Adaptive Behavior: A Framework for Improving Selling Effectiveness. Journal of Marketing, 50 (4), 174–191.

Williams, K. C., & Spiro, R. L. (1985). Communication Style in the Salesperson Customer Dyad. Journal of Marketing Research, 22, 434–442.

You, Y., Yang, X., Wang, L., & Deng, X. (2020). When and Why Saying “Thank You” Is Better Than Saying “Sorry” in Redressing Service Failures: The Role of Self-Esteem, Journal of Marketing, 84 (2), 133–150.

Paper I: Analyzing Successful Language Dimensions in Inside Salls Calls

Authors: Robert Muenster, Thomas Scholdra, and Werner Reinartz

Abstract

Language plays a critical role in sales, with effective communication determining whether a customer makes a purchase. Language is especially important in inside sales, in which clear communication over the phone is vital for providing information, solving problems, and closing sales. In this study, we use artificial intelligence–driven text analysis to examine the language styles of inside sales agents, analyzing 43,619 transcripts of sales calls from a leading German insurance company. From these data, we identify six language styles agents use and investigate their relationship to sales success. The results show that three styles are positively associated with sales while two are negatively associated. In addition, the call's intent (either purchase or inquiry) plays a key role in moderating these effects. Specifically, the negative impact of two language styles on sales success is mitigated in purchase-intended calls. Additionally, daytime is included as another moderator and significantly influences effects of language styles on sales success. These insights highlight the importance of language in shaping sales outcomes.

Keywords *Inside sales, Sales calls, Language styles, Sales success*

1 Introduction

Successful communication between sales agents and customers is fundamental for inside sales interactions (i.e., selling products or services remotely). When reaching out to companies, 76% of customers still prefer to use the phone over other means (CFI Group 2020). In addition, inside sales agents on the phone are responsible for 20% (in the travel industry) to 30% (in insurance) of all completed transactions (Invoca 2022). Therefore, inside sales is a vital driver of a company's revenue. Despite these statistics, however, 85% of all customers and prospects are dissatisfied with the inside sales agent conversation (Moyse 2018). To try to counteract this negativity, companies invest billions of dollars in the training of their internal sales forces each year (Cespedes and Wallace 2017). Moreover, replacing a sales agent costs an average of US$115,000, making finding and retaining the best sales agents crucial (Maestro 2017).

Successful inside sales agents must consequently be convincing and perform well on the phone. According to Nancarrow and Penn (1998, p. 14), “on the telephone the only cues available will be vocal or language used”. In other words, the language used in inside sales interactions is a decisive factor for performance outcomes. For decades, theory and practice have tried to determine sales agent attributes that increase sales performance and differentiate successful from less successful agents (e.g., Churchill et al. 1985; Claro et al. 2024; Verbeke et al. 2011). Communication skills, language use, and their effects on performance outcomes are among the most discussed sales agent attributes (e.g., Pace 1962; Webster 1968; Williams and Spiro 1985). Although some elements of language and communication have already been investigated and provide valuable insights for sales research, there are some gaps in the literature that this study aims to address.

First, the sales and service literature has analyzed the effects of specific content of agent language, such as specific questions (Castleberry et al. 1999), pronouns (Packard et al. 2018), concreteness in language (Packard and Berger 2021), precise words such as "thank you" and "sorry" (You et al. 2020), and upward counterfactual information (Li et al. 2023). In addition to the content of the messages, the manner in which agents communicate with customers has been examined, including the use of sensation words such as warmth and competence (Singh et al. 2018), the use of emoticons (Li et al. 2019), and paralanguage in terms of tone, pitch, and speed of speech (Hecht and LaFrance 1995; Peterson 1995; Van Zant and Berger 2020). Park and Yi (2023) also investigated when, i.e., at what time of the day, agent language works best. However, these studies only examine individual components and lack a holistic view of language. A holistic view of language is necessary because language is always used with all its facets and not just with single components (McConnell 2023). To address this critical gap in the literature, we develop a novel framework for understanding the impact of unique language styles on sales agent success. In this work, we define language style as the specific manner in which sales agents communicate, encompassing both "what" (i.e., content) is said and "how" (i.e., perception) it is said.

Second, a considerable number of the aforementioned studies utilize various metrics of sales performance, including customer satisfaction, purchase intention, purchase behavior, and customer interest (e.g., Li et al. 2023; Packard et al. 2018, 2021; Singh et al. 2018; You et al. 2020). As Bolander et al. (2021, p. 462) note, sales performance is a dependent variable of "extreme academic and managerial interest". However, there exists significant variation in the operationalization of sales performance. We utilize sales success as a concrete and specific outcome-based performance measure (see Anderson and Oliver 1987) that indicates if an agent sold a product (i.e., insurance in our context) to the customer with respect to a specific call.

Third, we address another literature gap by distinguishing the effectiveness of language styles between conversational situations in which these styles might be more or less effective. Customer call occasions are mainly not only sales-driven but also may be service-seeking (i.e., the dominant call foci are purchase- and inquiry-related) (Aksin and Harker 1999; CX Today

2021; Jasmand et al. 2012). Consequently, an inside sales agent must be capable of handling service requests, which often necessitate distinct customer management and agent operations (Ahearne et al. 2007). Moreover, cross-selling and converting service requests into sales attempts are prevalent practices in inside sales departments (Yu et al. 2013). Next to the call intent, the time of day at which certain language styles are used can influence sales success (Crandell 2014; Park and Yi 2023). Thus, we aim to answer the following three research questions:

1: Which language styles do sales agents use in inside sales calls?

2: Which language styles are more likely to generate sales success in inside sales calls?

3: How does the call intent (purchase vs. inquiry) and the time of day moderate the effect of sales agent language styles on sales success?

To address these questions, we first rely on Maynes and Podsakoff's (2014) *employee voice behavior framework* and identify four language styles. We then scrutinize related literature to identify language dimensions (e.g., goal-oriented, aggressive, empathic) sales agents use that have an effect on performance. We next collect data from 43,619 transcripts of sales agent–customer conversations from an inside sales department of a large German insurance company. We use artificial intelligence– (AI-) supported text analysis to differentiate between these language dimensions in the transcripts. We condense these language dimensions into six distinctive language styles that cover the language of inside sales agents holistically and fit into the employee voice behavior framework. Finally, we specify an empirical model that links these six distinct language styles to a sales success measure which determines the completion of a new insurance contract in respect to a certain call. We consider the call intent (i.e., product or inquiry) and the daytime as important contingency factors.

With our findings, we make three important contributions. First, we conceptually derive several language dimensions and empirically test the occurrence of unique language styles in inside sales calls. We confirm that sales agent language styles can be allocated to the employee voice behavior framework and can be intended both positively and negatively (Maynes and Podsakoff 2014). With language styles that consist of several dimensions, we cover the language of sales agents holistically and contribute to theoretical knowledge that previously investigated single components of content or perception of language (Packard and Berger 2018; Singh et al. 2018; You et al. 2020).

Second, we contribute to the literature of sales agent success factors and their impact on performance (Verbeke et al. 2011; Claro et al. 2024). We show that the novel language styles directly affect sales success in terms of the completion of new contracts, an important outcome-based performance criterion (Anderson and Oliver 1987; Bolander et al. 2021). Three language styles show positive effects, and two language styles show negative effects on this outcome.

Third, we offer the important insight that the language of sales agents per se can be decisive for performance and exert different effects depending on the call intent. This is a significant and novel contribution to the theoretical sales knowledge by investigating the influence of language styles of the same inside sales agents across contexts in purchase-intended and inquiry-intended situations. Language styles that have negative effects in service-related calls can still be advantageous in product-related calls. The time of day can also increase or decrease the impact of individual language styles on performance. This means that managers need to analyze their agents' language, train them in the most appropriate style and allocate them according to call occasions and time intervals. We identify concrete words and phrases that characterize a certain language style and also words that should be avoided for positive performance.

2 Literature Review

2.1 Studies on Agent Attributes and Sales Performance

In selling situations, sales agents interact directly with existing and potential customers. Several studies in this stream of research show that agents' personal attributes and characteristics play a pivotal role in the sales process (see Appendix Table A1). Multiple meta-analyses generalize the relationship between different agent attributes and performance metrics (e.g., Barrick and Mount 1991; Churchill et al. 1985; Claro et al. 2024; Good et al. 2022; Verbeke et al. 2011; Vinchur et al. 1998). One group of studies focuses on job-related sales force skills as drivers of sales performance. These skills include listening (e.g., Aggarwal et al. 2005; Itani et al. 2019), adaptive selling (e.g., Pettijohn et al. 2000; Spiro and Weitz 1990; Verbeke et al. 2011), presentation (Johlke 2006; Sparks and Areni 2002), and communication (e.g., Boorom et al. 1998; Pace 1962; Williams and Spiro 1985).

A second group of studies considers different behavioral concepts of salespeople and their relationship to job performance. Specific behavioral concepts describe beliefs, patterns, or actions that are externally stimulated but not reflected in personality traits (Parincu 2023). These can include concepts such as motivation (e.g., Barrick et al. 2002; Churchill et al. 1985; Good et al. 2022; Plotkin 1987), goal orientation (e.g., Brown et al. 1998; VandeWalle and Brett 1999), self-esteem (e.g., Bagozzi 1978; Ferris et al. 2010), humor (Lussier et al. 2017), and persistence (Chaker et al. 2018).

The third group of studies investigates agent-specific personality traits and their relationship to sales performance. These include the Big 5 personality traits extraversion, agreeableness, openness to experience, conscientiousness, and neuroticism (e.g., Barrick and Mount 1991; Conte and Gintoft 2005; Hurtz and Donovan 2000; Vinchur et al. 1998), but also empathy (Agnihotri and Krush 2015; Dawson et al. 1992; Mayer and Greenberg 1964), cynicism and competitiveness (Plotkin 1987), independence (Stanton and Bushkirk 1959), and narcissism (Satornino et al. 2023).

Although these factors provide valuable insights into the drivers of individual sales performance, agents' language per se, one of the most important salesperson characteristics that may affect performance, has largely been neglected in the literature. Understanding the effects of language on performance in sales is essential for one major reason: language is, on the one hand, one of the closest intrinsic attributes of individuals (Chomsky 1965), but on the other hand, language can be used consciously or unconsciously, depending on whether individuals communicate automatically or by following certain rules (Pinker 1994), and it can vary between contexts (Hymes 1972). These aspects also distinguish language from the other mentioned attributes. Although these findings are well-known in the field of language research and linguistics, we transfer them to the sales domain to investigate which language styles agents use, how these styles are linked to performance, and whether these style–performance relationships differ between contexts. For managers, the identification of sales agent language styles offers wide opportunities (Luo et al. 2021b). For example, with training, the amount of unconscious language sales agents use could be reduced, sales agents' use of styles that foster sales success could be bolstered, and sales agent performance could be optimized.

2.2 Studies on Language Use in Sales

Effective use of language in sales interactions is not just about what is said but also about how it is said. It involves understanding customers' needs, clearly communicating solutions, building trust, and ultimately guiding the customers through their buying journey. Indeed, 85% of customer note that they feel frustrated with inside sales calls (Moyse 2018), implying the need not only to convey information and facts but also to elaborate on the style of communication.

Existing research considers two main aspects of agent–customer communication: content and word choice (i.e., what agents say). Sensation, or the sensational and emotional perception of language, is also important, as is tone, speed, and volume of the spoken words (i.e., how agents say it). At the *what* level, research has investigated the use of specific questions (Castleberry et al. 1999), certain pronouns and concrete wording (Packard and Berger 2021; Packard et al. 2018), the impact of saying “thank you” in service interactions (You et al. 2020), and counterfactual information (Li et al. 2023) and linked these to customer satisfaction, purchase intention, customer appreciation, and customer impressions. Appendix Table A2 presents an overview of studies addressing language use in sales.

Other studies have analyzed *how* agents communicate with customers, focusing on, for example, language sensation and various levels of warmth and competence (e.g., Singh et al. 2018). Li et al. (2020) and Packard et al. (2024) enrich that research by considering the timing of affect and competence. In addition, research has considered emotional intelligence (Deeter-Schmelz and Sojka 2007) and emotional appeals (Pace 1962) in sales interactions. The *how* level also encompasses paralanguage, or nonverbal features such as speaking tone, pitch, speed, or volume in oral communication. For example, studies have examined audio parameters such as speaking rate or frequency contour variability (Peterson et al. 1995), tempo (Hecht and LaFrance 1995), and pitch and speed (Downing 2011; Van Zant and Berger 2020). However, these studies often focus on single linguistic characteristics, such as individual words or elements of paralanguage, and link them to outcome metrics (e.g., customer satisfaction); they do not analyze the whole set of words, sentences, and semantics within customer interactions or call transcripts to clarify which styles of language agents use.

In addition, many studies do not use concrete sales-related performance metrics. For example, Singh et al. (2018) use customer interest, You et al. (2020) use customer satisfaction and customer self-esteem, and Li et al. (2023) use experiencers’ impressions as dependent variables. In sales, the most important evaluation criterion is the performance of an agent (i.e., the number of products or services sold or the generated revenue). Therefore, we use sales success in individual calls as the focal performance measure to offer guidance to sales managers on which language styles lead to greater success than others.

2.3 Studies on the Effect of Sales Agent Language on Sales Performance

Several studies have investigated the influence of language and communication on sales performance and provided valuable insights in that field. Some of these studies included individual components such as pronouns and concrete terms (e.g., Packard and Berger 2021; Packard et al. 2018), but also various components of communication constructs (e.g., Ahearne et al. 1999; Williams and Spiro 1985). Table 1 provides an overview of these studies. In contrast, we analyze the language of sales agents holistically. First, we look for dimensions sales agents use in their language that can have a direct impact on performance. Second, we conceptionally and empirically group different dimensions into concrete language styles sales agents use in inside sales interactions with customers and measure their effect on direct sales success.

For methodology, studies commonly use observational data (e.g., Pace 1962), questionnaires (e.g., Ahearne et al. 1999; Dion and Notarantonio 1992; Williams and Spiro 1985), and developed scale measurements (e.g., Downing 2011). However, they do not take into account *real* language and communication elements, such as sales agent–customer conversations. The communication styles mentioned in these studies were not identified from actual language data, but rather through self-evaluation using questionnaires or observations by supervisors and experts after a conversation. However, self-evaluations and observations can be difficult and distorted (Baumeister et al. 2007; Paulhus and Vazire 2007). Therefore, analyzing communication styles using real language elements is essential. Furthermore, sample sizes in the aforementioned studies were often rather small. Therefore, increasing the sample size might help increase accuracy.

Other studies have used real language and text data on a larger scale to avoid these issues (e.g., Packard and Berger 2021; Packard et al. 2018; Packard et al. 2024; You et al. 2020). Although this approach avoids the bias of retrospective evaluation of language styles and conversations, these studies' analyses rely primarily on dictionary-based methods. To calculate specific linguistic components, prevalent words or terms are counted and matched with predefined dictionaries and lexicons (e.g., Pennebaker et al. 2015).

Studies using questionnaires or call transcripts as data also do not distinguish the context of a given call, despite its elementary nature, as customers usually contact the company with either a purchase or service inquiry (Aksin and Harker 1999). Customers can also contact the call-center at varying times of the day (Avramidis et al. 2004). As customers have different objectives, sales agents' communication styles might also vary depending on the intent of the conversation and thus have different effects on performance.

Table 1: Studies on Sales Agent Communication Styles and Sales Performance

Study	Context	Communication styles	DV's	Moderators	Key findings
Pace (1962)	Oral communication skills from 37 salespeople were rated based on observations and interviews	- Use of voice and language - Bodily behavior - Listening - Personal attitudes - Initial impression	Sales effectiveness (net dollar value of sales/hours devoted to active selling)	None	Oral communication skills are a reliable criterion to differentiate high-performing from low-performing salespeople.
Williams and Spiro (1985)	Communication styles of 64 salespeople were determined in 251 customer interactions using questionnaires	- Task-oriented, - Interaction-oriented - Self-oriented	Dollar amount of the sale	Combinations of sales–customer communication styles (n.s.)	Salespeople with different communication styles vary in sales.
Dion and Notarantonio (1992)	Communication of 74 salespeople was analyzed utilizing questionnaires and self-reports	Norton's (1978) communication style construct: - Dominant, friendly - Attentive, relaxed - Contentious, dramatic - Animated, open - Impression-leaving and precise	Number of units sold, contribution to company profit, and income	Combinations of precise communication and nine other communication styles	Precise communication is positively associated with company profits and salesperson income.
Boorom et al. (1998)	Communication traits of 239 insurance salespeople were tested with self-reports	- Communication apprehension (CA) - Interaction involvement (II)	Self-reported dimensions of sales performance, percentage of quota attained	None	Lower levels of CA increase II, and II increases sales performance
Ahearne et al. (1999)	Communication ability of 339 pharmaceutical sales reps were investigated using questionnaires	Communication ability as a mediator between salesperson attractiveness and performance, covering: - Tailoring customer needs - Listening - Effective use of time - Wastes time talking about unimportant issues	Brand-by-brand market share data of the subject physicians' prescriptions	None (regarding communication ability and sales performance)	Communication ability positively influences performance.
Downing (2011)	Communication styles of 45 sales agents were determined using questionnaires and ratings	Development of sales communication instrument, covering: - Volume, rate - Thought completion	Sales conversion rates	None	High-performing sales agents showed differences in communication styles compared with low-performing sales agents.

		- Emphases, less pauses - No interruptions - Affirmative words - Listening			
Packard et al. (2018)	Pronoun usage was analyzed in 2,098 customer service interactions using dictionary-based text analysis	- Pronouns used in email conversations	Customer satisfaction, purchase intentions, and purchase behavior	Linguistic and situated factors	Pronouns used in email conversations affect customer purchase volume.
Cron et al. (2021)	Level of no conversation was investigated for 81 salespeople using questionnaires and self-reports	- No conversation (disengaging from customers)	Sales revenue generated per quarter	Environmental factors (store traffic, peers' no conversation strategy) and accuracy-related factors (salesperson's domain-specific experience, relationship-building orientation)	Higher sales performance with no conversation when salespeople are experienced and with high store traffic
Packard and Berger (2021)	Concreteness level in language was determined in 941 customer service interactions using a dictionary of perceived concreteness	- Concreteness (i.e., being tangible, specific, and imaginative) in language	Customer satisfaction, customer spending	Relevance of sales agent response	Customers spend more after emails in which the employee uses more concrete language.
Packard and Berger (2024)	Level of warmth and competence was measured for 130 sales agents in 185 service calls using dictionary-based text analysis	- Affective (warmth) and cognitive (competence) language	Perceived helpfulness and customer purchases (robustness check)	None	Timing of warm or competent communication styles affect customer purchases.
This study	Unique language styles are identified utilizing AI-based text analysis in more than 43,000 customer call transcripts from 437 inside sales agents	- 22 language dimensions combined into six unique language styles	Sales success (contract completion within call)	Call intent (purchase vs. inquiry) Daytime (morning, afternoon, evening)	Language styles show different effects on sales success.

3 Conceptual Framework

3.1 Language Dimensions in Sales Calls

A language dimension is a single construct that characterizes how sales agent language is pronounced and perceived (e.g., friendly, motivating, aggressive). The basis for our text analysis of these dimensions is the substance (i.e., the "what," content and word choice) and perception (i.e., the "how," sensation). We conceptually derive these dimensions by analyzing sales agents' skills, behaviors, and traits and transfer these attributes to language; that is, we propose that a certain skill, behavior, or trait can be reflected in language. A language style comprises several language dimensions and characterizes a specific manner in which sales agents communicate, also encompassing both the substance (what, content) of their messages and the method of delivery (how, perception). We graphically illustrate the relationship between language dimensions and language styles in Figure A1 of Appendix A.

For the classification of language dimension in sales, we use the employee voice behavior framework developed by Maynes and Podsakoff (2014). This framework divides employee voice in four major categories encompassing both positively and negatively intended voice: supportive, constructive, defensive, and destructive. We believe that the framework is ideally applicable in the sales context for three main reasons: First, salespeople's language dimensions are also prone to be supportive, constructive, and therefore beneficially intended to build customer relationships, shape customer buying decisions, and increase sales performance. However, it is important to note that language dimensions must not be solely conductive as they may encompass a holistic picture of language which might differ across situations, customers, and moods (George 1998). Although inside sales agents use their language as an influencing tactic and attempt to persuade the customer, language is never neutral and reflects the attitudes, positions, or beliefs of individuals (e.g., Descarries 2014). These attitudes, positions, or beliefs may not be the same as the recipient's, which can then challenge or even damage the interpersonal relationship (Maynes and Podsakoff 2014). Inside sales agents statistically face failure more often than success, and the use of both positive and negative intended language styles is likely (Rapaille 2006).

Second, salespeople are an essential part of any organization and their employee voice has a significant force of expression to both inside and outside the company. Because of their proximity to customers, they are the first to notice market trends and developments and can communicate these changes internally (Rapp et al. 2006; 2011). In addition, their direct responsibility for sales means that they are interested in how the business works and can therefore respond to internal changes by addressing them directly. Third, a total of 38 voice-related behaviors were identified for the four quadrants of the employee voice behavior framework, which were collected from participants in professional service firms. This also links the framework into the sales and service direction and makes it a valuable matrix for classifying language dimensions of inside sales agents.

To identify which language dimensions exist in inside sales calls, how they are related to performance, and in which of the four quadrants of the employee voice behavior framework they fall, we conducted a comprehensive literature review. We analyzed leading marketing (e.g., *Journal of the Academy of Marketing Science*, *Journal of Marketing*), sales (e.g., *Journal of Personal Selling & Sales Management*, *Journal of Business Research*), and psychology (e.g., *Journal of Applied Psychology*, *Personnel Psychology*) journals as well as practitioner publications (e.g., *Harvard Business Review*, *Forbes*) that focus on sales agent attributes. For our context, we searched for the attributes described previously that can be translated into language dimensions—namely, the skills, behavioral concepts, and personality traits of sales agents. We propose that these attributes are represented in language, as the linguist and philosopher Noam Chomsky (1968) posits that language serves as an external manifestation of cognitive processes and structures within people's minds. In other words, language is not only a medium for communication but also a reflector of people's minds and behavior. Pennebaker and Francis (1996) also demonstrate that words and language reflect personality traits and behaviors, a view shared by Caplan et al. (2020). For this reason, we searched for attributes in the literature that represent general characteristics of sales agents, which we assume also to be reflected in language use. We provide a detailed derivation of sales language dimensions in Appendix B. Table 2 shows the derived language dimensions within the four quadrants of the employee voice behavior framework.

On the one hand, the division in either supportive or constructive language is in line with the work of Singh et al. (2018), who conceptualize sales agent behavior as either resolving or relating and emoting. On the other hand, Verbeke and Bagozzi (2002) suggest that shame and embarrassment, which sales agents experience during personal selling situations, can provoke avoidance behaviors, which we expect also to be reflected in defensive or destructive voice. As a result, we derived almost two dozens of language dimensions that can be classified into four different language styles. Following Linnenbürger (2020), we present short definitions of these dimensions (see Appendix A, Table A3).

Table 2: Grouping Language Dimensions in the Employee Voice Behavior Framework

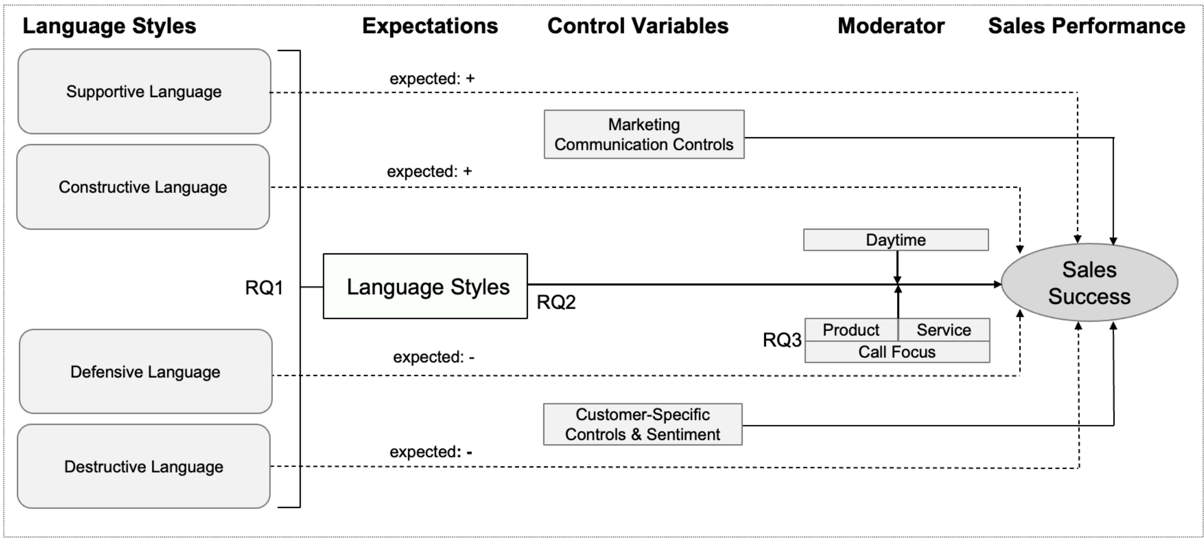
Dimension	Preservation	Challenge
Promotive	Supportive language dimensions	Constructive language dimensions
	• Structured • Empathic • Friendly • Helpful • Formal • Philosophical	• Goal-oriented • Reliable • Visionary • Positive • Optimistic • Motivating • Impressive • Composed • Self-confident
Prohibitive	Defensive language dimensions	Destructive language dimensions
	• Unconventional • Independent • Intellectual	• Impulsive • Aggressive • Authoritative • Dramatic

We expect positive effects of the two quadrants supportive language and constructive language on sales success, as Maynes and Podsakoff's (2014) definitions indicate that these language styles are conducive to conversations. These assigned dimensions have largely been positively associated with sales performance in the literature, so these styles represented in language should also have a positive influence on sales performance. The same applies to the two quadrants defensive language and destructive language, for which we expect negative effects on performance, as shown in our conceptual framework in Figure 1. All the language dimensions in the four quadrants are summarized in language styles and represented by the large, rounded boxes on the lift-hand side in Figure 1. They characterize language holistically and thus enable analyses of the effects of different language styles on performance.

However, language styles are not the only variables that might influence sales success of inside sales agents. We therefore include customer-specific and marketing communication variables in our model, represented by the square gray boxes in Figure 1. First, customers' age and the length of their relationship with the company are important characteristics as they can influence purchase behavior (Pocklington 2023; Reinartz et al. 2004). Second, the number of purchases (insurance contracts in our context) and the duration of the last contract affect future buying decisions (Jacobs et al. 2016). Third, marketing communication and advertising prominently influence purchase decisions (e.g., Mela et al. 1997), so we include the number of mail pieces, e-mails, phone calls, and offers a customer has received from the company. Last, we include the call length, because the duration of a customer interaction and the associated time spent with a customer might affect the possibility of a completion (Davis and Main 2024).

In addition, we include customer sentiment in the model. Measuring the feelings and attitudes of customers becomes relevant with the availability of huge amounts of text data (Homburg et al. 2015) and opens important possibilities for understanding customer reactions (Berger et al. 2020). Research has also shown that the sentiment customers display can influence the performance of investors (Eachempati et al. 2022) and that salesperson responses might be dependent on customer emotions (Menon and Dube 2000).

Figure 1: Conceptual Framework



3.2 Moderating Role of Call Intent and Daytime

The effectiveness of agent language might differ between contexts. First, call types in inside sales interactions can be classified into two categories: those dealing with purchases and those dealing with service inquiries (Aksin and Harker 1999; Jasmand et al. 2012; Yu et al. 2013). From a strategic standpoint, specializing in either a product or a service may be more efficient than attempting to implement both simultaneously (Rust et al. 2002). Nonetheless, cross-selling and converting service requests into sales attempts are common practices in call centers (Yu et al. 2013).

Generating an order in inquiry-intended phone calls can be more challenging than completing a transaction in purchase-intended calls. This may be due to the frequent use of a sales methodology in purchase-intended conversations. Customers asking questions about particular contract details in purchase-intended calls can easily receive an offer for the product in addition to an answer to their query. That is, an inside sales agent can answer the customer's questions about a current product and then promote a related supplementary offering that fits the context. Conversely, marketing a product and generating interest in it during an initial service conversation may be more challenging. Therefore, we expect direct positive (negative) effects of the moderators *purchase-intended call* (*inquiry-intended call*) on sales success. The small grey boxes in Figure 1 above show the moderators.

We also expect that the effects of language styles on sales success might differ depending on the intent of the specific call. That is, we expect the negative quadrants defensive and destructive language to be more successful in product- than service-oriented calls, as the likelihood of completing a deal is higher per se and no sales attempt needs to be made if the call intent is mainly an inquiry.

Second, the time of the day might also influence sales effectiveness of language styles. In their study, Nahm et al. (2022) find that customer interactions made midday might be more successful in mitigating negative momentum an agent might exhibit. Customers also evaluate products differently at certain times of the day (Park and Yi 2023) and Crandell (2014) suggests that Wednesday at noon is the best time for prospecting. We therefore expect the first half of the day as being more likely to generate sales success compared to the second half of the day. Furthermore, we expect that some language styles might work better or worse at certain daytimes.

4 Method and Empirical Derivation of Language Styles

4.1 Research Context

For our analysis, we scrutinized 43,619 call transcripts between sales agents and customers collected over a three-month period from August to October 2021 from a leading German insurance company. Due to the ongoing Covid-19 situation taking place in 2021, all calls made in the office during this period have been included in the data set. All the calls are inbound (i.e., calls received by the call center) with customers making product-related sales requests or having service issues. The calling customers were randomly assigned to the first available agent, i.e. every calling customer has the opportunity to speak to every available agent. The sales agents received instructions to conduct sales or cross-sales attempts on all the calls. The company internally transcribed the call-center audio recordings using an industry-standard transcription service. The following excerpts are examples of sales agent–customer conversations from the dataset:

> *Hello, my name is Smith,[1] what can I do for you? Please be so kind and tell me your name.... I'll check which tariff you have.... Yes, you have denture insurance, but it does not cover dental cleaning…. You're welcome to take out this supplementary insurance…. Of course, you will be reimbursed for a dental cleaning from September…. The "Large" tariff also covers better fillings.... Okay, I wish you all the best, stay healthy!*

> *Good morning, you are talking to Mrs. Miller[1] …. A moment of patience, sir…. No they talked to my colleague, I don't know… I cannot process your request without authorization…. Please wait…. No, I definitely can't, you have to call yourself…. Alright, bye.*

[1] We changed all names to protect the agents' anonymity.

The first excerpt belongs to the 1% quantile of the friendliest agent texts and the second to the 1% quantile of the most authoritative agent texts, as determined by AI text analysis of language dimensions. This analysis takes into account both individual words such as “please” and “lovely” in the first example (“wait” and “moment” in the second example) and bigrams such as “stay healthy” (“call yourself”) or sentences or partial sentences such as “what can I do for you” (“I cannot process your request”).

The data include an indicator for "sales success," which denotes whether a contract for a new insurance was directly initiated (=1) or not (=0) following a call. In the context of insurances, the contracting process typically occurs via telephone, with the customer subsequently receiving the requisite documentation at their residence. The formalization of the contract is deemed complete upon the customer's signature and the subsequent return of the documents to the insurer. Consequently, the specific call that led to the conclusion of the contract is considered a sales success and an outcome- as well as a conversion-based measure of sales performance (Bolander et al. 2021).

Moreover, the data include controls for customer characteristics, such as age, gender, and number of active contracts; marketing communications, such as the number of emails, calls, or offers customers received earlier; and duration of the customer relationship. Applying the *Syuzhet* package in R, we extract the customers’ sentiment within the calls.

We initially divided each transcript into segments of sales agent and customer communication. Segments represent the parts in which either the sales agent or the customer speaks exclusively until the other party responds and can range from single words to multiple sentences. This resulted in 2,738,000 individual text segments. We then collected all sales agent and customer-specific segments separately, creating two distinct transcripts at the call level. The dataset includes 437 sales agents and 25,268 unique customers over three months. The mean age of customers is 62.72 years (SD = 15.22) with a gender distribution of 59.04% female, 40.92% male, and 0.04% others. The relatively high average age may be due to younger people's infrequent use of phones to buy products. The average customer relationship is 12.45 years (SD = 7.99), and the average call length is 8.73 minutes (SD = 7.55). The sales success rate is 5.2% (SD = .22), which is within the normal range (e.g., Kim 2023).

We employed text mining techniques and used a reference list of terms provided from the company in the customer transcripts to create two count variables "purchase-intended" and "inquiry-intended" call that display the number of related words and bigrams for these intends. An overweight of the respective variable then signals the intent. The moderation variable indicates a purchase intent in 54,75% of cases and an inquiry intent in 24.62% of cases. In 20.63% of the calls, no clear call intent could be filtered out. The deal rate for the purchase-intended (inquiry-intended) calls is 9.4% (3.9%), respectively. Table A4 in Appendix A lists the summary statistics of these variables (Tables A5 and A6 for either the purchase-intended or inquiry-intended calls).

We worked with a German AI start-up to identify the theoretically derived language dimensions using its proprietary natural language processing algorithms and expertise in AI text analysis. By using an AI-based text analysis method, we endorse the remarks of Grewal et al. (2021) regarding the use of third-party tools in research and use proprietary algorithms for the analysis of multimedia data such as text (e.g., Borah and Tellis 2016). The AI tool is able to process large amounts of unstructured data such as call transcripts and provide new insights into the effect of language from inside ales agents (Balducci and Marinova 2018). A value of 0 means no incidence of the particular dimension during a call, while a value of 1 indicates a substantially high frequency of the dimension. These values establish the foundation for subsequent analyses. Table 3 shows summary statistics of the 22 language dimensions extracted from the sales agent language. A mean value of .905 for goal-oriented language, for example, indicates a high average level of this language dimension in sales agent language. We ran another analysis with the same text and received identical results to confirm the consistency of the AI tool. Table A7 in Appendix A shows the correlation matrix of the language dimensions.

Table 3: Summary Statistics of the 22 Language Dimensions

	M	SD	Minimum	25% Quantile	Median	75% Quantile	Maximum
Intellectual	0.077	0.081	0	0	0.057	0.127	0.953
Goal-oriented	0.905	0.049	0.453	0.879	0.910	0.939	1
Reliable	0.624	0.052	0.243	0.589	0.610	0.657	0.907
Structured	0.261	0.039	0.113	0.239	0.258	0.278	0.813
Formal	0.403	0.062	0.050	0.365	0.409	0.442	0.739
Empathic	0.432	0.082	0.071	0.381	0.415	0.474	0.901
Helpful	0.314	0.087	0	0.260	0.303	0.361	0.884
Friendly	0.480	0.062	0	0.444	0.491	0.521	0.859
Positive	0.465	0.060	0	0.431	0.479	0.504	0.776
Optimistic	0.389	0.037	0	0.379	0.397	0.407	0.713
Visionary	0.590	0.044	0.172	0.571	0.596	0.609	0.863
Authoritative	0.439	0.046	0.175	0.409	0.434	0.463	0.766
Self-confident	0.280	0.060	0.006	0.238	0.269	0.313	0.722
Composed	0.787	0.039	0.365	0.773	0.793	0.809	1
Unconventional	0.226	0.089	0	0.157	0.219	0.285	0.805
Philosophical	0.132	0.043	0	0.106	0.131	0.154	0.620
Impulsive	0.360	0.040	0.123	0.338	0.352	0.371	0.729
Aggressive	0.495	0.077	0.074	0.438	0.477	0.545	1
Motivating	0.546	0.049	0.211	0.515	0.540	0.574	0.844
Impressive	0.414	0.059	0.101	0.369	0.406	0.452	0.795
Dramatic	0.300	0.047	0.026	0.277	0.286	0.309	0.826
Independent	0.666	0.108	0	0.609	0.690	0.743	1

Notes: Results show output of sales agent language; n = 43,619.

4.2 Identifying Language Styles from Language Dimensions

Almost two dozen language dimensions are too many to allow for meaningful managerial implications. Moreover, we wanted to empirically test and verify the four language styles based on the four quadrants of the employee voice behavior framework (Maynes and Podsakoff 2014). To address this, we conducted a principal component analysis (PCA) (Becker et al. 2022; Tellis et al. 2019) to obtain these language styles. We used the oblique Promax rotation technique as we presumed that the language dimensions are correlated. A scree plot of the eigenvalues (shown in Appendix A, Figure A2) presents a six-factor solution that accounts for 78% of the variance within the 22 language dimensions, consistent with previous research (Becker et al. 2022). Table 4 shows the loadings for the six labeled language styles, and Table 5 shows descriptive statistics and correlations of the language style factors (Tables A8 and A9 in the Appendix show these statistics and correlations for either purchase- or inquiry-intended calls).

Table 4: Results of the PCA

Language dimensions	**Language styles**					
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Intellectual				.68		
Goal-oriented			.44	-.68		
Reliable	.81					
Structured					.82	
Formal		.55				
Empathic	.97					
Helpful	.88					
Friendly		.92				
Positive		.99				
Optimistic		.56	.61			
Visionary			1.02			
Authoritative						.82
Self-confident	.84					
Composed		.59	.47			
Unconventional				.92		
Philosophical					.99	
Impulsive		-.68				
Aggressive		-.85				
Motivating	.58		.50			
Impressive	.65					
Dramatic						.71
Independent	-.98					

Notes: Rotated Promax loadings. All loadings <.40 are suppressed.

Table 5: Descriptive Statistics and Correlations of Language Style Factors

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
M	0	0	0	0	0	0
SD	1.071	1.114	1.149	1.012	1.122	1.069
Minimum	-4.005	-8.690	-10.982	-2.601	-4.417	-8.083
Maximum	5.751	5.076	7.646	5.768	10.715	7.993
Factor 1	1	-.075	-.206	.001	.085	-.212
Factor 2	-.075	1	-.284	-.067	-.335	.271
Factor 3	-.206	-.284	1	.130	.354	-.142
Factor 4	.001	-.067	.130	1	-.009	-.023
Factor 5	.085	-.335	.354	-.009	1	-.116
Factor 6	-.212	.271	-.142	-.023	-.116	1

Using an AI-driven pattern analysis, we detected exemplary phrases and words for each language style to gain a better understanding of what these styles look like (i.e., words and phrases that are highly responsible for a high value of the specific language dimension). We supplemented this analysis by creating 1% quantiles of agent texts for each language dimension and used both word counts and manual coding to uncover additional words and phrases.

The first language style consists of high loadings of the dimensions "reliable," "empathic," and "helpful" as well as "self-confident," which is why we call this language style "Endorser." Exemplary words and phrases are "I understand" (empathic), "we can check for sure" (helpful), "secured" (reliable), "I know" (impressive), and "please wait a second" (self-confident).

The second language style consists of high loadings of the dimensions "friendly," "positive," and "aggressive," as a negative factor, which is why we call this language style "Adviser." Exemplary words and phrases are "lovely" (friendly), "question" (formal), "simply submit the invoice" (composed) and "money is on the way" (optimistic).

We name the third language style "Boss" because it has high factor loadings of the dimensions "optimistic" and "visionary" and medium-high loadings of "goal-oriented" and "motivating." Exemplary words and phrases are "new" and "future" (visionary), "professional," and "stay on the line" (goal-oriented).

We call the fourth language style "Freethinker" because it has a high factor loading of the dimension "unconventional" and medium-high loadings of the dimensions "intellectual" and negative "goal-oriented." "Name the parameters" (intellectual), "later" or "however" (non-goal-oriented), and "new" are examples of words and phrases in this language style.

The fifth language style consists of high loadings of the dimensions "structured" and "philosophical," which is why we call it "Educator." Exemplary words and sentences are "exactly" and "I note this" (structured) and "I think about that for a moment" (philosophical).

The sixth language style consists of high loadings of the dimensions "authoritative" and "dramatic," and therefore we call it "Diva." Exemplary words and phrases for this style are "instruction" and "quick" (authoritative) and "terrible" (dramatic).

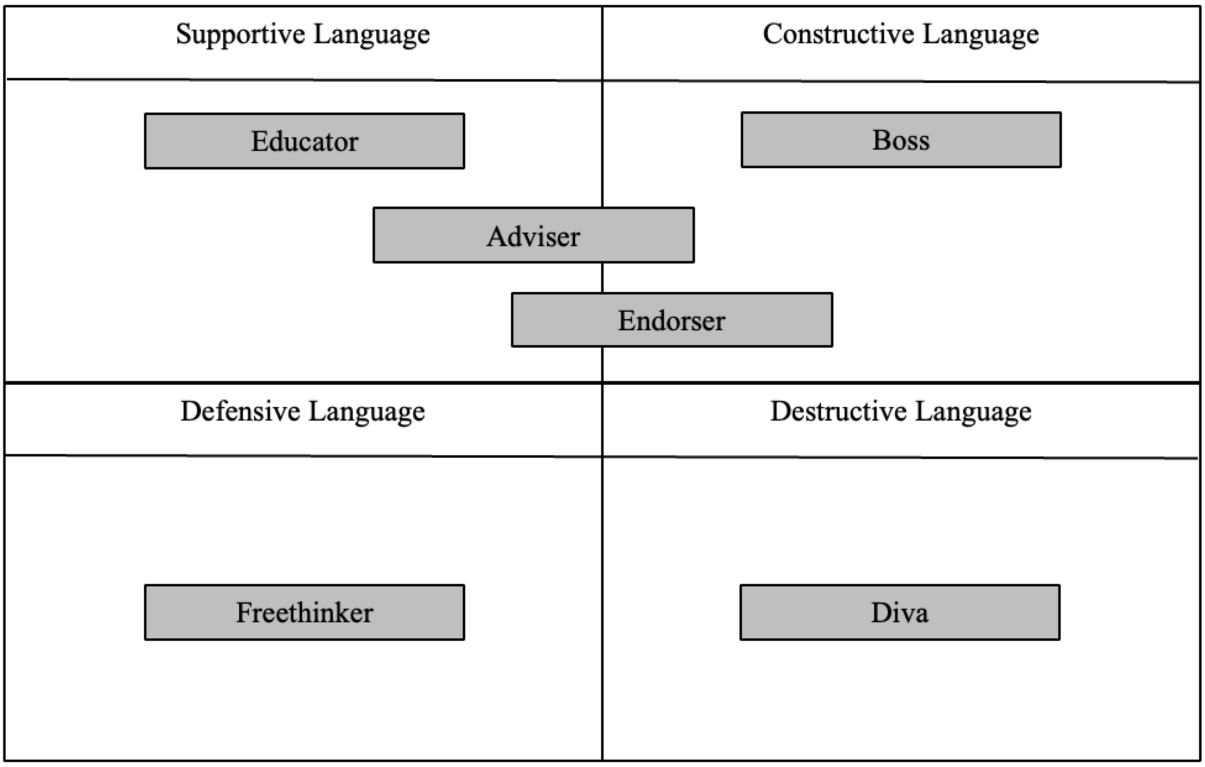
Table 6 presents these six language styles, their included language dimensions, and sample studies that address the respective dimension and its effect on sales performance (for detailed derivation of the language dimensions, see Appendix B). These language styles can be integrated into the employee voice behavior framework (Maynes and Podsakoff 2014) because of parallels between the conceptually derived four quadrants of the framework and the six styles we empirically obtained from the PCA. We categorized the language styles in the quadrants in which the individual language dimensions are located (see Figure 2).

We transfer the positive expected effect on sales success from the supportive and constructive language quadrants to the language styles Endorser, Adviser, Boss, and Educator and the negative expected effect of the defensive and destructive language quadrants to the language styles Freethinker and Diva.

Table 6: Summary of Language Dimensions Included in Language Styles

	Language dimensions	Example studies	Effects on sales performance (literature)	Language style quadrant
Factor 1: **Endorser**	• Reliable • Empathic • Helpful • Self-confident • Motivating • Impressive • Independent (–)	• Lowe 2022 • Mayer & Greenberg 1964; Zoltners et al. 2016 • Anderson 2013 • Greenacre et al. 2014 • Churchill et al. 1985 • Alavi et al. 2018 • Stanton & Bushkirk 1959	+ – + + + + + +	Constructive language
Factor 2: **Adviser**	• Formal • Friendly • Positive • Optimistic • Composed • Impulsive (–) • Aggressive (–)	• Jordan & Kelly 2015 • Marlow et al. 2018 • Frayne & Geringer 2000 • Sujan 1999 • Mulki et al. 2015 • Lockeman & Hallaq 1982 • Miner 1962	+ + + + + – –	Supportive language
Factor 3: **Boss**	• Goal-oriented • Optimistic • Visionary • Composed • Motivating	• VandeWalle et al. 1999 • Sujan 1999 • Thacker 2020 • Mulki et al. 2015 • Churchill et al. 1985	+ + + + +	Constructive language
Factor 4: **Freethinker**	• Intellectual • Goal-oriented (–) • Unconventional	• Weitz et al. 1986 • VandeWalle et al. 1999 • Szot 2023	+ + +/–	Defensive language
Factor 5: **Educator**	• Structured • Philosophical	• Shapiro & Posner 2006 • Mendes-Roter 2023	+ +	Supportive language
Factor 6: **Diva**	• Authoritative • Dramatic	• Lamont & Lundstrom 1977 • Luo et al. 2021a	– –	Destructive language

Figure 2: Inclusion of Language Styles in the Employee Voice Behavior Framework



4.3 Effects of Sales Agent Language Styles on Sales Success

Next, we modeled the effects of the six language styles on sales agents' sales success. To estimate the model, we used a binary logit model with fixed effects for both the sales agent and the day of the week (e.g., Becker et al. 2022; Luo et al. 2019). Our model specification is

$$(1) \qquad Sales\ success_{tc} = \frac{Exp(z_{ijc})}{Exp(z_{ijc}) + 1}$$

with

$$\begin{aligned} z_{ijc} = \beta_0 + \beta_1 * Supporter + \beta_2 * Adviser + \beta_3 * Boss + \beta_4 * Freethinker + \beta_5 \\ * Educator + \beta_6 * Diva + \beta_7 * CallIntentPurchase + \beta_8 \\ * CallIntentInquiry + \sum_{q=1}^{6} LangStyles\ x\ CallIntentPurchase \\ + \sum_{r=1}^{6} LangStyles\ x\ CallIntentInquiry + \sum_{s=1}^{12} CTRL_{jcs} + \gamma_{ic} + \delta_c + \varepsilon_{ijc}, \end{aligned}$$

where z_{icj} measures the probability that sales agent i (i = 1, …, 437) makes a sale in call c (c = 1, …, 43,619) with customer j (j = 1, …, 25,268). The parameters β_{1-6} determine the effects of the sales agents' language styles, β_7 determines the moderator purchase-intended call, and β_8 determines the moderator of an inquiry-intended call. The parameters q_{1-6} represent the six language styles that interact with the purchase-intended call moderator, and r_{1-6} represent the six language styles that interact with the inquiry-intended call moderator. The parameters θ_{1-12} are the effects for the vector of s (S = 1, …, 12) control variables (customer-specific, marketing communication, and sentiment). To account for unobserved agent and weekday characteristics, we include agent-level (γ_{ic}) and weekday (δ_c) fixed effects in the model. Finally, ε_{ijc} represents the error term. In a second model, call intend is replaced by the daytime moderators.

5 Results

We employed a sequential model-building process, first regressing the six language styles on sales performance, and then adding the control variables and the customer sentiment. Table 7 displays the regression results of both the main model and the moderation model with all the variables (see Appendix A, Table A10 for the two models with less variables included). The models exhibit a good fit, with pseudo-R-square values of .45 for Main Model 1 and .46 for Moderation Model 1. In Table 11 in the Appendix, we also provide variance inflation factors (VIF) to check for multicollinearity. All VIFs do not signal multicollinearity.

The main effects of the language styles on sales success stay constant across all six models. Main model 1 in Table 7 describes the results of the language styles and customer-specific and marketing communication variables, and moderation model 1 describes the effects of the moderator and the interaction effects. We also provide odds ratios of the coefficients to depict the effect sizes of the independent variables. With the odds ratios, we identify the strongest or weakest impact of the language styles or the control variables on sales success.

Table 7: Effects of Language Styles on Sales Success

	Main model 1		Moderation model 1		Odds ratios
	Sales success		Sales success		
Constant	-4.996***	(.550)	-5.167***	(.554)	
Language styles					
Endorser	-.014	(.051)	-.029	(.067)	.9859
Adviser	.593***	(.053)	.588***	(.076)	1.8098
Boss	.516***	(.056)	.474***	(.082)	1.6750
Freethinker	-2.374***	(.078)	-2.518***	(.106)	.0931
Educator	.300***	(.050)	.405***	(.072)	1.3502
Diva	-.131**	(.049)	-.216***	(.072)	.8776
Moderators					
Call intent purchase			.101***	(.019)	
Call intent inquiry			-.087**	(.040)	
Interaction effects					
Endorser × call intent purchase			.006	(.008)	
Adviser × call intent purchase			.011	(.009)	
Boss × call intent purchase			-.001	(.010)	
Freethinker × call intent purchase			.047***	(.015)	
Educator × call intent purchase			-.016	(.011)	
Diva × call intent purchase			.018*	(.010)	
Endorser × call intent inquiry			-.007	(.018)	
Adviser × call intent inquiry			-.020	(.019)	
Boss × call intent inquiry			.021	(.022)	
Freethinker × call intent inquiry			-.013	(.031)	
Educator × call intent inquiry			-.019	(.023)	
Diva × call intent inquiry			.003	(.020)	
Controls					
Customer age	.01	(.003)	.002	(.003)	1.0015
Customer relationship	.001*	(.001)	.001*	(.001)	1.0009
Number of mail pieces	.001**	(.001)	.001*	(.001)	1.0011
Number of offers	.037***	(.006)	.034***	(.007)	1.0380
Number of calls	-.024***	(.003)	-.023***	(.003)	0.9765
Number of emails	.001	(.0004)	.001	.0004	1.0006
Number of active contracts	-.095***	(.024)	-.089***	(.024)	.9095
Number of inactive contracts	-.024*	(.014)	-.021	(.014)	.9763
Duration last contract	-.004***	(.001)	-.004***	(.001)	.9959
Call duration	.001***	(.0001)	.001***	(.0001)	1.0013
Customer sentiment positive	-.008	(.009)	-.010	(.009)	.9925
Customer sentiment negative	-.054***	(.011)	-.048***	(.012)	.9478
Agent fixed effects	Yes		Yes		
Weekday fixed effects	Yes		Yes		
Log-likelihood	-3,838.868		-3,835,554		
Pseudo-R^2	.4542		.461250		
AIC	8,611.736		8,553.109		
BIC	12,099.600		12,155.33		
No. observations	26,064		26,064		

*$p < .1$; **$p < .05$; ***$p < .01$. Notes: Clustered standard errors (on sales agent-level) are in parentheses. Interaction variables are mean-centered for moderation model 1. AIC = Akaike information criterion; BIC = Bayesian information criterion.

5.1 Language styles

Endorser The language style of the Endorser is not significantly associated with sales success ($\beta_1 = -.014$, n.s.). This may be due to the inclusion of multiple language dimensions and the language dimension of empathy, whose effect on performance can be two-sided. While sales agents might communicate emphatically, this does not necessarily lead to closing deals. Sales agents cannot benefit from a conversation that lacks independence because it hinders their ability to convince customers. While dimensions such as reliable and motivating can have a positive influence on contract conclusion, when combined with the previously mentioned dimensions, they do not have a decisive effect on sales success and cancel each other out. Thus, we cannot confirm the conceptionally positive effect on sales success empirically.

Adviser The Adviser language style is significantly positively associated with sales success ($\beta_2 = .593$, $p < .01$). Furthermore, this style exerts the strongest positive effect on sales success when compared with the other language styles, as evidenced by an odds ratio of 1.8098. Both the favorable factor loadings friendly and positive and the unfavorable negative factor loadings impulsive and aggressive define a communication style that improves the likelihood of successfully completing contracts. The formal aspect of sales agent communication portrays the Adviser not only as amiable and approachable but also as highly professional. The Adviser style falls in the quadrant of supportive language, for which we also expect a positive impact on sales success.

Boss Consistent with our expectations, the Boss language style affects sales success significantly positively ($\beta_3 = .516$, $p < .01$) and falls in the quadrant of constructive language. The positive effect is mainly due to the combination of the language dimensions goal-oriented and composed. While the first dimension ensures that the main objective of a customer sales call—namely, acquiring a new contract—is kept in focus, the second dimension ensures the maintenance of verbal composure in difficult customer calls, while reducing nervousness.

Furthermore, the sales-enhancing language dimensions of optimism, vision, and motivation contribute to this successful language style.

Freethinker The language style of the Freethinker shows a negative association with sales success ($\beta_4 = -2.374$, $p < .01$) and thus falls in the quadrant of defensive language. Moreover, as Table 7 shows, the odds ratio of this language style is .0931, indicating the strongest negative effect of the Freethinker style on sales success as compared with the other language styles. The Freethinker's communication approach lacks a goal-oriented focus, hindering contract completion. The unconventional communication style is prohibitive and deviates frequently from best practices and well-known argumentation patterns, which negatively affects sales performance.

Educator The language style of the Educator has a significant, positive effect on sales success ($\beta_5 = .300$, $p < .01$). The Educator effectively employs highly structured communication, strategically addressing customer inquiries or concerns at the appropriate junctures rather than making uncontrolled statements. The philosophical dimension contributes to the willingness of sales agents to employ this communication style to learn and consistently reassess their communication methods and thus improves their likelihood of executing successful contracts. The Educator style falls in the quadrant of supportive language, which we expect to positively influence sales success.

Diva The sixth language style, the Diva, has a negative association with sales success ($\beta_6 = -0.13$, $p < 0.05$) and falls in the quadrant of destructive language. Divas exhibit exclusively negative characteristics classified as prohibitive and destructive, including personality traits and language use that harmfully affect customers' purchase intent, ultimately lowering the sales success of sales agents.

5.2 Quadratic Effects of Language Styles on Sales Success

To test for quadratic effects of language styles on sales success, we included the squared terms of the six language styles in the logit model and left all other variables in the model. The results in Appendix Table A12 show significant effects of all squared terms. The main effects of the language styles remained stable with the exception of Diva, which is slightly not significant in this case. We observe that the Adviser has a positive quadratic effect on sales success ($\beta = .155$, $p < 0.01$), indicating that an extensive use of this language style further increases the likelihood of a sales success. All other squared effects are negatively significant, indicating that the probability of sales success decreases if the language styles are used too intensively and exuberantly. This follows an inversed U-shape relationship. For the negative language styles, especially for the Freethinker in this model, this means that the negative influences of the language style on sales success become even worse as the extent of this style increases, i.e. the curve goes concavely downwards.

5.3 Moderators

5.3.1 Call Intent Purchase Analyzing the interaction with language styles, we found two positive and significant effects of purchase-intended calls on both the Freethinker's ($\beta = .047$, $p < .01$) and the Diva's ($\beta = .018$, $p < .1$) relationship with sales success. Both language styles had negative impacts on sales success in the main models. Therefore, adopting a more product-centered approach mitigates the negative effects of these two language styles on sales success. Consequently, sales agents who use a Freethinker (e.g., intellectual, unconventional, not goal-oriented) or Diva (e.g., dramatic, authoritative) language style should cater solely to customers with purchase-intended calls. A greater emphasis on products has no significant impact on the effects of the other language styles on sales success, and the positive main effects remain unchanged.

5.3.2 Call Intent Inquiry We find no significant effects of inquiry-intended calls on the interactions between language styles. This means that a greater or lesser service intent neither positively nor negatively affects the impact of each language style on sales success. Nevertheless, four of the six language styles have a negative, though not statistically significant, sign and show a tendency to have a potentially negative influence.

5.3.3 Daytime Appendix Table A13 shows the effects of the interactions of the language styles with the time of the day. We calculated three moderation models, and a specific time of the day is integrated to interact with the language styles. We took this approach to avoid overfitting the model and to facilitate the drawing of comparisons between a time of day and the rest of the day. The findings reveal that the Adviser exhibits diminished efficacy during the morning hours compared to the remainder of the day ($\beta = -.184$, $p < 0.1$), and that the negative impact of the Diva on sales success can be mitigated in the morning ($\beta = .217$, $p < 0.01$). Conversely, at lunchtime ($\beta = -.167$, $p < 0.1$) and in the evening ($\beta = -.421$, $p < 0.05$), the negative effect of the Diva intensifies, and the Educator's efficacy diminishes midday compared to other times of the day ($\beta = -.235$, $p < 0.01$). Conversely, the effect of the Freethinker is observed to be less negative during evening hours ($\beta = .540$, $p < 0.05$).

5.4 Marketing Communication and Customer-Specific Variables

In addition to the six language styles, we examine the impacts of the control variables included in the model. For the marketing communication variables, we find positive associations between sales success and the number of mail pieces and offers sent from the company to customers, as mail promotes new products and enhances customer engagement, which may be valid for older customers (M = 61.35 years in the sample) who still prioritize mail. The strong positive effect of the number of offers on sales success is evident in the odds ratio of 1.0380, which is the highest among all control variables. This finding is rational, as an active call from a customer to a sales agent after receiving an offer indicates a stronger inclination to purchase, thereby increasing the likelihood of closing a deal. We also find a negative effect of the number of calls made to customers for advertising products on sales success. This is likely because customers are more exasperated by telemarketing cold calls, which diminishes their interest in the product and reduces their willingness to purchase (Jolson and Wotruba 1992).

The number of purchases (active and inactive contracts) shows a negative association with sales success. The odds ratio of .9095 for active contracts is the lowest among all the control variables, indicating a negative effect of the number of active contracts on the likelihood of closing a deal. This is reasonable as an increase in contracts reduces the need for new contracts and, in turn, decreases the probability of closing a deal.

Contrary to our expectations, the probability of a new sale decreases with the passage of time since the last contract, indicated by a negative and significant effect on sales success. This may be because when a new contract is recently concluded, the customer is still informed and more likely to consider additional insurance options. Call length is again positively associated with sales success, as prolonged conversations indicate a heightened level of interest in the product on the part of customers, which sales agents take note of and use to tailor their arguments accordingly. Longer conversations in the dataset include service requests and can raise the possibility of a cross-selling opportunity, with a product deal stemming from the initial service request.

Regarding customer sentiment, we find a nonsignificant effect of positive customer sentiment and a significant and negative effect of negative customer sentiment on sales success. Therefore, the negative feelings a customer exhibits have an impact on the performance of the agent; such an attitude suggest that the customer is not satisfied and is likely not to complete a new contract in this situation. Positive sentiment in inside sales calls might be multi-faceted and is not generally measurable, while negative sentiment can be more clearly determined.

5.5 Additional Analyses and Robustness Checks

Conceptually, we developed four language style quadrants using the employee voice behavior framework (Maynes and Podsakoff 2014) into which we classified six language styles empirically identified by PCA. With 78%, the six-factor solution explained the most variance. However, we were interested in determining whether a four-factor solution would also contain the language dimensions positioned in the four language style quadrants. A four-factor PCA explains 66% of the variance and therefore is inferior to the six-factor solution in terms of performance. The results show that the majority of language dimensions in each factor belong to a single language style quadrant, enabling us to form the four quadrants from this solution (for the PCA results, see Appendix A, Table A14). Subsequently, we performed a logit regression with these four language style quadrants and obtained the same effects as expected—namely, significantly positive effects for supportive and constructive language and significantly negative effects for defensive and destructive language.

Due to data protection regulations, the company was unable to provide us with any agent characteristics. However, in order to control for gender and work experience, we first extracted the first name and salutation from the text transcript beginnings where possible. We then compared them with dictionaries containing German male and female first names. This process created a binary gender variable (n = 16,239, 71.49% female, 28.51% male). Work experience was approximated by the number of calls in the dataset. Both variables were included in the model, and the main effects remained stable. However, the probability of a sales success was significantly higher if the agents were female.

In another analysis, we formed the four language style quadrants from the values of the AI-based text analysis by aggregating the individual values into one value (the respective quadrant). We also used these values to perform the logit regression and obtained a significant, positive effect for constructive language and significant, negative effects for defensive and destructive language. Contrary to our expectations, supportive language had a significant, negative effect in this model.

As an additional moderator of interest, we included scaled customer age as another interaction effect in the model. The results show a positive significant effect of the Adviser with customer age, indicating that this style is associated with higher probability of sales success for older customers. Other interaction effects did not reveal any significant relationships.

We also conducted a battery of robustness checks and additional analyses for both the main and moderation models. First, we reran the logit regressions and excluded all observations with fewer than 100 words of sales agent language to ensure that shorter calls do not negatively influence the effects. This adjustment did not change any of the language style results.

Second, we performed another analysis using the average values of the PCA-based language styles and the control variables for each sales agent on any given day of the week in the dataset. As not every sales agent worked every day, this aggregation results in 4,427 observations. After data transformation, the dependent variable is now averaged rather than binary. We find average daily performance for each sales agent on every day in the sample with a mean of .075. Five of the six language styles exhibit similar effects; the Diva style, though having the same effect direction, is not significant in this model.

Third, we conducted a LASSO regression to determine the relevance of variables in estimating sales success. In this type of regression, less significant coefficients are shrunk to zero and removed from the model, depending on the value of the chosen regularization parameter lambda. Here, we use the same dataset and variable set as in main model 1. Furthermore, we employed a tenfold cross-validation and separately chose the sequence of lambda values for each fold to aid convergence. The resultant lambda values range from .0001 to .08, which falls within the typical range of values according to Friedman et al. (2010). The results for the chosen sequence of lambdas show that while some of the control variables shrunk to zero and thus are excluded from the model, four of the language styles remain in the model and have the same effect directions as in the main model. Only the Endorser style, which shows no significant effect, and the Diva style, which shows only a medium-strong significant effect, are excluded using this lambda sequence.

Fourth, in order to measure the influence of language styles on service quality, we employed text mining methods to create a dummy variable, "solved service inquiry," which indicates whether a service inquiry has been resolved or not. Additionally, a subset of the dataset was created with inquiry-intended calls. The dummy variable was then employed as the dependent variable in the model, with language styles and control variables (with the exception of the number of contracts, as it is not applicable in this context) regressed on it. The Adviser also demonstrates a significant positive effect in this context, and the effect directions align with those observed in the primary models, with the exception of the Boss language style.

Fifth, for the moderation models, we first used the same adjustment as in the main models and reduced the dataset to calls with more than 100 words of sales agent language, which did not change any of the results. We also reversed the mean centering of our interaction variables because it may not be necessary in regression models (Echambadi and Hess 2007). Reverting all variables back to their original values yielded identical results.

Sixth, as purchase-intended calls (vs. inquiry-intended calls) may naturally have a stronger association with sales success, we added the total frequency of sales-related words and bigrams such as "contract," "deal," "complete contract," and "take insurance" to the purchase-intended moderator variable. We then reran the logit regressions. However, this modified moderation variable did not change any of the results.

Seventh, a high occurrence of product-related words and bigrams does not necessarily exclude a high occurrence of service-related words and bigrams ($\rho = .40$). To measure the difference between the number of product- and service-related words and bigrams, we computed a variable called "delta," which served as an alternative moderator in the models. Positive values for the delta moderator suggest a stronger purchase intent during a call, while negative values indicate a greater inquiry intent. The results from the moderated logit model show a positive and significant main effect of the delta variable on sales performance, corroborating the conclusions from the previous moderated models. In addition, the Freethinker and Diva language styles showed positive and significant interactions with the delta variable.

Eighth, to minimize collinearity with a moderately strong correlation coefficient between purchase-intended and inquiry-intended calls, we ran two separate models, each with only the purchase intent moderator variable or the inquiry intent moderator variable. The analysis confirms that the Freethinker and Diva styles have positive and significant impacts on more purchase-intended calls.

6 Discussion

Research question 1 focuses on the language styles of sales agents in customer calls. Using the employee voice behavior framework of Maynes and Podsakoff (2014), we identified 22 language dimensions sales agents use in inside sales calls and then allocated them to six unique language styles: Endorser, Adviser, Boss, Freethinker, Educator, and Diva.

Research question 2 concentrates on identifying the styles most effective in generating sales success during calls. The findings suggest that sales success is positively related to the Adviser, Boss, and Educator styles, but negatively related to the Freethinker and Diva styles. The Endorser role shows no statistically significant impact because the language dimensions that make up this style are diverse and have different performance outcomes according to our literature review.

Research question 3 investigates whether the call intent moderates these effects. In particular, we examined whether an inside sales call has a higher purchase or inquiry intent, as these are the main reasons for customers to make a call. We find that focusing on a purchase during a call can reduce the negative impact of the Freethinker and Diva styles and that language styles that show positive direct effects on sales success are not influenced by whether the intent is on a purchase or an inquiry, resulting in the occurrence of strong language styles that sales agents can effectively use in inside sales calls. The time of day also influences the effectiveness of some language styles and therefore provides novel insights into language use in sales.

7 Managerial Implications

Annually, US companies invest billions of dollars in supporting and training their sales force (Cespedes and Wallace 2017). Considering that the phone remains a primary mode of contact, managers want to enhance communication within their inside sales force. Research has demonstrated that specific linguistic aspects, including the use of personal pronouns (Packard et al. 2018) or concrete language (Packard and Berger 2021), can affect customer relationships. The use of words such as "thank you" and "sorry" (You et al. 2020) or specific grammar (Scaros 2016) can also have impacts on sales agent–customer communication. Our research shows that the language styles sales agents employ can have different effects on sales success.

Therefore, managers can use these findings to improve their internal sales forces by the following four issues: Identification, training, allocation, and hiring. First, in Table 9, we present exemplary words and phrases that belong to certain language styles and are either advisable (“do”) or not (“don’t) based on our results. Managers could implement real-time guidance systems into inside sales agents’ workplace that detect the occurrence of these words and phrases to use or not in customer conversations to improve performance. These guidance systems could then record the agents' language (as common in call-centers) and document the number of “do” and “don't” terminologies for subsequent evaluation for training purposes. Agents can in this way identify which language styles inside sales agents use and how, i.e., by using more words and phrases from the “do”-section, they can improve their language. Gamification could also support this form of application of our results—for example, using a green light when inside sales agents use a “do” term and a red light when they use a “don't” term. In addition, lists of all agents in the inside sales department could be developed to compare agents’ performance with one another.

Second, in sales trainings, the language styles of inside sales agents can be optimized by showing them which styles they frequently use in customer conversations and which "do's" and "don'ts" they use more often. Evaluations from recorded conversations of the guidance systems mentioned in the previous point could be used to visualize the language styles used. This allows for individualized training of agents who predominantly use a successful (or unsuccessful) language style to reinforce (diminish) this style. In trainings, calls of successful agents' calls could also serve as templates to demonstrate effective language style usage.

Third, as our research findings suggest, managers can optimize customer–agent allocations. When contacting the company's hotline, customers must identify their reason for calling in advance, pressing buttons on their phone for either a product- or service-related request. Customers with a product-related request can be assigned to any sales agent, while those with a service-related request should not be assigned to agents with Freethinking or Diva language styles. The main intent of the call could, as usual with call center calls, be queried in advance by means of preselection, which then simplifies the assignment. As inbound calls come from existing customers, information about the number of contracts or customer lifetime value is frequently and easily obtainable. Customers with a strong history of loyalty or renewing contracts should be assigned to Advisers, who tend to have a friendly and nonaggressive communication style. In contrast, given their potential limited product knowledge, new or potential customers should be assigned to Educators. Furthermore, sales and call-center managers could use the daytime for agent allocations. The Diva language style works best in the morning, so managers should try to fill so many shifts at this time with agents who primarily use this language style. As Advisers work better at other times of the day, agents who primarily exhibit this language style should be working from lunch to the evening for optimal performance outcomes. Elderly customers should also prioritized put through to Advisers.

Table 8: Examples of Words and Phrases for Language Styles

Language style	Positive language dimensions	Do examples	Don't examples
Endorser	• Reliable	• Exactly, secured • "I inform my colleague"	• Somehow, maybe
	• Empathic	• Understand • "I understand"	• Doesn't matter, bad
	• Helpful	• Please, sure • "Of course we will clarify this"	• Self
	• Self-confident	• Good, contract • "Please wait a second"	• Maybe, wait
	• Motivating	• Great • "you can shorten this"	• Unfortunately, ask
	• Impressive	• Always, yes sure • "I know"	• Need, question, ask
Adviser	• Formal	• Know, secured • "You want to know the status"	• Enough
	• Friendly	• Please, help, love • "No problem"	• Quick, unfortunately
	• Positive	• Good, glad • "That's awesome"	• Broken, separated
	• Optimistic	• Really, sure • "Money is on the way	• Happens, missing
	• Composed •	• Definitely • "Simply submit the invoice"	• Out, likely
Boss	• Goal-oriented	• Perfect, professional • "Please pass this on to me"	• Again, soon
	• Optimistic	• Good, really • "There is a way to secure this"	• Unfortunately
	• Visionary	• New, future, help • "We should safeguard this in future"	• Maybe, something
	• Composed	• Definitely, for sure • "I'll give you some music to listen to"	• Out, likely
	• Motivating	• Pleasure, great • "Please send us the detailed plans"	• Minus, wait, ask
Educator	• Structured	• Always, again, immediately • "I write that down"	• Actually, well
	• Philosophical	• Nevertheless • I think about this for a moment	• End, unfortunately

Notes: Only positive loading language dimensions are displayed. Example words and phrases are from AI-based pattern analysis; word counts of 99% quantiles with highest language style values and manual screenings. Words and phrases are translated from German to English language.

Fourth, managers could also try to identify sales agents with the possibility of being top performers during the hiring process. Job interviews or trial work sessions in the inside sales department could be transcribed and analyzed in terms of the six language styles. Also, sales simulations are a valuable tool for evaluating candidates. In these simulations, applicants are tasked with speaking to customers on the phone and taking out insurance. The language style used in these simulations can provide valuable insights into an applicant's language styles, which can be a crucial factor in determining their fit for the role. Better performing language styles could then be an argument for employment and an innovative aid and decision support for hiring and sales managers.

8 Theoretical Implications for AI Text Analysis in Sales Contexts

This study carries significant implications for sales researchers engaged in the analysis of future sales data, particularly in relation to the application of artificial intelligence as a tool for text analysis. The present study adopts an innovative approach to the analysis of unstructured data, such as text (Berger et al. 2020). Conventionally, the examination of language data in sales and service contexts has been predominantly undertaken through dictionary-based methodologies (e.g. Packard and Berger 2021; Packard et al. 2018) and through self-reported questionnaires that asked about reflective behavior (e.g., Ahearne et al. 1999; Williams and Spiro 1985). AI-based methods are capable of giving sales researchers a major advantage over non-automated methods:

AI-based tools have the capacity to comprehend semantic meaning and context, thereby obviating the necessity of pre-defined dictionaries or questionnaires (Grewal et al. 2021; Humphreys et al. 2018). In our context, the AI-based text analysis encompasses components such as individual words, word classes, combinations, repetitions, and semantic structures, which are employed to calculate the values of our derived language dimensions (Linnenbuerger et al. 2018). This approach enables more comprehensive recognition of language styles and facilitates the analysis of future data, such as customer transcripts, to gain deeper insights into communication in specific situations, such as real-time feedback or query handling (Davenport et al. 2020). Furthermore, due to the substantial learning foundation of certain AI tools (the tool we used had over 38 million texts), they can learn from extensive data sets and reduce recall biases based on human judgment, as is more likely with questionnaires and self-reports.

Additionally, AI text analysis and natural language processing (NLP) tools facilitate the analysis of voluminous data sets with greater expediency and efficiency than non-automated models. This development engenders a large number of opportunities for researchers to automatically analyze the language styles of a substantial number of unstructured sales-related data sets, including customer conversations, reviews, and product texts (Grewal et al. 2021). These insights can then be scrutinized for theory-building in sales communication and CRM.

9 Limitations and Future Research Directions

Our study has limitations that could be addressed in future research. First, we acquire our six language styles solely from one industry (i.e., insurance). While we compiled all sales agent–specific transcripts into an aggregated dataset and obtained the same results in our PCA, expanding the sample to other industries (e.g., travel, mobile communication, financial institutions), customers (especially younger vs. older customers), and other products outside insurance would be beneficial to generalize our language styles and to enhance the external validity. Generalization could also be improved by conducting controlled experiments where the effect of language styles on sales success could be isolated.

Second, we lack data on sales agent–specific characteristics despite our efforts to control for their effects on sales success by adding sales agent fixed effects to our models and to extract gender and a proxy for experience by using names in the transcript and the number of calls made. Thus, exploring potential influencing variables such as real work experience, education level, age, learned skills, or past job performance would be valuable. In addition, we could not access call recording audio files given privacy concerns. While Van Zant and Berger (2020) explore the volume of customer–sales agent communication and Rizzo and Berger (2023) investigate communication speed, exploring whether audio-related characteristics can indicate personality traits would also be worthwhile. For example, Rizzo and Berger (2023) found that speaking at a slower pace is linked with greater empathy, while volume and speed are connected with aggressiveness and goal orientation, respectively.

Third, our data do not include future performance. An intriguing area for future research would be exploring how language training can enhance future performance. For example, does the use of AI-powered text analysis to train sales agents to communicate in a more "advisory" than "freethinking" manner result in improved performance over time? By collecting more data on sales agents' past performance, researchers could follow Luo et al.'s (2021b) approach and classify sales agents as low, medium, or high performers. From there, they could analyze whether AI-based language training affects these groups differently. In this case, researchers could consider running a field experiment to observe the performance of sales agents before and after training on specific language styles.

Finally, a worthwhile avenue for future research would be to analyze sales agent speech styles across various customer interactions, including face-to-face conversations and video meetings, in addition to phone calls. During a phone conversation, the voice is the sole mode of transmission and must encapsulate a wide range of information, emotion, and persuasion. Nevertheless, gestures and eye contact with customers may also affect the language styles sales agents employ. For example, does a customer service representative who adopts a Diva style with exaggerated and forceful speaking, combined with exaggerated hand gestures, worsen an already unsatisfactory customer experience?

10 References

Aggarwal, P., Castleberry, S. B., Ridnour, R., & Shepherd, C. D. (2005). Salesperson Empathy and Listening: Impact on Relationship Outcomes. Journal of Marketing Theory and Practice, 16–30.

Agnihotri, R., & Krush, M. T. (2015). Salesperson empathy, ethical behaviors, and sales performance: the moderating role of trust in one's manager. Journal of Personal Selling and Sales Management, 35 (2), 164–174.

Ahearne, M., Gruen, T. W., & Jarvis, C. B. (1999). If looks could sell: Moderation and mediation of the attractiveness effect on salesperson performance. International Journal of Research in Marketing, 16, 269–284.

Ahearne, M., Hughes, D. E., & Schillewaert, N. (2007). Why sales reps should welcome information technology: Measuring the impact of CRM-based IT on sales effectiveness. International Journal of Research in Marketing, 24, 336–349.

Aksin, O. Z., & Harker, P. T. (1999). To Sell or Not to Sell: Determining the Trade-offs Between Service and Sales in Retail Banking Phone Centers. Journal of Service Research, 2 (1), 19–33.

Alavi, S., Habel, J., Guenzi, P., & Wieseke, J. (2018). The role of leadership in salespeople's price negotiation behavior. Journal Academy of Marketing Science, 46, 703–724.

Anderson, E., & Oliver, R. L. (1987). Perspectives on Behavior-Based Versus Outcome-Based Salesforce Control Systems. Journal of Marketing, 51, 76–88.

Anderson, K. (2013). Five Ways Helpfulness Wins Hearts and Sales Report. Retrieved March 13, 2024 from https://www.forbes.com/sites/kareanderson/2013/04/23/five-ways-helpfulness-wins-hearts-and-sales/

Avramidis, A. N., Deslauriers, A., & L'Ecuyer, P. (2004). Modeling Daily Arrivals to a Telephone Call Center. Management Science, 50 (7), 896–908.

Bagozzi, R. P. (1978). Salesforce Performance and Satisfaction as a Function of Individual Difference, Interpersonal, and Situational Factors. Journal of Marketing Research, 15, 517–531.

Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. Journal of the Academy of Marketing Science, 46, 557–590.

Barrick, M. R., & Mount, M. K. (1991). The Big Five Personality Dimensions and Job Performance: A Meta-Analysis. Personnel Psychology, 44, 1–26.

Barrick, M. R., Steward, G. K., & Piotrowski, M. (2002). Personality and Job Performance: Test of the Mediating Effects of Motivation Among Sales Representatives. Journal of Applied Psychology, 87 (1), 43–51.

Baumeister, R. F., Vohs, K. D., & Funder, D. C. (2007). Psychology as the Science of Self-Reports and Finger Movements. Perspectives on Psychological Science, 2 (4), 396–403.

Becker, M., Scholdra, T. P., Berkmann, M., &. Reinartz, W. J. (2022). The Effect of Content on Zapping in TV Advertising. Journal of Marketing, 87 (2), 275–297.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the Tribes: Using Text for Marketing Insight. Journal of Marketing, 84 (1), 1–25.

Bolander, W., Chaker, N. N., Pappas, A., & Bradbury, D. R. (2021). Operationalizing salesperson performance with secondary data: aligning practice, scholarship, and theory. Journal of the Academy of Marketing Science, 49, 462–481.

Boorom, M. L., Goolsby, J. R., & Ramsey, R. P. (1998). Relational Communication Traits and Their Effects on Adaptiveness and Sales Performance. Journal of the Academy of Marketing Science, 26 (1), 16–30.

Borah, A., & Tellis, G. J. (2016). Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands? Journal of Marketing Research, 53, 143–160.

Brown, S. P., Cron, W. L., & Slocum Jr., J. W. (1998). Effects of Trait Competitiveness and Perceived Intraorganizational Competition on Salesperson Goal Setting and Performance. Journal of Marketing, 62 (4), 88–98.

Caplan, J. E., Adams, K., & Boyd, R. L. (2020). Personality and Language. In B. J. Carducci & C. S. Nave (Eds.), The Wiley Encyclopedia of Personality and Individual Differences: Models and Theories, Vol. I, First Edition (pp. 311–316). Hoboken, NJ: John Wiley & Sons.

Castleberry, S. B., Shepherd, C. D., & Ridnour, R. (1999). Effective Interpersonal Listening in the Personal Selling Environment: Conceptualization, Measurement, and Nomological Validity. Journal of Marketing Theory and Practice, 7 (1), 30–38.

Cespedes, F. V., & Wallace, C. (2017). Executives and Salespeople Are Misaligned - and the Effects are Costly. Retrieved August 15, 2023 from https://hbr.org/2017/01/executives-and-salespeople-are-misaligned-and-the-effects-are-costly

CFI Group (2020). Contact Center Satisfaction Index (CCSI). Retrieved November 4, 2022 from https://cdncom.cfigroup.com/wp-content/uploads/CFI-contact-center-satisfaction-2020.pdf

Chaker, N. N., Zablah, A. R., & Noble, C. H. (2018). More than one way to persist: Unpacking the nature of salesperson persistence to understand its effects on performance. Industrial Marketing Management, 71, 171–188.

Chomsky, N. (1965). Aspects of the Theory of Syntax. Cambridge: MIT Press.

Chomsky, N. (1968). Language and Mind. Cambridge: Cambridge University Press.

Churchill, G, A., Ford, N. M., Hartley, S. W., & Walker, O. C. (1985). The Determinants of Salesperson Performance: A Meta-Analysis. Journal of Marketing Research, 22, 103–118.

Claro, D. P., Ramos, C., & Palmatier, R. W. (2024). Dynamic and global drivers of salesperson effectiveness. Journal of the Academy of Marketing Science, 52, 399–425.

Conte, J. M., & Gintoft, J. N. (2005). Polychronicity, Big Five Personality Dimensions, and Sales Performance. Human Performance, 18 (4), 427–444.

Crandell, C. (2014). Wednesday At Lunch Time Is Best Time for Prospecting Calls. Retrieved March 20, 2025 from https://www.forbes.com/sites/christinecrandell/2014/01/18/wednesday-at-lunch-time-is-best-time-for-prospecting-calls/

Cron, W. L., Alavi, S., Habel, J., Wieseke, J., & Ryari, H. (2021). No conversion, no conversation: Consequences of retail salespeople disengaging from unpromising prospects. Journal of the Academy of Marketing Science, 49 (3), 502–520.

CX Today (2021). What is the Difference between Sales and Service Call Durations. Retrieved July 17, 2024 from https://www.cxtoday.com/contact-centre/what-is-the-difference-between-sales-and-service-call-durations/

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48, 24–42.

Davis, L., & Main, K. (2024). 11 Essential Call Center Metrics And KPIs (2024 Guide). Retrieved August 26, 2024 from https://www.forbes.com/advisor/business/software/call-center-metrics/

Dawson, L. E., Soper, B., & Pettijohn, C. E. (1992). The Effects of Empathy on Salesperson Effectiveness. Psychology & Marketing, 9 (4), 297–310.

Deeter-Schmelz, D. R., & Sojka, J. Z. (2007). Developing Effective Salespeople: Exploring the Link between Emotional Intelligence and Sales Performance. The International Journal of Organizational Analysis, 11 (3), 211–220.

Descarries, F. (2014). Language is Not Neutral: The Construction of Knowledge in the Social Sciences and Humanities. Signs, 39 (3), 564–569.

Dion, P. A., & Notarantonio, E. M. (1992). Salesperson Communication Style: The Neglected Dimension in Sales Performance. The Journal of Business Communication, 29 (1), 63–77.

Downing, J. R. (2011). Linking Communication Competence with Call Center Agents' Sales Effectiveness. Journal of Business Communication, 48 (4), 409–425.

Eachempati, P., Srivastava, P. R., Kumar, A., Muñoz de Prat, J., & Delen, D. (2022). Can customer sentiment impact firm value? An integrated text mining approach. Technological Forecasting & Social Change, 174, 1–17.

Echambadi, R., & Hess, J. D. (2007). Mean-Centering Does Not Alleviate Collinearity Problems in Moderated Multiple Regression Models. Marketing Science, 26 (3), 438–445.

Ferris, D. L., Lian, H., Pang, F. X. J., & Keeping, L. M. (2010). Self-Esteem and Job Performance: The Moderating Role of Self-Esteem Contingencies. Personnel Psychology, 63, 561–593.

Frayne C. A., & Geringer, J. M. (2000). Self-Management Training for Improving Job Performance: A Field Experiment Involving Salespeople. Journal of Applied Psychology, 85 (3), 361–372.

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. Journal of Statistical Software, 33 (1), 1–22.

George, J. M. (1998). Salesperson Mood at Work: Implications for Helping Customers. Journal of Personal Selling and Sales Management, 18 (3), 23–30.

Good, V., Hughes, D. E., Kirca, A: H., & McGrath, S. (2022). A self-determination theory-based meta-analysis on the differential effects of intrinsic and extrinsic motivation on salesperson performance. Journal of the Academy of Marketing Science, 50, 586–614.

Greenacre, L., Tung, N. M., & Chapman, T. (2014). Self-Confidence, and the Ability to Influence. In C. R. Bateman (Ed.), Academy of Marketing Studies Journal, 18 (2) (pp. 169–180). Weaverville, NC: Whitney Enterprises, Inc.

Grewal, R., Gupta, S., & Hamilton, R. (2021). Marketing Insights from Multimedia Data: Text, Image, Audio, and Video. Journal of Marketing Research, 58 (6), 1025–1033.

Hecht, M. A., & LaFrance, M. (1995). How (Fast) Can I Help You? Tone of Voice and Telephone Operator Efficiency in Interactions. Journal of Applied Social Psychology, 23 (23), 2086–2098.

Homburg, C., Ehm, L., & Artz, M. (2015). Measuring and Managing Consumer Sentiment in an Online Community Environment. Journal of Marketing Research, 52 (5), 629–641.

Humphreys, A., & Wang, R. J.-H. (2018). Automated Text Analysis for Consumer Research. Journal of Consumer Research, 44 (6), 1274–1306.

Hurtz, G. M., & Donovan, J. J. (2000). Personality and Job Performance: The Big Five Revisited. Journal of Applied Psychology, 85 (6), 869–879.

Hymes, D. (1972). On Communicative Competence. In J. Pride, & J. Holmes (Eds.), Sociolinguistics (pp. 269–285). Harmondsworth: Penguin Books.

Invoca (2022). Customer Experience Expectations In the Face of Inflation. Retrieved November 4, 2022 from https://experience.invoca.com/2022-invoca-buyer-experience-report/p/1

Itani, O. S., Goad, E. A., & Jaramillo F. (2019). Building customer relationships while achieving sales performance results: Is listening the holy grail of sales? Journal of Business Research, 102, 120–130.

Jacobs, B. J. D., Donkers, B., & Fok, D. (2016). Model-Based Purchase Predictions for Large Assortments. Marketing Science, 35 (3), 389–404.

Jasmand, C., Blazevic, V., & de Ruyter, K. (2012). Generating Sales While Providing Service: A Study of Customer Service Representatives' Ambidextrous Behavior. Journal of Marketing, 76, 20–37.

Johlke, M. C. (2006). Sales presentation skills and salesperson job performance. Journal of Business & Industrial Marketing, 21 (5), 311–319.

Jolson, M. A., & Wotruba, T. R. (1992). Prospecting: A New Look at this Old Challenge. Journal of Personal Selling and Sales Management, 12 (4), 59–66.

Jordan, J. & Kelly, R. (2015). Companies with a Formal Sales Process Generate More Revenue. Retrieved April 28, 2024 from https://hbr.org/2015/01/companies-with-a-formal-sales-process-generate-more-revenue

Kim, L. (2023). What's a Good Conversion Rate? (It's Higher Than You Think). Retrieved April 29, 2024 from https://www.wordstream.com/blog/ws/2014/03/17/what-is-a-good-conversion-rate#:~:text=Hint%3A%20it's%20a%20lot%20higher,seems%20like%20a%20massive%20jump

Lamont, L. M., & Lundstrom, W. J. (1977). Identifying Successful Industrial Salesmen by Personality and Personal Characteristics. Journal of Marketing Research, 14, 517–529.

Li, X., Chan, K. W., & Kim, S. (2019). Service with Emoticons. Journal of Consumer Research, 45 (5), 973–987.

Li, X., Hsee, C. K., & O'Brien, E. (2023). "It Could Be Better" Can Make It Worse: When and Why People Mistakenly Communicate Upward Counterfactual Information. Journal of Marketing Research, 60 (2), 1–18.

Linnenbürger, A. (2020). Kommunikation und Führungserfolg: Entwicklung eines Instruments zur Messung von Kommunikationsstilen und Analyse des Zusammenhangs mit Führungserfolgsvariablen. Bergische Universität Wuppertal [in German].

Lockeman, B. D., & Hallaq, J. H. (1982). Who are your successful Salespeople? Journal of the Academy of Marketing Science, 10 (4), 457–472.

Lowe, J. (2022). How To Succeed In Sales: Become A Trusted Advisor. Retrieved March 26, 2024 from https://www.forbes.com/sites/forbescoachescouncil/2022/08/01/how-to-succeed-in-sales-become-a-trusted-advisor/

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases. Marketing Science, 38 (6), 937–947.

Luo, H., Cheng, S., Zhou, W., Yu, S., & Lin, X. (2021). A Study on the Impact of Linguistic Persuasive Styles on the Sales Volume of Live Streaming Products in Social E-Commerce Environment. Mathematics, 9 (1576), 1–21.

Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2021). Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions. Journal of Marketing, 85 (2), 14–32.

Lussier, B., Gregoire, Y., & Vachon, M.-A. (2017). The role of humor usage on creativity, trust and performance in business relationships: An analysis of the salesperson-customer dyad. Industrial Marketing Management, 65, 168–181.

Maestro (2017). The Cost of Replacing a Sales Rep. Retrieved July 24, 2024 from https://maestrolearning.com/blogs/the-cost-of-replacing-a-sales-rep/

Marlow, S. L., Lacerenza, C. N., Paoletti, J., Burke, C. S., & Salas, E. (2018). Does team communication represent a one-size-fits-all approach? A meta-analysis of team communication and performance. Journal Organizational Behavior and Human Decision Processes, 144, 145–170.

Mayer, D., & Greenberg, H. M. (1964). What makes a good salesman. Harvard Business Review, 42, 119–125.

Maynes, T. D., & Podsakoff, P. M. (2014). Speaking More Broadly: An Examination of the Nature, Antecedents, and Consequences of an Expanded Set of Employee Voice Behaviors. Journal of Applied Psychology, 99 (1), 87–112.

McConnell, K. (2023). Individual Differences in Holistic and Compositional Language Processing. Journal of Cognition, 6 (1), 1–24.

Mela, C. F., Gupta, S., & Lehmann, D. R. (1997). The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice. Journal of Marketing Research, 34 (2), 248–261.

Mendes-Roter, J. (2023). Communication Management: How Innovation Can Bring More Business With Less Cost. Retrieved February 1, 2024 from https://www.forbes.com/councils/forbescommunicationscouncil/2023/04/25/communication-management-how-innovation-can-bring-more-business-with-less-cost/

Menon, K., & Dube, L. (2000). Ensuring Greater Satisfaction by Engineering Salesperson Response to Customer Emotions. Journal of Retailing, 76 (3), 285–307.

Miner, J. B. (1962). Personality and Ability Factors in Sales Performance. Journal of Applied Psychology, 46 (1), 6–13.

Moyse, I. (2018). The Phone is Dead, Long Live the Phone. Retrieved July 1, 2024 from https://www.uctoday.com/meeting-rooms-and-devices/the-phone-is-dead-long-live-the-phone/

Mulki, J. P., Jaramillo, F., Goad, E. A., & Pesquera, M. R. (2015). Regulation of emotions, interpersonal conflict, and job performance for salespeople. Journal of Business Research, 68, 623–630.

Nahm, I, Y., Ahearne, M. J., Lee, N., & Tirunillai, S. (2022). Managing Positive and Negative Trends in Sales Call Outcomes: The Role of Momentum. Journal of Marketing Research, 59 (6), 1120–1140.

Nancarrow, C., & Penn, S. (1998). Rapport in telemarketing – mirrow, mirrow on the call? Marketing Intelligence & Planning, 16 (1), 12–21.

Pace, R. W. (1962). Oral Communication and Sales Effectiveness. Journal of Applied Psychology, 46 (5), 321–324.

Packard, G., Moore, S. G., & McFerran, B. (2018). (I'm) Happy to Help (You): The Impact of Personal Pronoun Use in Customer–Firm Interactions. Journal of Marketing Research, 55 (4), 541–555.

Packard, G., & Berger, J. (2021). How Concrete Language Shapes Customer Satisfaction. Journal of Consumer Research, 47 (5), 787–806.

Packard, G., Li, Y., & Berger, J. (2024). When Language Matters. Journal of Consumer Research, 51 (3), 634–653.

Parincu, Z. (2023). Behavioral Psychology: Definition, Theories, & Examples. Retrieved January 25, 2024 from https://www.berkeleywellbeing.com/behavioral-psychology.html

Park, Y., & Yi, Y. (2023). Morning deals make me feel smart: Consumer evaluations of online sales promotions differ by time of day. Journal of Retailing and Consumer Services, 73, 1–8.

Paulhus, D. L., & Vazire, S. (2007). The Self-Report method. In R. W. Robins, R. C. Fraley, & R. F. Krueger (Eds.), Handbook of Research Methods in Personality Psychology (pp. 224–239). New York, NY: The Guilford Press.

Pennebaker, J. W., & Francis, M. E. (1996). Cognitive, Emotional, and Language Processes in Disclosure. Cognition & Emotion, 10 (6), 601–626.

Pennebaker, James W., Ryan L. Boyd, Kayla Jordan, and Kate Blackburn (2015), "The Development and Psychometric Properties of LIWC2015". Retrieved on July 9, 2024 from https://www.liwc.app/static/documents/LIWC2015%20Manual%20-%20Development%20and%20Psychometrics.pdf

Peterson, R. A., Cannito, M. P., & Brown, S. P. (1995). An Exploratory Investigation of Voice Characteristics and Selling Effectiveness. Journal of Personal Selling & Sales Management, 15 (1), 1–15.

Pettijohn, C. E., Pettijohn, L. S., Taylor, A. J., & Keillor, B. C. (2000). Adaptive Selling and Sales Performance: An Empirical Examination. Journal of Applied Business Research, 16 (1), 91–111.

Pinker, S. (1994). The Language Instinct. New York: William Morrow and Company.

Plotkin, H. M. (1987). What makes a successful salesperson? Training and Development Journal, 54–56.

Pocklington, A. (2023). Age Matters: Why You Need To Know Your Customers. Retrieved August 26, 2024 from https://www.forbes.com/councils/forbescommunicationscouncil/2023/07/28/age-matters-why-you-need-to-know-your-customers/

Rapaille, G. C. (2006). Leveraging the Psychology of the Salesperson. Harvard Business Review, 42–47.

Rapp, A., Ahearne, M., Mathieu, J., & Schillewaert, N. (2006). The impact of knowledge and empowerment on working smart and working hard: The moderating role of experience. International Journal of Research in Marketing, 23, 279–293.

Rapp, A., Agnihotri, R., & Baker, T. (2011). Conceptualizing Salesperson Competitive Intelligence: An Individual-Level Perspective. Journal of Personal Selling and Sales Management, 31, 141–155.

Reinartz, W., Krafft, M., & Hoyer, W. D. (2004). The Customer Relationship Management Process: Its Measurement and Impact on Performance. Journal of Marketing Research, 41, 293–305.

Rizzo, G. L. C., & Berger, J. A. (2023). The Power of Speaking Slower. Retrieved October 31, 2023 from https://ssrn.com/abstract=4580994

Rust, R. T., Moorman, C., & Dickson, P. R. (2002). Getting Return on Quality: Revenue Expansion, Cost Reduction, or Both? Journal of Marketing, 66, 7–24.

Satornino, C. B., Allen, A., & Bolander, W. (2023). Understanding the Performance Effects of "Dark" Salesperson Traits: Machiavellianism, Narcissism, and Psychopathy. Journal of Marketing, 87 (2), 298–318.

Scaros, C. (2016). The Importance of Good Grammar in Business Communications. Retrieved September 23, 2022 from https://www.linkedin.com/pulse/importance-good-grammar-business-communications-cecile-scaros

Shapiro, B. P., & Posner, R. S. (2006). Making the Major Sale. Retrieved March 15, 2024 from https://hbr.org/2006/07/making-the-major-sale

Singh, S., Marinova, D., Singh, J., & Evans, K. R. (2018). Customer query handling in sales interactions. Journal of the Academy of Marketing Science, 46, 837–856.

Sparks, J. R., & Areni, C. S. (2002). The effects of sales presentation quality and initial perceptions on persuasion: a multiple role perspective. Journal of Business Research, 55, 517–528.

Spiro, R. L., & Weitz, B. A. (1990). Adaptive Selling: Conceptualization, Measurement, and Nomological Validity. Journal of Marketing Research. 27, 61–69.

Stanton, W. J., &. Bushkirk, R. H. (1959). Management of the Salesforce. Homewood: Richard D. Irwin.

Sujan, H. (1999). Optimism and Street-Smarts: Identifying and Improving Salesperson Intelligence. The Journal of Personal Selling and Sales Management, 19 (3), 17–33.

Szot, D. (2023). How Considering Alternatives Changes Ways Of Thinking About Creativity. Retrieved March 26, 2024 from https://www.forbes.com/sites/forbescoachescouncil/2023/05/02/how-considering-alternatives-changes-ways-of-thinking-about-creativity/

Tellis, G. J., MacInnis, D. J., Tirunillai, S., & Zhang, Y. (2019). What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence. Journal of Marketing, 83 (4), 1–20.

Thacker, M. (2020). 20/20 Foresight In 2020 And Beyond: How To Boost Sales By Looking Forward. Retrieved March 26, 2024 from https://www.forbes.com/councils/forbescoachescouncil/2020/02/14/2020-foresight-in-2020-and-beyond-how-to-boost-sales-by-looking-forward/

VandeWalle, D. & Brett, J. F. (1999). Goal orientation and goal content as predictors of performance in a training program. Journal of Applied Psychology, 84 (6), 863–873.

Van Zant, A. B., & Berger, J. (2020). How the Voice Persuades. Journal of Personality and Social Psychology: Interpersonal Relations and Group Processes, 118 (4), 661–682.

Verbeke, W., & Bagozzi, R. P. (2002). A Situational Analysis on How Salespeople Experience and Cope with Shame and Embarrassment. Psychology & Marketing, 19 (9), 713–741.

Verbeke, W., Dietz, B., & Verwaal, E. (2011). Drivers of sales performance: a contemporary meta-analysis. Have salespeople become knowledge brokers? Journal of the Academy of Marketing Science, 39, 407–428.

Vinchur, A. J., Schippmann, J. S., Switzer, III, F. S., & Roth, P. L. (1998). A Meta-Analytic Review of Predictors of Job Performance for Salespeople. Journal of Applied Psychology, 83 (4), 586–597.

Webster, F. E. (1968). Interpersonal Communication and Salesman Effectiveness. Journal of Marketing, 32 (July), 7–13.

Weitz, B. A., Sujan, H., & Sujan, M. (1986). Knowledge, Motivation, and Adaptive Behavior: A Framework for Improving Selling Effectiveness. Journal of Marketing, 50 (4), 174–191.

Williams, K. C., & Spiro, R. L. (1985). Communication Style in the Salesperson Customer Dyad. Journal of Marketing Research, 22, 434–442.

You, Y., Yang, X., Wang, L., & Deng, X. (2020). When and Why Saying “Thank You” Is Better Than Saying “Sorry” in Redressing Service Failures: The Role of Self-Esteem, Journal of Marketing, 84 (2), 133–150.

Yu, T., Patterson, P. G., & de Ruyter, K. (2013). Achieving Service-Sales Ambidexterity. Journal of Service Research, 16 (1), 52–66.

Zoltners, A. A., Sinha, P., & Lorimer, S. E. (2016). Great Salespeople Are Born, but Great Sales Forces Are Made. Retrieved March 27, 2024 from https://hbr.org/2016/05/great-salespeople-are-born-but-great-sales-forces-are-made

Appendix A

Table A1: Overview of Sales Agent Attributes and their Effect on Sales Performance

Sales agent Attributes	Effect on performance	Publication
Job-related skills		
Adaptive selling skills	+/-	Spiro and Weitz (1990)
	n.s.	Pettijohn et al. (2000)
	+	Verbeke et al. (2011)
Cognitive aptitude	+	Verbeke et al. (2011)
Communication skills	+	Pace (1962)
	+	Williams and Spiro (1985)
Listening skills	+	Castleberry et al. (1999)
	+	Aggarwal et al. (2005)
	+	Itani et al. (2019)
Polychronicity	+	Conte and Gintoft (2005)
Selling-related knowledge	+	Verbeke et al. (2011)
Presentation skills	+	Johlke (2006)
Behavioral concepts		
Goal orientation	+	Brown et al. (1997)
	+	VandeWalle et al. (1999)
Humor	+	Lussier et al. (2017)
Motivation	+	Churchill et al. (1985)
	+	Plotkin (1987)
	+	Barrick et al. (2002)
Persistence	+/-	Chaker et al. (2018)
Self-esteem	+	Bagozzi (1978)
Personality traits		
Agreeableness	n.s.	Barrick and Mount (1991)
Conscientiousness	+	Barrick and Mount (1991)
	+	Vinchur et al. (1998)
	n.s.	Conte and Gintoft (2005)
Cynicism and competitiveness	+	Plotkin (1987)
Emotional stability	+	Barrick and Mount (1991)
Empathy	-	Mayer and Greenberg (1964)
	-	Dawson et al. (1992)
Extraversion	+	Barrick and Mount (1991)
	+	Vinchur et al. (1998)
	+	Conte and Gintoft (2005)
Independence	+	Stanton (1959)
Narcissism	-	Satornino et al. (2023)
Openness to experience	n.s.	Barrick and Mount (1991)

Table A2: Language Use in Sales

Language styles in sales	Methodology	Dependent variable	Publication
"What" level			
Pronouns	Word count	Customer satisfaction, purchase intention, purchase behavior	Packard et al. (2018)
Concrete wordings	Concreteness score based on predefined dictionary	customer satisfaction, customer spending	Packard and Berger (2021)
Saying "thank you"	Manipulation of wordings in several studies	Customer satisfaction, customer self-esteem	You et al. (2020)
Counterfactual information	Wordings in several lab studies	Experiencers' impressions	Li et al. (2023)
"How" level: Sensation			
Warmth and competence	Word count	Customer interest	Singh et al. (2018)
	Word count	Customer satisfaction, purchases	Li et al. (2023)
Emotional intelligence	In-depth interviews	Sales performance	Deeter-Schmelz and Sojka (2007)
Emotional appealing	Interviews, ratings	Sales effectiveness	Pace (1962)
"How" level: Paralanguage			
Speaking rate	Audio analysis, customer ratings	Sales performance	Peterson et al. (1995)
Frequency contour variability	Audio analysis, customer ratings	Sales performance	Peterson et al. (1995)
Tempo	Expert ratings of audio excerpts	Job performance	Hecht and LaFrance (1995)
	Questionnaire, ratings		Downing (2011)
	Randomized experiments, audio analyses	Conversion rates	Van Zant and Berger (2020)
		Confidence appearance and persuasiveness	
Pitch	Questionnaire, ratings	Conversion rates	Downing (2011)
Volume	Questionnaire, ratings	Conversion rates	Downing (2011)
	Randomized experiments, audio analyses	Confidence appearance and persuasiveness	Van Zant and Berger (2020)

Table A3: Definitions of Language Dimensions

Language dimension	Definition
Empathic	The empathic communication style conveys a high sensitivity for the feelings of other people. The communication is cautious, focuses on feelings, and tries to understand other people's perspectives. It deals directly with the statements of others and reacts sensitively to their feelings.
Friendly	The friendly communication style expresses social closeness to others and is perceived as sympathetic and warm-hearted. It conveys a general feeling of goodwill and a willingness to compromise.
Helpful	The supportive communication style involves encouraging others and helping them to develop further. The focus is not on own well-being but the well-being of others. Those who communicate supportively encourage others and convey a great willingness to help. Appreciation for others is shown.
Positive	The positive communication style describes a positive and cheerful charisma that causes a pleasant mood.
Optimistic	The optimistic communicative style conveys confidence. The result is a positive view of the future that draws positive conclusions even from negative experiences and believes that anything is possible. The confident attitude also means that risks are assessed more positively and are more likely to be taken.
Visionary	People with a visionary communication style often refer to a glorious future and make promising statements. It is often a question of how more can be achieved and what potential improvements look like. Visions are communicated that indicate positive expectations and a promising future.
Formal	The formal communicative style presents facts as objectively as possible. It often consists of numbers, data, and facts, resulting in a rational, fact-based, and down-to-earth effect.
Structured	In the structured communication style, individual statements of a narrative build on each other. Communication follows a logical structure and has a common thread, which creates an organized effect.
Goal-oriented	The goal-oriented communication style makes clear and unambiguous statements. Communication is as efficient and concise as possible with the goal of finding a pragmatic solution.
Reliable	People who choose the reliable communication style convey a sense of commitment. It is clearly stated what responsibility is taken, and the interlocutor knows that the statements of the other person will still be equally valid the next day.
Intellectual	The intellectual communication style creates a well thought-out and deliberate effect. Its structure is precise and rather complex. Content is described in detail. All in all, a high standard of performance is imparted.
Unconventional	Unconventional communication means adding unusual, imaginative ideas to conversations, opening up innovative or unusual perspectives and making generally surprising statements.
Philosophical	Philosophical communicators talk about the theoretical background of their statements. They discuss philosophical and significant topics in depth.
Impulsive	The impulsive style of communication is impatient, stormy, or unsteady. Often a sudden impulse or intuition is the trigger for communication rather than thinking about

	the consequences of own statements and reflecting on them. This quickly gives rise to heated discussions.
Aggressive	The aggressive communication style is about quick-tempered, relentless communication that puts pressure on others and provokes the interlocutor or the person addressed. This often leads to discussions.
Authoritative	The authoritarian communication style determines the direction and tone of a conversation.
Self-confident	Self-confident communicators tend to place themselves at the center of communication. They rarely hold back, seem unreserved, and do not get easily discouraged. They also do not shy away from confrontation.
Composed	Composed communication relaxes conversational situations rather than causing nervousness and excitement. Even in stressful situations, people are still able to express themselves appropriately.
Dramatic	Dramatic communication means to exaggerate, to embellish stories, and to present events more interesting and exciting than they really were.
Motivating	The motivating communication style conveys enthusiasm and activity. This effect makes it easier to carry away and inspire listeners. Conversations or texts are more likely to be experienced as exciting.
Impressive	The impressive communication style is captivating and leaves a lasting impression on other people.
Independent	Independent communication means making statements independent of common opinions of other people. Those who communicate independently do not ensure the acceptance of their statements from others. They do not allow themselves to be influenced in what they say by the predominant opinion or the supposed judgments of others.

Notes: Definitions extracted from VIER Emotion Analytics based on Linnenbürger (2020).

Table A4: Summary Statistics of the Dependent Variable and Control Variables

	M	SD	Min	1st Quantile	Median	3rd Quantile	Max
Sales success	.0521	.2222	0	0	0	0	1
Customer age	62.846	15.222	9	53	65	74	121
Customer relationship	152.216	95.834	1	67	163	227	314
Number of mail pieces	98.401	84.930	0	19	81	164	418
Number of offers	9.176	9.320	0	3	6	12	183
Number of calls	28.498	30.457	0	8	20	39	877
Number of emails	40.579	73.783	0	0	0	44.500	347
Number of active contracts	2.132	1.643	0	1	2	3	19
Number of inactive contracts	2.287	3.257	0	0	1	3	61
Duration last contract	58.371	57.554	0	12	40	90	394
Call duration	602.046	463.629	1	295	474	757	7,306
Customer sentiment pos.	4.641	3.750	0	2	4	6	41
Customer sentiment neg.	1.812	2.611	0	0	1	2	34

Table A5: Summary Statistics for Purchase-Intended Calls

	M	SD	Min	1st Quantile	Median	3rd Quantile	Max
Sales success	.0936	.2912	0	0	0	0	1
Customer age	62.581	14.982	17	53	64	74	121
Customer relationship	150.290	96.091	1	65	160	226	314
Number of mail pieces	97.713	84.797	0	19	80	162	404
Number of offers	9.433	9.522	0	3	7	12	183
Number of calls	28.496	30.758	1	8	20	39	877
Number of emails	41.537	74.539	0	0	0	47	334
Number of act. contracts	2.171	1.636	0	1	2	3	18
Number of inact. contracts	2.297	3.351	0	0	1	3	61
Duration last contract	55.485	55.396	0	11	37	85	394
Call duration	661.941	497.681	1	325	527	835	7,306
Customer sentiment pos.	5.663	4.170	0	3	5	8	41
Customer sentiment neg.	2.330	3.007	0	0	1	3	34

Table A6: Summary Statistics for Inquiry-Intended Calls

	M	SD	Min	1st Quantile	Median	3rd Quantile	Max
Sales success	.0391	.1939	0	0	0	0	1
Customer age	63.279	15.336	18	54	65	75	121
Customer relationship	152.418	95.898	1	68	164	227	314
Number of mail pieces	98.015	84.886	0	17	83	164	354
Number of offers	8.865	9.074	0	3	6	12	123
Number of calls	28.575	29.790	0	9	20	39	385
Number of emails	38.337	71.932	0	0	0	38	339
Number of act. contracts	2.085	1.667	0	1	2	3	19
Number of inact. contracts	2.238	3.154	0	0	1	3	41
Duration last contract	61.122	60.111	0	13	42	94	359
Call duration	583.690	435.974	55	297	467	729	7,097
Customer sentiment pos.	5.224	3.931	0	2	4	7	37
Customer sentiment neg.	2.132	2.837	0	0	1	3	31

Table A7: Correlation Matrix of Speech Dimensions

	INT	GOA	REL	STR	FOR	EMP	SUP	FRI	POS	OPT	VIS	AUT	SEL	COM	UNC	PHI	IMPU	AGG	MOT	IMPR	DRA	IND
Intellectual	1	-0.441	-0.110	0.222	0.461	-0.056	0.075	0.347	0.375	0.064	-0.045	-0.027	-0.095	0.066	0.551	0.153	-0.194	-0.332	-0.044	-0.060	-0.092	0.116
Goal-oriented	-0.441	1	0.183	-0.166	-0.057	0.059	0.015	0.011	-0.012	0.272	0.390	0.180	-0.076	0.202	-0.445	-0.073	0.039	-0.062	0.239	0.259	0.075	-0.016
Reliable	-0.110	0.183	1	-0.045	-0.245	0.770	0.646	0.119	0.009	0.095	0.068	0.462	0.635	0.159	-0.031	-0.063	0.045	-0.142	0.652	0.745	0.018	-0.673
Structured	0.222	-0.166	-0.045	1	0.211	-0.048	-0.036	-0.008	0.041	0.034	-0.024	0.100	0.079	-0.008	-0.054	0.437	-0.069	0.040	-0.176	-0.006	0.033	0.026
Formal	0.461	-0.057	-0.245	0.211	1	-0.242	0.023	0.368	0.452	0.122	-0.025	-0.140	-0.289	0.128	-0.097	0.322	-0.232	-0.443	-0.365	-0.173	-0.196	0.263
Empathic	-0.056	0.059	0.770	-0.048	-0.242	1	0.852	0.263	0.094	0.221	0.130	0.237	0.666	0.157	0.013	0.107	-0.149	-0.328	0.660	0.620	-0.086	-0.843
Supportive	0.075	0.015	0.646	-0.036	0.023	0.852	1	0.551	0.404	0.288	0.171	0.173	0.578	0.279	0.066	0.060	-0.188	-0.622	0.590	0.532	-0.154	-0.811
Friendly	0.347	0.011	0.119	-0.008	0.368	0.263	0.551	1	0.940	0.631	0.321	-0.096	-0.081	0.650	0.246	-0.061	-0.437	-0.913	0.201	0.119	-0.317	-0.127
Positive	0.375	-0.012	0.009	0.041	0.452	0.094	0.404	0.940	1	0.621	0.271	0.015	-0.119	0.641	0.211	-0.067	-0.429	-0.822	0.081	0.049	-0.187	0.019
Optimistic	0.064	0.272	0.095	0.034	0.122	0.221	0.288	0.631	0.621	1	0.652	0.038	-0.164	0.725	0.163	0.030	-0.487	-0.576	0.256	0.178	-0.233	-0.037
Visionary	-0.045	0.390	0.068	-0.024	-0.025	0.130	0.171	0.321	0.271	0.652	1	0.037	-0.158	0.490	0.281	0.041	0.023	-0.321	0.500	0.260	-0.077	-0.009
Authoritative	-0.027	0.180	0.462	0.100	-0.140	0.237	0.173	-0.096	0.015	0.038	0.037	1	0.496	0.047	-0.037	-0.076	0.012	0.157	0.360	0.529	0.317	-0.293
Self-confident	-0.095	-0.076	0.635	0.079	-0.289	0.666	0.578	-0.081	-0.119	-0.164	-0.158	0.496	1	-0.063	-0.026	0.073	0.136	0.105	0.443	0.532	0.182	-0.775
Composed	0.066	0.202	0.159	-0.008	0.128	0.157	0.279	0.650	0.641	0.725	0.490	0.047	-0.063	1	0.146	-0.013	-0.303	-0.528	0.212	0.150	-0.238	-0.084
Unconventional	0.551	-0.445	-0.031	-0.054	-0.097	0.013	0.066	0.246	0.211	0.163	0.281	-0.037	-0.026	0.146	1	-0.107	0.076	-0.156	0.269	-0.022	-0.042	0.022
Philosophical	0.153	-0.073	-0.063	0.437	0.322	0.107	0.060	-0.061	-0.067	0.030	0.041	-0.076	0.073	-0.013	-0.107	1	-0.019	-0.008	-0.099	0.006	-0.133	-0.037
Impulsive	-0.194	0.039	0.045	-0.069	-0.232	-0.149	-0.188	-0.437	-0.429	-0.487	0.023	0.012	0.136	-0.303	0.076	-0.019	1	0.446	0.165	-0.017	0.360	0.059
Aggressive	-0.332	-0.062	-0.142	0.040	-0.443	-0.328	-0.622	-0.913	-0.822	-0.576	-0.321	0.157	0.105	-0.528	-0.156	-0.008	0.446	1	-0.227	-0.114	0.360	0.172
Motivating	-0.044	0.239	0.652	-0.176	-0.365	0.660	0.590	0.201	0.081	0.256	0.500	0.360	0.443	0.212	0.269	-0.099	0.165	-0.227	1	0.639	0.100	-0.549
Impressive	-0.060	0.259	0.745	-0.006	-0.173	0.620	0.532	0.119	0.049	0.178	0.260	0.529	0.532	0.150	-0.022	0.006	-0.017	-0.114	0.639	1	-0.022	-0.570
Dramatic	-0.092	0.075	0.018	0.033	-0.196	-0.086	-0.154	-0.317	-0.187	-0.233	-0.077	0.317	0.182	-0.238	-0.042	-0.133	0.360	0.360	0.100	-0.022	1	0.038
Independent	0.116	-0.016	-0.673	0.026	0.263	-0.843	-0.811	-0.127	0.019	-0.037	-0.009	-0.293	-0.775	-0.084	0.022	-0.037	0.059	0.172	-0.549	-0.570	0.038	1

Notes: Correlation coefficients shown are Pearson. N = 43,619.

Table A8: Summary Statistics and Correlations of Factors for Product-Intended Calls

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
M	.075	-.090	.010	-.350	.119	-.034
SD	.967	1.035	.998	.882	.921	.939
Minimum	-2.700	-8.690	-8.049	-2.446	-4.249	-5.181
Maximum	5.239	2.745	5.386	4.031	7.276	5.808
Factor 1	1	-.042	-.222	.099	.025	-.172
Factor 2	-.042	1	-.279	-.114	-.280	.286
Factor 3	-.222	-.279	1	.116	.378	-.128
Factor 4	.099	-.114	.116	1	.030	-.039
Factor 5	.025	-.280	.378	.030	1	-.085
Factor 6	-.172	.286	-.128	-.039	-.085	1

Table A9: Summary Statistics and Correlations of Factors for Inquiry-Intended Calls

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
M	.098	-.041	-.033	-.160	.066	.001
SD	1.030	1.074	1.062	.889	1.010	1.000
Minimum	-2.891	-8.499	-7.880	-2.601	-4.330	-4.771
Maximum	5.223	3.338	5.115	4.578	6.629	7.226
Factor 1	1	-.035	-.214	.064	.070	-.164
Factor 2	-.035	1	-.278	-.100	-.288	.276
Factor 3	-.214	-.278	1	.137	.334	-.183
Factor 4	.064	-.100	.137	1	.042	-.029
Factor 5	.070	-.288	.334	.042	1	-.110
Factor 6	-.164	.276	-.183	-.029	-.110	1

Table A10: Main and Moderated Logit Models without Controls

	Model 1a Sales success		Moderation model 1a Sales success	
Constant	-4.852***	(.426)	-5.100***	(.433)
Language styles				
Endorser	.073	(.040)	.068	(.043)
Adviser	.400***	(.042)	.460***	(.047)
Boss	.534***	(.045)	.554***	(.049)
Freethinker	-3.013***	(.062)	-2.971***	(.067)
Educator	.281***	(.039)	.305***	(.041)
Diva	-.121**	(.039)	-.140***	(.042)
Moderators				
Call intent purchase			.109***	(.015)
Call intent inquiry			-.054	(.033)
Interaction effects				
Endorser × call intent purchase			.097***	(.029)
Adviser × call intent purchase			-.025	(.033)
Boss × call intent purchase			-.032	(.037)
Freethinker × call intent purchase			.159***	(.049)
Educator × call intent purchase			-.089**	(.037)
Diva × call intent purchase			.055*	(.032)
Endorser × call intent inquiry			-.040	(.035)
Adviser × call intent inquiry			-.065*	(.038)
Boss × call intent inquiry			.012	(.045)
Freethinker × call intent inquiry			-.023	(.059)
Educator × call intent inquiry			-.030	(.042)
Diva × call intent inquiry			.034	(.037)
Agent fixed effects	Yes		Yes	
Weekday fixed effects	Yes		Yes	
Log-likelihood	-5,664.458		-5,674.016	
Pseudo-R^2	.413031		.423261	
AIC	12,224.92		12,072.03	
BIC	16,115.01		16,083.14	
No. observations	43,619		43,567	

Notes: AIC = Akaike information criterion; BIC = Bayesian information criterion.

Table A11: Variance Inflation Factors (VIF) for Language Styles and Controls

Independent variables	VIF
Endorser	1.129
Adviser	1.502
Boss	1.571
Freethinker	1.266
Educator	1.302
Diva	1.162
Customer age	1.454
Customer relationship	2.901
Number of mail pieces	2.493
Number of offers	3.103
Number of calls	3.337
Number of emails	1.093
Number of active contracts	1.354
Number of inactive contracts	1.788
Duration last contract	1.391
Call duration	1.663
Customer sentiment positive	1.872
Customer sentiment negative	1.731

Table A12: Quadratic Effects of Language Styles

	Non-linear model	
	Sales success	
Constant	-4.593***	(.562)
Language styles		
Endorser	.163*	(.084)
Adviser	.588***	(.077)
Boss	.406***	(.097)
Freethinker	-3.318***	(.248)
Educator	.764***	(.103)
Diva	.089	(.091)
Endorser^2	-.314***	(.055)
Adviser^2	.155***	(.028)
Boss^2	-.231***	(.054)
Freethinker^2	-.636***	(.126)
Educator^2	-.545***	(.071)
Diva^2	-.315***	(.052)
Moderators		
Call intent purchase	.078***	(.021)
Call intent inquiry	-.127**	(.044)
Interaction effects		
Endorser × call intent purchase	.004	(.009)
Adviser × call intent purchase	.013	(.009)
Boss × call intent purchase	.003	(.012)
Freethinker × call intent purchase	.028*	(.017)
Educator × call intent purchase	-.016	(.013)
Diva × call intent purchase	.009	(.011)
Endorser × call intent inquiry	-.014	(.019)
Adviser × call intent inquiry	-.015	(.018)
Boss × call intent inquiry	.027	(.025)
Freethinker × call intent inquiry	-.048	(.034)
Educator × call intent inquiry	-.017	(.026)
Diva × call intent inquiry	-.004	(.022)
Controls		
Customer age	.001	(.003)
Customer relationship	.001*	(.001)
Number of mail pieces	.001*	(.001)
Number of offers	.032***	(.007)
Number of calls	-.022***	(.003)
Number of emails	.001	.0004
Number of active contracts	-.094***	(.025)
Number of inactive contracts	-.023	(.014)
Duration last contract	-.004***	(.001)
Call duration	.001***	(.0001)
Customer sentiment positive	-.015	(.010)
Customer sentiment negative	-.048***	(.012)
Agent & weekday fixed effects	Yes	
Log-likelihood	-3,835,554	
Pseudo-R^2	.4852	
AIC	8,267.995	
BIC	11,919.230	
No. observations	26,064	

Table A13: Moderation Model with Daytime Interaction Effects

	Mod. model 1		Mod. model 2		Mod. model 3	
	Sales success		Sales success		Sales success	
Constant	-5.081***	(.557)	-5.048***	(.558)	-5.005***	(.552)
Language styles						
Endorser	-.037	(.066)	-.045	(.064)	-.035	(.053)
Adviser	.680***	(.072)	.525***	(.069)	.587***	(.054)
Boss	.521***	(.077)	.575***	(.074)	.483***	(.058)
Freethinker	-2.320***	(.101)	-2.441***	(.098)	-2.388***	(.080)
Educator	.349***	(.067)	.189***	(.067)	.329***	(.052)
Diva	-.238***	(.068)	-.055	(.065)	-.120**	(.051)
Moderator						
Daytime morning	.024	(.162)				
Daytime afternoon			-.058	(.162)		
Daytime evening					-.084	(.306)
Interaction effects						
Endorser × daytime morning	-.119	(.087)				
Adviser × daytime morning	-.184*	(.099)				
Boss × daytime morning	-.005	(.107)				
Freethinker × daytime morning	-.149	(.135)				
Educator × daytime morning	-.114	(.097)				
Diva × daytime morning	.217***	(.093)				
Endorser × daytime afternoon			.061	(.087)		
Adviser × daytime afternoon			.147	(.100)		
Boss × daytime afternoon			-.126	(.108)		
Freethinker × daytime afternoon			.105	(.135)		
Educator × daytime afternoon			-.235**	(.097)		
Diva × daytime afternoon			-.167*	(.094)	-	
Endorser × daytime evening					-.084	(.306)
Adviser × daytime evening					.221	(.168)
Boss × daytime evening					.171	(.199)
Freethinker × daytime evening					.540**	(.227)
Educator × daytime evening					.010	(.252)
Diva × daytime evening					-.421**	(.185)
Controls						
Customer age	.001	(.003)	.002	(.003)	.001	(.003)
Customer relationship	.001*	(.001)	.001*	(.001)	.001*	(.001)
Number of mail pieces	.001*	(.001)	.001*	(.001)	.001*	(.001)
Number of offers	.038***	(.006)	.038***	(.006)	.037***	(.006)
Number of calls	-.024***	(.003)	-.024***	(.003)	-.024***	(.003)
Number of emails	.001	(.0004)	.001	.0004	.001	.0004
Number of act. contracts	-.098***	(.024)	-.096***	(.024)	-.095***	(.024)
Number of inact. contracts	-.025*	(.014)	-.024*	(.014)	-.024*	(.014)
Duration last contract	-.004***	(.001)	-.004***	(.001)	-.004***	(.001)
Call duration	.001***	(.0001)	.001***	(.0001)	.001***	(.0001)
Customer sent. positive	-.007	(.009)	-.007	(.009)	-.007	(.009)
Customer sent. negative	-.053***	(.011)	-.053***	(.011)	-.054***	(.011)
Agent fixed effects	Yes		Yes		Yes	
Weekday fixed effects	Yes		Yes		Yes	
Log-likelihood	-3,870.044		-3,871.744		-3,872.156	
Pseudo-R^2	.4557		.4554		.4553	

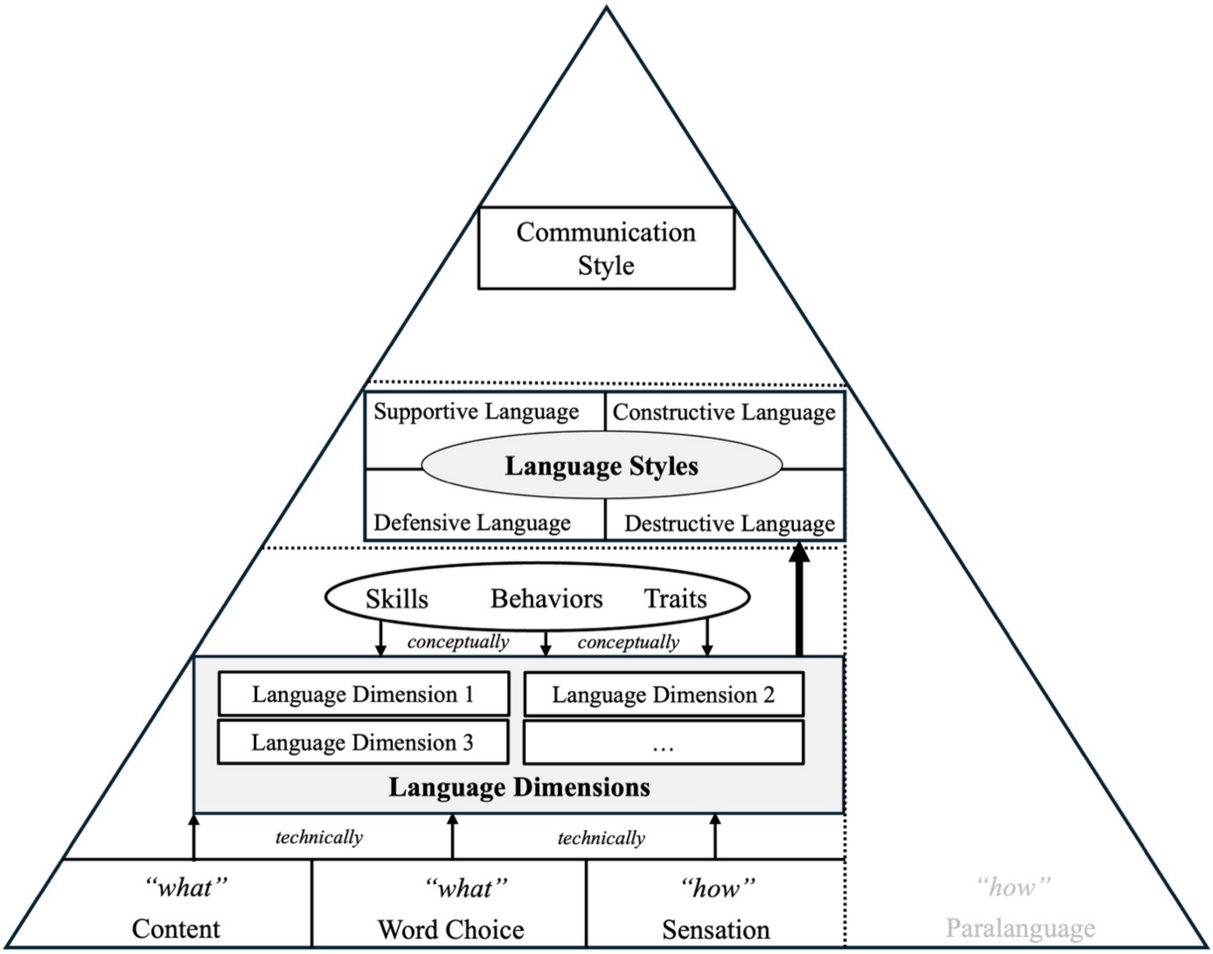
AIC	8,608.089	8,611.487	8,612.312
BIC	12,153.140	12,156.530	12,157.360
No. observations	26,064	26,064	26,064

Table A14: PCA with Four Components

	Language style quadrants			
Language dimensions	Supportive language factor	Constructive language factor	Defensive language factor	Destructive language factor
Intellectual			.75	
Goal-oriented			**-.78**	
Reliable		**.84**		
Structured				**-.51**
Formal	**.43**			**-.55**
Empathic		.90		
Helpful	**.39**	.81		
Friendly	**.91**			
Positive	.88			
Optimistic	.83			
Visionary	.54			.57
Authoritative		.48		
Self-confident		.88		
Composed	**.77**			
Unconventional			**.88**	.57
Philosophical				-.59
Impulsive	**-.54**			**.37**
Aggressive	**-.88**			
Motivating		**.61**		.57
Impressive		**.73**		
Dramatic	**-.41**			
Independent		**-.91**		

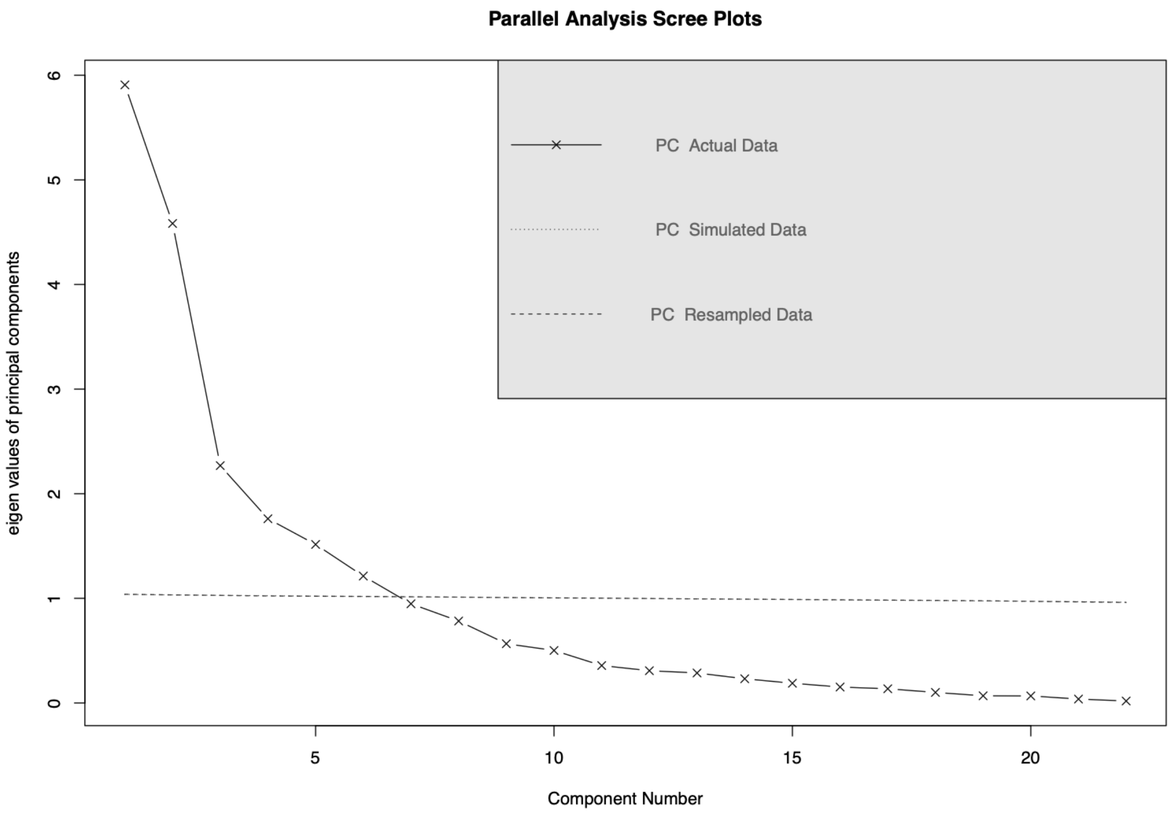
Notes: Rotated Promax loadings. Bold values indicate conceptual affiliation of language dimension into the respective language style quadrant.

Figure A1: Derivation of Language Dimensions and Language Styles



Notes: Language style quadrants based on the employee voice behavior framework (Maynes and Podsakoff 2014).

Figure A2: Scree Plot of Eigenvalues



Appendix B: Detailed Derivation of Sales Language Dimensions

What effect does salespeople's language have? We derive various language dimensions that salespeople use in their communication from scientific literature and practical journals. We conducted a comprehensive literature review of well-known marketing (e.g., *Journal of the Academy of Marketing Science*, *Journal of Marketing*), sales (e.g., *Journal of Personal Selling & Sales Management*, *Journal of Business Research*), and psychology (e.g., *Journal of Applied Psychology*, *Personnel Psychology*) journals as well as practitioner publications (e.g., *Harvard Business Review*, *Forbes*) that focus on sales agent attributes (i.e., the skills, behavioral concepts, and personality traits of sales agents that can be translated into language dimensions). We also relied on the definitions of language dimensions provided by VIER Emotion Analytics based on the work of Linnenbürger (2020) to perform our text analysis. The short definitions appear in Table A3 of Web Appendix A.

For classification, we rely on the employee voice behavior framework (Maynes and Podsakoff 2014), which divides employees' voice behavior (i.e., their voluntary and open communication toward other individuals to influence the context of their work) into two major dimensions: preservative versus challenging voice and promotive versus prohibitive voice. The division of voice behavior results in a matrix with four quadrants. Preservative and promotive voice represents "supportive voice," challenging and promotive voice "constructive voice," prohibitive and preservative "defensive voice," and prohibitive and challenging voice "destructive voice."

Arguably, this division is highly transferable in the sales context for grouping language dimensions of sales agents. Salespeople are a fundamental part of every organization and have a high degree of verbal acuity (Martin 2015). The division into either supportive or constructive voice is also in line with the work of Singh et al. (2018), who conceptualize salespeople behavior as either resolving or relating and emoting. On the other hand, Verbeke and Bagozzi

(2002) suggest that the shame and embarrassment salespeople experience during personal selling situations can provoke avoidance behaviors, which we expect also to be reflected in defensive or destructive voice.

Supportive Language

According to Maynes and Podsakoff (2014), supportive language is the voluntary expression of support for worthwhile work-related topics. In telesales interactions, the expression of support and helpfulness is essential, and helpful language aids customers in situations of service requests or sales conversations. The focus is therefore not on own well-being but on the well-being of customers (Linnenbürger 2020). It reduces hassle and may foster sales success (Anderson 2013). Friendliness and empathy are two other language dimensions that we classify as supportive language, as they are characterized by warm-hearted language (friendly) and sensitivity toward the feelings of others (Linnenbürger 2020). Friendliness is a key trait of salespeople and positively associated with sales performance (Forbes Expert Panel 2021). Friendliness and empathy in language are key parts of cooperative language essential for supportive voice. Cooperative language occurs when two or more communication participants exchange information and behave like a team (Marlow et al. 2018). Often, these interdependent team behaviors lead to certain outcomes (Marks et al. 2001). Agents not only profit from a friendly communication style but also try to empathically communicate with customers; that is, they use empathic language to understand customer needs and concerns. While practitioner publications find that empathy is strongly positively associated with performance because it fosters a deeper understanding of customer needs (e.g., Makela 2021; Zoltners et al. 2016), Mayer and Greenberg (1964) argue that empathy alone can lead to negative effects on sales performance if the behavioral concept of ego drive is absent. They argue that without ego drive, empathic salespeople will lack the willingness or toughness to sell. Other research has also confirmed this negative relationship of empathy with sales performance (Dawson et al. 1992;

Lamont and Lundstrom 1977). However, empathy in language frequently occurs in sales situations.

Supportive communication in sales also requires analytical skills generally favorable for sales agents (Peesker et al. 2022). For this, certain rules and structures must be clearly communicated. Communication that follows a centralized structure enhances performance outcomes (Mulder 1960). In sales, having a structure and accompanying customers through the entire buying process are crucial for success (Shapiro and Posner 2006). If structuredness is communicated properly, agents can also guide customers through an agenda and shape their own buying process strategically (Wagner et al. 2001).

Supportive and analytical communication can also be formal (i.e., objective, rational, and fact-based) (Linnenbürger 2020). A formal sales process generates more revenue as it implies clearly defined stages and milestones and endurance (Jordan and Kelly 2015). Formally communicating salespeople make use of concrete information about what the product contains and what features it possesses, though whether this—contrary to solution and value-based selling—enhances sales success remains unclear (Dennehy 2022).

Last, supportiveness in language can be expressed with the help of in-depth, value-oriented customer conversations that lack rigid sales pitches and are sometimes rather philosophical (Mendes-Roter 2023) and can educate customers over and above what they already know (Krogue 2017). Philosophical communication also aids in customer interactions as it uncovers the theoretical background of a topic (Linnenbürger 2020). It also creates a more personalized atmosphere in communications (Masjedi 2014).

Constructive Language

The expression of ideas, information, and opinions to change something in the work context is the definition of constructive voice (Maynes and Podsakoff 2014). “Change" in the sales context is one of the main drivers for success, as agents always try to bring about a change in customers, whether by solving a specific problem or by improving their lives with a new product or service. To implement change-focused language, agents might apply innovative language elements. According to Yohn (2016), successful salespeople do not imitate, they innovate.

Successful salespeople must demonstrate that customers will improve their situation by buying the product, such as by using visionary language (Forbes Expert Panel 2022). Through such language (e.g., promises of future achievements or potential improvements) (Linnenbürger 2020), agents can also imply forward-looking outcomes, which can further motivate customers to complete a deal (Thacker 2020).

Constructive language can also be straightforward, inspiring, and venturing. Agents use this kind of language to actively lead customers to the conclusion of a contract. First, we find that motivation is a language dimension that fits into this categorization. Motivation is a behavioral concept that describes an inner state that powers individuals to do or achieve something (Mitchell 1982). In the sales context, this can be the level of effort an agent invests in working activities (Churchill et al. 1985). Effort, which includes long-term engagement and short-term endeavors, is positively associated with sales performance (Blau 1993; Brown and Peterson 1994). In their meta-analyses, Plotkin (1987), Churchill et al. (1985), and Barrick et al. (2002) identify motivation as positively affecting sales performance. Motivation in language leads to commitment (Visser 2009), excitement, and inspiration (Linnenbürger 2020) and is often present in sales agents’ language styles, especially more successful ones.

Second, optimism (Sujan 1999) is crucial for sales jobs. Webster (1968) characterizes salesperson stereotypes and argues that optimism belongs to these kinds of people. Sujan (1999) adds that optimism fosters salesperson intelligence and performance. Jensen et al. (2007) also find that high levels of optimism significantly improve performance. Optimistic communication is characterized by the expression of readiness to take risks and positive conclusions from experiences (Linnenbürger 2020); thus, optimism is a language dimension displayed by salespeople.

Third, agents with positive thinking, those who set goals (Frayne and Geringer 2000), and those who do not quickly become discouraged (Villa 2023) outperform those whose beliefs and moods are more negative (Goudreau 2010). According to Anglin et al. (2018), positive psychological capital signaled in language is positively related to performance measurements. Thus, better performing sales agents might also express higher degrees of positivity in their language. Positivity is also important in sales as the job is fraught with more failures than successes, and without positivity, salespeople cannot be successful (Mayer and Greenberg 1964).

Impressive language is also a dimension of constructive voice (Alavi et al. 2018). Sales agents need to spark enthusiasm for the product and persuade customers to buy, buy repeatedly, or tell friends about their positive experiences (Gibbons 2022). As a consequence, we identify impressiveness in language as part of successful communication because it is captivating, motivating, and inspiring (Linnenbürger 2020).

Also related to constructive language is the dimension of self-confidence. Individuals with higher self-confidence trust more in their own abilities and opinions (Luthans and Peterson 2002; Schyns and Sczesny 2010) and can more easily manage their social interactions (Greenacre et al. 2014). In language, self-confidence means not becoming easily discouraged and putting high weight on own opinions, which might help inside sales agents persuade prospects and customers to buy (Linnenbürger 2020).

More successful agents tend to show higher levels of goal orientation (Brown et al. 1998; Porath and Bateman 2006; VandeWalle and Brett 1999). Goal orientation helps people achieve their aims in situations (Sujan et al. 1994) and fosters clear decision-making processes that improve agents' willingness to close a deal. In addition, selling orientation increases if salespeople show higher levels of performance orientation in selling situations (Harris et al. 2005). As goal orientation in language also helps agents not to lose their focus and to keep customer-centered (Gilmore 2022), we include this dimension in the constructive language quadrant of Maynes and Podsakoff (2014) and find this dimension in sales agent language styles.

Furthermore, composure signals understanding and facilitates ways to advise customers. Being composed (i.e., controlled and regulated emotions) (Mulki et al. 2015) results in reduced role ambiguity and role conflict (MacKenzie et al. 1998), and appearing relaxed rather than nervous or excited (Linnenbürger 2020) might help achieve performance goals in cooperative communication situations. Composure also signals a low level of excitement in agent–customer interactions (i.e., no exaggerated behavior, which in some product categories might backfire in terms of sales) (Luo et al. 2021).

The last language dimension we classify as constructive language is reliability. Salespeople need to appear reliable in the buying process (Lowe 2022). We argue that reliability is part of the Big 5 personality trait conscientiousness, which is positively related to performance outcomes (Barrick and Mount 1991; Vinchur et al. 1998). Using reliable language helps build loyalty (Rush 2021), as it suggests that statements given are valid with responsibilities clearly stated (Linnenbürger 2020).

Defensive Language

Defensive language belongs to the prohibitive dimension of Maynes and Podsakoff's (2014) employee voice behavior framework. It refers to the expression of opposition to something that might have merit or is to some degree necessary. The first language dimension that involves actively being against something is independency. Stanton and Bushkirk (1959) argue that salespeople are often lone wolves and responsible for their own success. They must make decisions by themselves and cannot rely on their managers' expertise in these situations. Armstrong (2018) indicates that top performers in sales love "being out in front" and are not loyal to any cause except their own drive to achieve a deal. So, independent communication with customers must be implemented with care, as it is not influenced by the opinions of others, which could offend some customers (Linnenbürger 2020).

The second language dimension we add to the quadrant of defensive language is unconventional communication, or the expression of unusual ideas, surprising statements, and innovative ideas (Linnenbürger 2020). This communication style abandons learned structures, by asking, for example, BANT (budget, authority, need, timing) questions and trying out new methods. An unconventional alternative could also change ways of thinking about creativity (e.g., impulsively offering something a customer did not initially ask for) (Szot 2023). However, the extent to which unconventional language promotes sales or merely engenders creativity remains unclear.

Third, being intellectual is also a language dimension that is part of defensive language and appears in sales interactions. Weitz et al. (1986) indicate that knowledge about customers and sales strategies affects performance. Sales agents should ensure they come across as experts to customers and know what they are talking about (Gold 2020). In doing so, they can more easily give advice and support customers in terms of sales and service requests.

Destructive Language

Agents who apply destructive language voluntarily express hurtful and negative work-related opinions (Maynes and Podsakoff 2014). Destructive sales language can also be an uncontrolled component in situations when agents are cranky, are unsatisfied, or lose professionality and endurance. Such salespeople score the highest in the “dark triad” of personality traits, which consists of Machiavellianism, narcissism, and psychopathy (Satornino et al. 2023), which can manifest in impulsive and aggressive language. Lockeman and Hallaq (1982) argue that deliberate, nonimpulsive selling behavior positively affects performance. This unexpected finding shows that impulsive language should be avoided to reap positive sales success. Aggressive selling behavior (Ahmad et al. 2021; Miner 1962; Ryals and Davies 2010) is also negatively associated with sales performance and should be avoided in customer conversations. However, sales agents with narcissism and ego-drive traits might show these language dimensions (Armstrong 2018; Mayer and Greenberg 1964).

Dramatic (i.e., exaggerating and with a tendency to go overboard) and authoritative (i.e., setting a direction and taking control of a conversation) attributes are two other language dimensions we sort into the destructive language quadrant (Linnenbürger 2020). Exaggerated behavior might backfire in some product categories (Luo et al. 2021), and drama in general negatively influences the workspace climate (Teicke 2023). Therefore, the level of drama should be controlled in sales conversations, as the primary character is always the customer; dramatic language can put the agent at the forefront.

In contrast, attributes of authoritativeness such as dominance (Lamont and Lundstrom 1977) and pressure selling tactics (Plouffe et al. 2016) might positively affect performance outcomes. Linkner (2012) argues that salespeople should use an authoritative tone in cold calls when they want to increase the likelihood of recall. According to Villa (2023), salespeople are “hungry,” and good salespeople are willing to go the extra mile to complete a deal, even if the use of some authoritativeness in language is necessary.

We propose, however, that destructive language dimensions can negatively influence sales success. However, recent findings of Satornino et al. (2023) show that “dark traits” of salespeople might at specific times and under social network structures enhance performance.

Appendix B References

Ahmad, B., Akbar, M. I. D., Asif, M. H., & Nureen N. (2021). An investigation of sales managers‘ aggressiveness in B2B sales leadership: The sequential mediation model of emotional exhaustion and adaptive selling. Management Science Letters, 11, 2243–2254.

Alavi, S., Habel, J., Guenzi, P., & Wieseke, J. (2018). The role of leadership in salespeople's price negotiation behavior. Journal Academy of Marketing Science, 46, 703–724.

Anderson, K. (2013). Five ways helpfulness wins hearts and sales report. Retrieved March 13, 2024 from https://www.forbes.com/sites/kareanderson/2013/04/23/five-ways-helpfulness-wins-hearts-and-sales/

Anglin, A. H., Short, J. C., Drover, W., Stevenson, R. M., McKenny, A. F., & Allison, T. H. (2018). The power of positivity? The influence of positive psychological capital language on crowdfunding performance. Journal of Business Venturing, 33, 470–492.

Armstrong, K. G. (2018). Why are salespeople so difficult to manage? Retrieved March 15, 2024 from https://www.forbes.com/sites/forbesbooksauthors/2018/05/04/why-are-salespeople-so-difficult-to-manage/

Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: A meta-analysis. Personnel Psychology, 44, 1–26.

Barrick, M. R., Steward, G. K., & Piotrowski, M. (2002). Personality and job performance: test of the mediating effects of motivation among sales representatives. Journal of Applied Psychology, 87 (1), 43–51.

Blau, G. (1993). Operationalizing direction and level of effort and testing their relationships to individual job performance. Organizational Behavior and Human Decision Processes, 55, 152–170.

Brown, S. P., & Peterson, R. A. (1994). The effect of effort on sales performance and job satisfaction. Journal of Marketing, 58 (2), 70–80.

Brown, S. P., Cron, W. L., & Slocum Jr., J. W. (1998). Effects of trait competitiveness and perceived intraorganizational competition on salesperson goal setting and performance. Journal of Marketing, 62 (4), 88–98.

Churchill, G. A., Ford, N. M., Hartley, S. W., & Walker, O. C. (1985). The determinants of salesperson performance: A meta-analysis. Journal of Marketing Research, 22 (2), 103–118.

Dawson, L. E., Soper, B., & Pettijohn, C. E. (1992). The effects of empathy on salesperson effectiveness. Psychology & Marketing, 9 (4), 297–310.

Dennehy, J. (2022). Sell the emotions, not the facts. Retrieved March 15, 2024 from https://www.forbes.com/sites/forbesbusinesscouncil/2022/10/11/sell-the-emotions-not-the-facts/

Forbes Expert Panel (2021). 14 important transferable skills to help drive sales success. Retrieved February 1, 2024 from https://www.forbes.com/sites/forbesbusinessdevelopmentcouncil/2021/05/18/14-important-transferable-skills-to-help-drive-sales-success/

Forbes Expert Panel (2022). 15 foolproof strategies for encouraging repeat purchases. Retrieved February 1, 2024 from https://www.forbes.com/sites/forbesbusinesscouncil/2022/06/01/15-foolproof-strategies-for-encouraging-repeat-purchases/

Frayne C. A., & Geringer, J. M. (2000). Self-management training for improving job performance: A field experiment involving salespeople. Journal of Applied Psychology, 85 (3), 361–372.

Gibbons, S. (2022). 5 things service-driven businesses can do to impress clients. Retrieved March 26, 2024 from https://www.forbes.com/sites/serenitygibbons/2022/02/24/5-things-service-driven-businesses-can-do-to-impress-clients/

Gilmore N., (2022). How to align marketing and sales goals for success. Retrieved March 26, 2024 from https://www.forbes.com/sites/forbesbusinessdevelopmentcouncil/2022/04/15/how-to-align-marketing-and-sales-goals-for-success/

Gold, E. (2020). The importance of knowing your products. Retrieved March 27, 2024 from https://www.forbes.com/sites/theyec/2020/06/01/the-importance-of-knowing-your-products/

Goudreau, J. (2010). Are you investing in the happiness advantage? Retrieved January 31, 2024 from https://www.forbes.com/sites/jennagoudreau/2010/10/26/are-you-investing-in-the-happiness-advantage/#

Greenacre, L., Tung, N. M., & Chapman, T. (2014). Self-confidence, and the ability to influence. Academy of Marketing Studies Journal, 18 (2), 169–180.

Harris, E. G., Mowen, J. C., & Brown, T. J. (2005). Re-examining salesperson goal orientations: personality influencers, customer orientation, and work satisfaction. Journal of the Academy of Marketing Science, 33 (1), 19–35.

Jensen, S. J., Luthans, K. W., Lebsack, S. A., & Lebsack, R. L. (2007). Optimism and employee performance in the banking industry. Journal of Applied Management and Entrepreneurship, 12 (3), 57–72.

Jordan, J. & Kelly, R. (2015). Companies with a formal sales process generate more revenue. Retrieved April 28, 2024 from https://hbr.org/2015/01/companies-with-a-formal-sales-process-generate-more-revenue

Krogue, K. (2017). A selling secret: Have better conversations. Retrieved March 27, 2024 from https://www.forbes.com/sites/kenkrogue/2017/11/01/a-selling-secret-have-better-conversations/

Lamont, L. M., & Lundstrom, W. J. (1977). Identifying successful industrial salesmen by personality and personal characteristics. Journal of Marketing Research, 14 (4), 517–529.

Linkner, J. (2012). Four secrets to master the art of selling. Retrieved March 15, 2024 from https://www.forbes.com/sites/joshlinkner/2012/06/28/four-secrets-to-master-the-art-of-selling/

Linnenbürger, A. (2020). Kommunikation und Führungserfolg: Entwicklung eines Instruments zur Messung von Kommunikationsstilen und Analyse des Zusammenhangs mit Führungserfolgsvariablen. Bergische Universität Wuppertal [in German].

Lockeman, B. D., & Hallaq, J. H. (1982). Who are your successful salespeople? Journal of the Academy of Marketing Science, 10 (4), 457–472.

Lowe, J. (2022). How to succeed in sales: Become a trusted advisor. Retrieved March 26, 2024 from https://www.forbes.com/sites/forbescoachescouncil/2022/08/01/how-to-succeed-in-sales-become-a-trusted-advisor/

Luo, H., Cheng, S., Zhou, W., Yu, S., & Lin, X. (2021). A study on the impact of linguistic persuasive styles on the sales volume of live streaming products in social e-commerce environment. Mathematics, 9 (1576), 1–21.

Luthans, F., & Peterson, S. J. (2001). Employee engagement and manager self-efficacy Implications for managerial effectiveness and development. Journal of Management Development, 21 (5), 376–387.

MacKenzie, S. B., Podsakoff, P. M., & Ahearne, M. (1998). Some possible antecedents and consequences of in-role and extra-role salesperson performance. Journal of Marketing, 62 (3), 87–98.

Makela, R. (2021). Is empathy the most important selling skill? Retrieved February 2, 2024 from https://www.forbes.com/sites/forbesbusinessdevelopmentcouncil/2021/06/16/is-empathy-the-most-important-selling-skill/#

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A temporally based framework and taxonomy of team processes. Academy of Management Review, 26 (3), 356–376.

Marlow, S. L., Lacerenza, C. N., Paoletti, J., Burke, C. S., & Salas, E. (2018). Does team communication represent a one-size-fits-all approach? A meta-analysis of team communication and performance. Journal Organizational Behavior and Human Decision Processes, 144, 145–170.

Martin, W. Stewe, (2015) What separates the strongest salespeople from the weakest. Retrieved March 12, 2024 from https://hbr.org/2015/03/what-separates-the-strongest-salespeople-from-the-weakest

Masjedi Y. (2014). Sales calls: The art of the personalized follow-up. Retrieved March 26, 2024 from https://www.forbes.com/sites/salesforce/2014/09/15/personalized-follow-up/

Mayer, D., & Greenberg, H. M. (1964). What makes a good salesman. Harvard Business Review, 42, 119–125.

Maynes, T. D., & Podsakoff, P. M. (2014). Speaking more broadly: An examination of the nature, antecedents, and consequences of an expanded set of employee voice behaviors. Journal of Applied Psychology, 99 (1), 87–112.

Mendes-Roter, J. (2023). Communication management: how innovation can bring more business with less cost. Retrieved February 1, 2024 from https://www.forbes.com/councils/forbescommunicationscouncil/2023/04/25/communication-management-how-innovation-can-bring-more-business-with-less-cost/

Miner, J. B. (1962). Personality and ability factors in sales performance. Journal of Applied Psychology, 46 (1), 6–13.

Mitchell, T. R. (1982). Motivation: New directions for theory, research, and practice. Academy of Management Review, 7 (1), 80–88.

Mulder, M. (1960). Communication structure, decision structure and group performance. Sociometry, 23 (1), 1–14.

Mulki, J. P., Jaramillo, F., Goad, E. A., & Pesquera, M. R. (2015). Regulation of emotions, interpersonal conflict, and job performance for salespeople. Journal of Business Research, 68, 623–630.

Peesker, K. M., Kerr, P. D., Bolander, W., Ryals, L. D., Lister, J. A., & Dover, H. F. (2022). Hiring for sales success: The emerging importance of salesperson analytical skills. Journal of Business Research, 144, 17–30.

Plotkin, H. M. (1987). What makes a successful salesperson? Training and Development Journal, 41 (9), 54–56.

Plouffe, C. R., Bolander, W., Cote, J. A., & Hochstein, B. (2016). Does the customer matter most? exploring strategic frontline employees' influence of customers, the internal business team, and external business partners. Journal of Marketing, 80 (1), 106–123.

Porath, C. L., & Bateman, T. S. (2006). Self-regulation: From goal orientation to job performance. Journal of Applied Psychology, 91 (1), 185–192.

Rush, L. (2021). Strategies to satisfy existing customers. Retrieved March 26, 2024 from https://www.forbes.com/sites/forbesbusinesscouncil/2021/12/29/strategies-to-satisfy-existing-customers/

Ryals, L., & Davies, L. (2010). Do you really know who your best salespeople are? Retrieved February 1, 2024 from https://hbr.org/2010/12/vision-statement-do-you-really-know-who-your-best-salespeople-are

Satornino, C. B., Allen, A., & Bolander, W. (2023). Understanding the performance effects of “dark” salesperson traits: Machiavellianism, narcissism, and psychopathy. Journal of Marketing, 87 (2), 298–318.

Schyns, B., & Sczesny, S. (2010). Leadership attributes valence in self-concept and occupational self-efficacy. Career Development International, 15 (1), 78–92.

Shapiro, B. P., & Posner, R. S. (2006). Making the major sale. Retrieved March 15, 2024 from https://hbr.org/2006/07/making-the-major-sale

Singh, S., Marinova, D., Singh, J., & Evans, K. R. (2018). Customer query handling in sales interactions. Journal of the Academy of Marketing Science, 46, 837–856.

Stanton, W. J., & Bushkirk, R. H. (1959). Management of the salesforce. Richard D. Irwin.

Sujan, H., Weitz, B. A., & Kumar, N. (1994). Learning orientation, working smart, and effective selling. Journal of Marketing, 58 (3), 39–52.

Sujan, H. (1999). Optimism and street-smarts: Identifying and improving salesperson intelligence. Journal of Personal Selling & Sales Management, 19 (3), 17–33.

Szot, D. (2023). How considering alternatives changes ways of thinking about creativity. Retrieved March 26, 2024 from https://www.forbes.com/sites/forbescoachescouncil/2023/05/02/how-considering-alternatives-changes-ways-of-thinking-about-creativity/

Teicke, J. (2023). “No drama culture”—The #1 productivity hack for any organization. Retrieved February 2 , 2024 from https://www.forbes.com/sites/julianteicke/2023/10/14/no-drama-culturethe-1-productivity-hack-for-any-organization/

Thaker, M. (2020). 20/20 foresight in 2020 and beyond: How to boost sales by looking forward. Retrieved March 26, 2024 from https://www.forbes.com/councils/forbescoachescouncil/2020/02/14/2020-foresight-in-2020-and-beyond-how-to-boost-sales-by-looking-forward/

VandeWalle, D., & Brett, J. F. (1999). Goal orientation and goal content as predictors of performance in a training program. Journal of Applied Psychology, 84 (6), 863–873.

Verbeke, W., & Bagozzi, R. P. (2002). A situational analysis on how salespeople experience and cope with shame and embarrassment. Psychology & Marketing, 19 (9), 713–741.

Villa, D. (2023). What elite salespeople do that the rest don’t. Retrieved January 31, 2024 from https://www.forbes.com/sites/forbesagencycouncil/2023/03/27/what-elite-salespeople-do-that-the-rest-dont/

Vinchur, A. J., Schippmann, J. S., Switzer, F. S., III., & Roth, P. L. (1998). A meta-analytic review of predictors of job performance for salespeople. Journal of Applied Psychology, 83 (4), 586–597.

Visser, L. (2009). Motivational conversation. In R. Watkins & D. Leigh (Eds.), Handbook of improving performance in the workplace (pp. 515–535). Pfeiffer.

Wagner, J. A., Klein, N. M., & Keith, J. E. (2001). Selling strategies: The effects of suggesting a decision structure, to novice and expert buyers. Journal of the Academy of Marketing Science, 29 (3), 289–306.

Webster, F. E. (1968). Interpersonal communication and salesman effectiveness. Journal of Marketing, 32 (3), 7–13.

Weitz, B. A., Sujan, H., & Sujan, M. (1986). Knowledge, motivation, and adaptive behavior: a framework for improving selling effectiveness. Journal of Marketing, 50 (4), 174–191.

Yohn, D. L. (2016). The best salespeople do what the best brands do. Retrieved February 1, 2024 from https://hbr.org/2016/08/the-best-salespeople-do-what-the-best-brands-do

Zoltners, A. A., Sinha, P., & Lorimer, S. E. (2016). Great salespeople are born, but great sales forces are made. Retrieved March 27, 2024 from https://hbr.org/2016/05/great-salespeople-are-born-but-great-sales-forces-are-made

Paper II: Automated Pre-Selection of Sales Job Candidates

Authors: Robert Muenster, Thomas Scholdra, and Werner Reinartz

Abstract

The selection of suitable salespeople is crucial for organizational success but remains challenging due to high uncertainty and efforts associated with the hiring process of sales job candidates. This study develops a four-stage AI-driven hiring framework to pre-select sales candidates efficiently. By integrating personality traits, facial emotions, and paralanguage features from video interviews, alongside with a developed Sales Performance Score (SPS) measured in a chatbot-based sales performance assessment, the proposed Support Vector Machine (SVM) classifier achieves a 95% accuracy in predicting suitable candidates. This approach streamlines recruitment, reducing time-to-hire and supports sales managers and recruiters in the pre-selection of suitable sales job candidates. The findings contribute to sales efficiency research by linking behavioral characteristics to sales performance in an automated hiring process.

Keywords *Sales performance, Sales candidate selection, AI-driven recruitment, Support vector machine*

1 Introduction

The selection of suitable salespeople is of critical importance to any organization, as salespeople have the capacity to directly drive revenues, establish and maintain long-term customer relationships, and execute marketing strategies at the point of sale (Kim et al. 2019; Tanner et al. 2005; Terho et al. 2015). Consequently, the identification of the most suitable candidates for sales roles presents a substantial challenge for recruitment professionals. Erroneous hiring decisions can incur substantial costs, including the loss of potential sales and the damage of customer relationships, an outcome that companies seek to avert. However, it is important to acknowledge that the process of recruiting sales personnel can often be a tough endeavor for both the sales job candidate and the recruiter.

Consider the following two scenarios: First, a young sales job candidate successfully navigates the selection process and gets an offer of employment as a sales representative within a company. However, the process of hiring new sales personnel is often costly, time-consuming, and comes with uncertainty, as recent statistics indicate. On average, the cost of replacing a salesperson is $100,000, the time required to hire new salespeople can take up to 1.5 months, and the process of onboarding new salespeople can take up to 5.7 months (LinkedIn 2024). Furthermore, the turnover rate for sales personnel is 34%, which is double that of other professions (LinkedIn 2024). Recruiters and sales managers are aware of the fact that hiring a new sales representative incurs significant expenses, demands considerable time, and carries an element of uncertainty. However, the recruiters and sales managers lack insight into the performance – especially for young sales representatives and job starters with little or no proved performances. But determining and comparing the performance level of experienced sales job candidates is also difficult, despite the candidate's qualifications and previous work experience. The selection of an individual as a sales representative is not a straightforward process, and the recruiter or sales manager may not have the requisite knowledge to determine whether the candidate is truly a suitable for the position. Consequently, the first research problem we identify is therefore *finding the right salesperson*.

In the second scenario, a sales manager is responsible for hiring salespeople. Her primary concerns pertain to the stretched hiring processes and the escalating challenge of employee retention (Flair 2024). Her overarching objective is to optimize the hiring process, a pursuit that, according to recent statistics from Cronofy (2023), significantly impacts the final decisions of the majority of sales applicants. A further challenge pertains to the optimal filling of sales vacancies, given the substantial number of available sales positions in the United States alone, as reported by Sampat (2023). A survey of the job board *Stepstone* reveals that the number of open sales positions far exceeds that of vacant positions in marketing or finance, with a ratio of four to five. Consequently, the second research problem that was identified is to *optimize the sales hiring process.*

With these two research problems and the addition of some expert interviews, which also claim the importance of the correct selection of sales job candidates and the need to increase efficiency and streamline the hiring process, we have developed the following research question: **How to efficiently detect a suitable salesperson during the hiring process?**

In order to answer this question, we conducted a 4-step process. First, we extracted the most significant drivers of sales performance and the most common sales and influence tactics from the sales literature and developed a multidimensional Sales Performance Score (SPS). Sales performance has many facets and is measured by researchers in multiple ways considering activities, outcomes, relationship buildings and conversions of salespeople (Anderson and Oliver 1987; Bolander et al. 2021). Moreover, some studies frequently discuss sales performance in a vacuum, neglecting to specify the methodology or the specific type of performance being assessed (e.g., Claro et al. 2024). However, to the best of our knowledge, there are no studies that measure sales performance multidimensionally with a holistic approach, as we do in the form of the SPS including both behavioral- and outcome-based aspects (Anderson and Oliver 1987).

Moreover, we wanted to ascertain the personality and character attributes of effective salespeople and to determine whether these attributes could predict performance. To this end, the Big 5 personality traits, the seven basic emotions according to Ekman (1999), and paralanguage, i.e., non-verbal communication conveyed through voice, are examined as these personal attributes influence the performance of salespeople (Bande et al. 2015; Barrick and Mount 1991; Kidwell et al. 2021; van Zant and Berger 2020).

In the second step, we collected data from 208 sales job candidates in a framed job application process including a survey and a short introduction and motivation video in which we employed automated and AI-based text and video analyses methods to collect personality traits, emotional expressions on the faces of the candidates, and paralanguage from the audio data of the video. Short videos for sales job applications are increasingly common in practice (Fried 2023; Indeed 2024; York 2022) and suitable for detecting job performance indicators (Pentland et al. 2025). Chakraborty et al. (2024) use conversational video interviews for detecting salesperson persuasion skills during the hiring process, but there is no groundbreaking research on video applications and AI-driven video analyses for sales job candidates.

In the third step, the candidates must complete an own-programmed chatbot assignment in which they had to sell a product and in which a final SPS was calculated. To ensure the validity of the chatbot and to generate a reference SPS for "suitable" sales job candidates, the chat-bot assignment was also completed by a professional sales call center with 30 experienced sales professionals. The average SPS of the sales professionals was used as a benchmark for the classification of the sales job candidates. Chatbots are already researched in terms of anthropomorphism (Crolic et al. 2021), effects on stock returns (Fotheringham and Wiles 2023) or effectiveness compared to humans (Luo et al. 2019), but little is known how chatbots can be used during the hiring process and help to determine sales performance of sales job candidates.

In the fourth and last step, we applied a Support Vector Machine (SVM) classifier that is capable of accurately categorizing sales job candidates based on the personality traits, facial emotions, paralanguage and demographical data collected during the application process experiment. This development furnishes sales managers and recruiters with a potent instrument to identify the most suitable salespeople in an efficient manner.

With our development of an AI-driven, multi-stage hiring framework, we make two major contributions: First, we provide sales managers and recruiters an automated pre-selection tool that streamlines hiring, reduces the time-to hire and serves as a powerful method that can assist to balance data-driven decision making with human intuition. Second, we contribute to the literature of salespeople efficiency by demonstrating that sales performance can be determined prior to the begin of an employment in a holistic, multi-faceted way using a SPS that contains outcome- as well as behavior-based performance data (Bolander et al. 2021). Through the measurement in a chatbot environment to evaluate salespeople we also contribute to the chatbot literature in demonstrating the effectiveness of virtual agents in agent-customer interactions and for determining sales performance (Luo et al. 2019). With the SPS, we are also able to predict the suitability of sales job candidates based on personal characteristics of salespeople collected from video interview data and thus make a contribution to the literature that deals with the character composition of successful salespeople.

2 Literature Review

2.1 Automated Methods for Hiring Decisions

In practice, the recruitment of suitable salespeople is already partly supported by AI-based tools such as Charly, Talogy, or OMG for reasons of cost and time savings. These tools assist companies in evaluating competencies, traits, and skills but do not link these characteristics to performance measurements. Concurrently, tools such as HireVue, which facilitate the automated screening of CVs, have already entered the market (HireVue 2025). However, the marketing and sales literature has thus far predominantly addressed the topic in a conceptual manner. Black and van Esch (2020) posit that the advent of AI-driven recruitment is imperative, as companies' competitive advantages have transitioned from tangible to intangible assets and the selection of suitable personnel has become paramount. Concurrently, the inadequate incorporation of AI-driven recruiting assessments into organizational processes and the unfavorable perception of AI-aided tools in sales hiring have been met with skepticism by both recruiters and applicants (Capelli et al. 2019; Chowdhury et al. 2023; Sartori and Theodorou 2022). Hunkenschroer and Luetge (2022) add that ethical risks may occur in using AI for hiring decisions, such as a lack of transparency due to a black-box problem of AI decision making, a reinforcement of biases and data privacy issues due to extensive data collection. However, they also state that AI may on the other side help to reduce human inconsistency and subjectivity, which might also foster fairness and equality in hiring processes.

A recently published article by Chakraborty et al. (2024), for instance, addresses the automated recognition of persuasion skills in salespeople and demonstrates that AI-hybrid screening of persuasion skills is most effective. Moreover, hybrid models have already proven to work better in sales training (Luo et al. 2021) and marketing research (Arora et al. 2025) but also in other contexts such as medical consultancy (Longoni et al. 2019). However, the extant literature on this subject is scant yet indispensable from both practical and conceptual standpoints.

2.2 Operationalization of Sales Performance

The performance of salespeople is the most relevant dependent variable in personal selling and sales research studies (Anderson and Oliver 1987; Bolander et al. 2021; Verbeke et al. 2011). When evaluating sales performance, scholars use a variety of measurement parameters that can be divided in either activity-, outcome-, relationship-, or conversion-based (Bolander et al. 2021). Activity-based sales performance encompasses the overall effort put in by salespeople like, e.g., the number of calls made (Ahearne et al. 2007). Outcome-based performance describes monetary metrics that directly contribute to a firm's revenue generation like, e.g., dollar amount of sales (Williams and Spiro 1985). Relationship-based sales performance refers to the strength of building and maintaining (long-term) customer relationships and encompasses, e.g., customer satisfaction (Packard et al. 2018). Finally, conversion-based performance is defined as the ratio between input effort and output results (e.g., the ratio of cold calls and contract completions).

Additionally, as Bolander et al. (2021) state, the measurement of sales performance relies either on primary, i.e., generated by researchers for a more multidimensional evaluation of performance in terms of behaviors, or secondary data, i.e., provided by the firm for quantifying financial outputs. However, all these kinds of measures fall under the collective term of sales performance and only cover the specific performance type in the respective studies. In our work, we develop a holistic Sales Performance Score (SPS) that measures both how the agent sells, i.e. how he or she behaves and communicates with the customer, thus covering activity- and relationship-based performance aspects, as well as what the agent sells and at what price, in order to measure outcome- and conversion-based aspects.

2.3 Success Drivers of Salespeople

The question of which key factors successful salespeople possess has been a popular research topic in the marketing and sales literature for many years (a classification of the following drivers into superordinate categories is extensively discussed in Paper III of this dissertation). Given that salespeople are responsible for the company's revenue generation, building and strengthening customer relationships, and executing marketing strategies, a high-performance salesforce is essential for successful companies (Kim et al. 2019; Tanner et al. 2005; Terho et al. 2015). Sales and marketing literature has analyzed the many relevant success drivers of salespeople and linked them to above-described performance metrics. However, as Table 1 shows, these success drivers are often extracted from traditional data sources and measured utilizing diverse instruments including tests, interviews, questionnaires, surveys, and self-reports. This methodological approach, which incorporates self-reporting and human coding, inherently introduces a degree of subjectivity into the measurement of these factors (Paulhus and Vazire 2007). Our AI-based approach with automated methods represents an innovative procedure for later integrating the following important key success drivers derived from these studies into the Sales Performance Score (SPS) and measuring them automatically using the chatbot application.

2.3.1 Empathy and Engagement. Empathy is defined as the ability to experience another person's emotions. Empathy is a critical component of sales effectiveness, particularly in the context of customer-facing roles. Prospective salespeople must possess a high degree of empathy to understand the customer's situation and to initiate the need identification process (Mayer and Greenberg 2006). However, empathy alone may result in being perceived as a "nice guy," rather than a closer salesperson, potentially hindering sales performance (Dawson et al. 1992; Mayer and Greenberg 2006). Therefore, it is imperative for salespeople to complement empathy with high levels of engagement and drive. Engagement, defined as a persistent and positive state of fulfillment (Sonnentag 2003), has been shown to have a significant positive relationship with sales performance (Chaker et al. 2022; Verbeke et al. 2011).

2.3.2 Selling Skills. The ability to effectively build relationships with customers and address customer needs is referred to as "selling skills," and it is a key determinant of sales performance (Pettijohn et al. 2002). Selling skills are imperative for the initiation of a sales interaction and have been substantiated as a positive driver of sales performance in numerous studies and meta-analyses (Churchill et al. 1985; Claro et al. 2024; Lockeman and Hallaq 1982; Verbeke et al. 2011; Vinchur et al. 1998).

2.3.3 Product Knowledge. Product knowledge involves the possession and distribution of specified information regarding products and services (Singh et al. 2020). It was posited by Baier and Dugan (1957) as one of the earliest key performance drivers of salespeople, a notion subsequently validated in the meta-analysis of Verbeke et al. (2011). In this analysis, salespeople were characterized as "knowledge brokers," thereby underscoring their pivotal role in the dissemination of information to customers.

2.3.4 Competitiveness. Competitiveness refers to a person's willingness to succeed and is a trait that is positively correlated with sales performance (Brown and Peterson 1994; Plotkin 1987; Shannahan et al. 2013). The underlying rationale pertains to the tendency of competitive salespeople to prioritize the retention of customers over competition and their pronounced inclination to secure customer acquisitions for their own sales outcomes (Shannahan et al. 2013).

2.3.5 Persuasiveness and Drive. Persuasiveness and drive are combined the strong willingness of salespeople to persuade and convince customers in personal interactions (Mayer and Greenberg 2006). The authors elucidate that salespeople with elevated levels of ego-drive possess the capacity to employ empathy in a targeted manner to facilitate sales, as opposed to merely demonstrating compassion. Furthermore, the efficacy of persuasion is enhanced when it is complementary, that is, when it is employed through diverse methods and with a variety of persuasion tactics (Pöyry et al. 2017).

2.3.6 Communication Skills and Motivation. The ability to communicate verbally and non-verbally with customers in a manner that fosters relationships and generates profit, while also demonstrating an aptitude for active listening, is a significant predictor of sales performance. The ability to understand and appropriately respond to customer interactions is contingent upon applicable communication skills, which are associated with enhanced sales performance (Aggarwal et al. 2005; Williams and Spiro 1985). Furthermore, motivation, defined as the level of effort salespeople voluntarily exert to achieve specific objectives, is a key driver of sales performance (Barrick et al. 2002; Churchill et al. 1985). According to Good et al. (2022), especially intrinsic motivation, i.e., based on self-fulfillment needs of salespeople, strongly fosters performance.

2.3.7 Self-Confidence. The capacity to place one's trust in one's own capabilities to accomplish a specific objective is designated as self-confidence. This psychological attribute has been identified as a significant predictor of superior sales performance (Greenacre et al. 2014). As Miner previously asserted in 1962, self-confident salespeople are capable of achieving success and recognition through their own efforts. Moreover, the self-confidence of salespeople fosters strong resilience to rejection, a crucial aspect in sales, where failure and rejection occur more frequently than in other industries (Bande et al. 2015).

Table 1: Measurement Methods of Sales Success Drivers and Character Components

Sales success drivers as components for the SPS			**Character components as predictors for sales performance**		
Driver	**Example reference**	**Measurement**	**Component**	**Example reference**	**Measurement**
Empathy	Mayer & Greenberg 2006	Test	Big 5 traits	Gupta et al. 2013	Questionnaires
Engagement	Chaker et al. 2022	Interviews		Thoresen et al. 2014	Survey
Selling skills	Pettijohn et al. 2002	Questionnaires	Emotions	Brown et al. 1997	Questionnaires
Product knowledge	Sujan et al. 1988	Self-reports		Kidwell et al. 2021	Survey
Competitiveness	Brown & Peterson 1994	Self-reports	Paralanguage	Hecht & LaFrance 1995	Human listening
Persuasiveness	Pöyry et al. 2017	Survey		Peterson et al. 1995	Reading time
Drive	Mayer & Greenberg 2006	Test			Human listening
Communication	Williams & Spiro 1985	Questionnaires			
Motivation	Miao & Evans 2007	Survey			
Self-confidence	Bande et al. 2015	Survey			
All Drivers	**This study**	Chatbot	All Components	**This study**	AI/automated tools

2.4 Tactics in Sales

Sales tactics are strategic communication methods used by agents to shape customer perceptions and behaviors to achieve a certain goal, e.g., lead generation, product selling, and retaining customer satisfaction (Frazier and Summers 1984; MacFarland et al. 2006) They are an elementary part of successful sales agents and are able to objectively predict sales performance (Plouffe et al. 2014). We have searched the literature on influence and sales tactics and compiled the most relevant ones for the development of a sales performance score. We provide a list of all identified sales tactics with definitions and objectives in Table 2.

Frazier and Summers (1984) initially uncovered six different influence tactics that appear in distribution channels, namely: information exchange, recommendations, requests, threats, promises, and legalistic pleas. These tactics should change the behavior of the target in the way the applicant of the tactics wants it. McFarland et al. (2006) discussed these influence tactics in the context of sales and personal selling and add ingratiation and inspirational appeals as emotional utilities to the list of tactics, while simultaneously eliminating requests and legalistic pleas from the list of tactics. They argued that the tactic of requests is implicit and not solely a sales influence tactic and the tactic legalistic pleas was not used in their sample, concluding that this tactic is not relevant in personal selling. Requests and legalistic pleas as sales-related influence tactics were also excluded in another study by Plouffe et al. (2014) who also discussed the degree of coerciveness of these tactics. Singh et al. (2020) add assertiveness and buyer attention as another two sales tactics. As the customer in our experimental setting is bot-programmed and the degree of interest is fixed in this context, we exclude buyer attention as a sales tactic in this study.

Table 2: Tactics in Sales

Tactic	Definition	Goal	Literature
Information exchange	Providing details about products	Shape the customer's perception of the product	Frazier & Summers (1984) McFarland et al. (2006) Plouffe et al. (2014) Singh et al. (2020)
Recommendations	Proposing a specific product	Enhance the customer's confidence in choosing the recommended option	
Promises	Offering future benefits associated with purchasing a product	Motivate the customer through incentives for committing to a product	
Threats	Highlighting potential losses from not purchasing a product	Encourage commitment by emphasizing consequences of inaction	
Ingratiation/Flattery	Using compliments and friendly interactions to gain favor	Build rapport and foster a positive connection with the customer	
Inspirational appeals	Leveraging emotions, values, and ideals to spark enthusiasm	Stir positive emotions to influence purchasing decisions	McFarland et al. 2006 Singh et al. 2020
Assertiveness	Creating a strong call-to-action to continue the transaction	Maintain customer focus and drive progress toward completing the purchase	Singh et al. 2020
Scarcity	Emphasizing the limited availability of a product	Increase the perceived value and urgency to act	Bozkurt and Gligor 2019 Cialdini 2013
Reciprocity	Offering free samples or testimonials to the customer	Build goodwill and enhance the customer relationship	Heiman et al. 2001 Regan 1971
Social proof	Referring to others who have benefited from or used a product	Strengthen customer trust and confidence through shared experiences	Cialdini 2013 Wooten and Reed 1998

There are also a few tactics not considered in these papers which we nevertheless include in our list of sales tactics: First, the tactic of scarcity describes the emphasis that a product is limited or rare (Bozkurt and Gligor 2019; Cialdini 2013). Second, the reciprocity tactic offers customers free samples or the possibility to test a product free of charge (Heiman et al. 2001; Regan 1971). Third, the social proof sales tactic signals customers that other individuals or the agent herself has tested or used the product before and have good experiences with it (Cialdini 2013; Wooten and Reed 1998).

2.5 Character Identification of Sales Job Candidates

In addition to the factors that contribute to success in sales and the tactics employed in persuasion, it is imperative to understand the personality of a salesperson or a sales job candidate for a sales position. Beyond personal information, such as age or gender, specific personality traits and emotional tendencies are conducive to a comprehensive assessment of an individual. Non-verbal communication, also known as paralanguage, is also a suitable method for assessing individuals' character (Hecht and LaFrance 1995; Van Zant and Berger 2020).

However, as illustrated in Table 1 above, the examination of personality traits, emotions, and paralanguage is predominantly supported by studies employing questionnaires and surveys completed by salespeople themselves. Additionally, it is informed by human analysis of components of paralanguage (e.g., Hecht and LaFrance 1995; Peterson et al. 1995). The extraction of the components discussed in the following from text, audio, and video data, as implemented in this study through the utilization of AI and automated methods, is a novel technique that has not been widely adopted in the academic literature (see Chakraborty et al. 2024 for a sales-relevant approach).

2.5.1 Personality Traits. In the domain of sales research, the Big 5 personality model (Goldberg 1990; McCrae and Costa 1987) has been a prevalent framework for personality determination. This model delineates the five fundamental personality traits that are widely recognized in the field: Openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. It is frequently employed to investigate specific personality traits that serve as performance indicators. The dimensions of the Big 5 model have been repeatedly associated with job performance. According to numerous meta-analyses, conscientiousness exerts the most significant influence on sales performance, followed by extraversion and agreeableness (Barrick and Mount 1991; Hurtz and Donovan 2000; Vinchur et al. 1998). These results have been confirmed by more recent individual studies, which indicate that neuroticism can even negatively impact the sales performance of some agents who often have to adapt to new customers and situations (Gupta et al. 2013; Thoresen et al. 2004). In previous studies, specially designed questionnaires were developed to identify the dimensions of the Big 5 model. Today, a range of tools and software are available to measure the respective characteristics in texts (e.g. *Linguistic Inquiry and Word Count* by Pennebaker et al. 2015).

2.5.2 Emotions. In sales, emotions can serve as another important characteristic for the determination of salesperson types. The six-factor model of basic emotions developed by Ekman (1999) has become the prevailing framework for the identification and measurement of emotions. This model encompasses happiness, sadness, fear, disgust, anger, and surprise, as well as a neutral emotion. According to Ekman, these emotions are particularly salient in facial expressions. Given that salespeople present their faces to customers in direct customer contact, knowledge about the use and perception of emotions is of great importance for sales managers.

Indeed, emotions constitute a powerful psychological force that can significantly influence the behavior and performance of salespeople (Bande et al. 2015). Research has demonstrated that positive emotions, such as happiness, are associated with enhanced performance outcomes, and vice versa (Brown et al. 1997). According to Kidwell et al. (2021), optimal performance by salespeople is achieved through the regulation and calibration of emotions, without excessive or insufficient confidence. The curvilinear relationship between the extent of emotions displayed by salespeople and performance, as confirmed by Wang et al. (2022), further substantiates the notion that emotional expressions positively impact sales performance, though the effect is diminished for high levels of emotional intensity. Since Ekman's basis emotions are best measured in faces, photos or videos are best suited for data analysis.

2.5.3 Paralanguage. A third dimension that can provide information about the character of salespeople or sales job candidates is paralanguage, i.e., non-verbal communication that can be conveyed using the voice in the form of volume, speed, or speech rate (van Zant and Berger 2020). These characteristics are employed to transfer messages, which are primarily utilized in sales to persuade customers in different ways and which ultimately provide information about the person. Sales research has identified a correlation between specific components of paralanguage and sales performance, including speaking rate or frequency contour variability (Peterson et al. 1995), tempo (Hecht and LaFrance 1995), pitch, and speed (Downing 2011; Van Zant and Berger 2020). Audio data such as recorded job interviews or customer interactions are required to extract paralanguage characteristics.

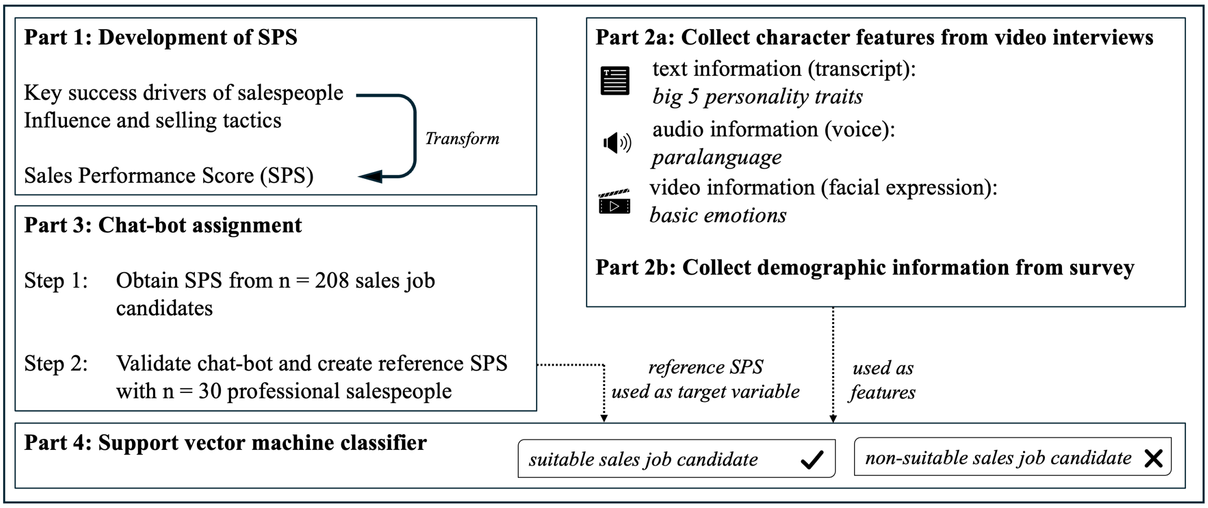
3 Research process

3.1 Preliminary Expert Insights on the Research Problems

In order to gain a more profound understanding of the discussed research problems, we conducted a series of expert interviews with senior sales recruiters from prominent international companies. In their responses, the recruiters highlighted the complexity of filling sales vacancies, attributing this challenge to the need to evaluate both the professional qualifications and the personality of candidates. They noted that this multifaceted assessment process complicates the prediction of future performance. Additionally, the recruiters emphasized the highly volatile and dynamic nature of sales roles. Some recruiters also disclosed that their sales applicants typically work on a trial basis for a designated period, thereby enabling both the recruiters and the sales managers to form a comprehensive understanding of the applicant's aptitude and suitability. While this approach facilitates a comprehensive evaluation of a candidate's suitability, it is a time-consuming and costly process.

On the other hand, all expert recruiters agreed that “you have to be quick to get the good people,” “we need to decrease the time-to-hire for our salesforce,” or that “speed in the sales application process is super important.” They hence underlined the importance of optimizing - especially streamlining and accelerating - the whole hiring process. It is surprising to note that the utilization of automated methods and AI applications to optimize the application process for sales jobs is very low among the senior recruiters surveyed, despite the fact that speed and effectiveness are among the recruiters' primary concerns. The majority of recruiters state that they have not yet employed AI tools for the pre-selection of candidates, primarily due to a lack of experience in using these tools.

Figure 1: Four-Stage Process of Automated Pre-Selection of Sales Job Candidates



After identifying the most relevant success factors and influence tactics of salespeople and the most significant personality predictors with the assistance of the extant literature, a 4-step process is currently being carried out. Figure 1 illustrates this process. The subsequent step involves the development of the SPS, followed by the collection of data through an experimental investigation of a framed application process. The third step entails the execution of a chatbot assignment with sales job candidates to ascertain their individual SPS by selling a product (bike) to the bot. This assessment is then used to categorize suitable and non-suitable sales job candidates based on the identified personality predictors and demographic variables.

3.2 Part 1: Developing the Sales Performance Score (SPS)

In the literature review part, we uncovered the most important success drivers of salespeople measured on the job. Afterwards, we identified several sales and influencing tactics that are used by successful salespeople in customer interactions. In order to assess sales performance prior to the start of a recruitment, it is necessary to detect it in advance. To this end, we measured sales performance in multiple categories within the chatbot assignment. To assess sales performance, we employed the *contestant evaluation sheet* developed by Loe and Chonko (2000), which has been utilized in previous studies by Chakraborty et al. (2024) and is used for sales and selling competitions. This method was employed to derive a sales performance score.

The Loe and Chonko (2000) sheet does not evaluate sales performance in terms of mere sales; rather, it evaluates sales performance as a process involving five distinct selling stages that describe a typical selling process and two general competencies of salespeople. These stages and competencies are queried at different points and evaluated in a weighted ratio. The five stages within the selling process are as follows: approach (5% weight of the SPS), need identification (25% weight of the SPS), product demonstration (25% weight of the SPS), overcoming objections (15% weight of the SPS), and close (10% weight of the SPS). The two general sales competencies measured within this concept are communication skills (15% weight of the SPS) and overall skills, which include enthusiasm and self-confidence (5% weight of the SPS). Doing this, we allocate the seven above derived sales success factors into the components of the contestant evaluation sheet, as Table 3 below shows.

We also measure the occurrence of sales tactics as part of the sales performance score by automatically detecting words and phrases used that come along with these tactics. We here follow the approach by Singh et al. (2020) to detect tactics by linguistic markers. We also grouped the determined sales and influence tactics into the components of the contestant evaluation sheet, as Table 3 shows. In the following, we describe the single SPS components and how we measure sales performance in these components.

Table 3: Sales Success Drivers and Tactics Allocation into the SPS Components

SPS component	Sales success driver(s)	Measurement criteria	Sales tactic(s)	Linguistic markers
Approach	Engagement & empathy	Greeting and direct approach	Ingratiation/flattery	Affective words
Need identification	Selling skills	Number and content of questions	Recommendations	Action verbs
Product demonstration	Product knowledge	Product features	Information sharing	Product features & Definite verbs
Overcoming objectives	Competitiveness	Problem-solving words	Promise	Action verbs & modals
			Social Proof	Context nouns
			Scarcity	Context nouns
Close	Persuasiveness	Degree of discount	Assertiveness	Action verbs, nouns
	Drive	Product offered	Reciprocity	Context nouns
		Upselling approach		
		Offering an alternative		
Communication skills	Communication skills	Pronoun usage		
		Positive sentiment		
Overall	Motivation	Motivational words		
	Self-confidence	Self-confidence words		

Notes: SPS components based on the contestant evaluation sheet developed by Loe and Chonko (2000).

3.2.1 Approach. The approach component of the sales performance score encompasses the engagement and empathy exhibited by the sales agent. It aims to measure the addressing skills and how the sales agent gains sympathies and initial customer interest. It is important to note that addressing skills and tactics exclusively take action in the introductory part of the conversation. Therefore, in this study, we measured these components of the SPS only in the first 25% of the bot conversation (Packard et al. 2024). The measurement criteria encompassed the presence of greetings and the occurrence of a direct approach. Given the customer's (Christian) first name, which is clearly visible to all agents in the chat, we were able to ascertain whether agents employed a concrete address by saying his name and also introducing themselves with a greeting and their concrete own name (Packard et al. 2021). Concerning the utilization of sales tactics, ingratiation and flattery might be employed in the approach section to simulate customer willingness to provide assistance. To identify this tactic, we created a dictionary of affective words (e.g., "nice," "glad," or "welcome") and counted the occurrence of these words in the introductory section (Singh et al. 2020).

3.2.2 Need Identification. The SPS component need identification pertains to the comprehension of the customer's circumstances. This is achieved by employing general selling skills, primarily through the formulation of pertinent inquiries. The assessment of this component entails the quantitative analysis of the inquiries posed, meticulously enumerated and filtered to eliminate redundancy. The performance of the agents is not solely determined by the number of questions asked; therefore, we have developed two additional dictionaries to assess the content of the questions. The first tool is a dictionary of relevant words, including terms such as "need," "purpose," and "budget." The second tool is a dictionary of relevant bigrams, such as "which model," "what kind," and "how often." In the context of sales tactics, recommendations are considered to be a component of need identification. The occurrence of recommendations is measured using two dictionaries containing action verbs, such as "recommend" or "suggest," as outlined by Singh et al. (2020).

3.2.3 Product Demonstration. The product demonstration component is associated with the sales success driver of product knowledge and contains the presentation of product benefits. It is also strongly associated with the sales tactic of information sharing. For this reason, two dictionaries were created containing all relevant product specifications (in this case, e.g., "gear shift," "brakes," or "rear light"), general description nouns (e.g., "feature," "attribute," or "information"), and definite verbs (e.g., "provide," "consult," or "show") that characterize this tactic (Singh et al. 2020).

3.2.4 Overcoming Objectives. Sales performance in the section of overcoming objectives is defined as the elimination of concerns and the retention of the customer. It is associated with the sales success driver of competitiveness and measured with two dictionaries containing words and bigrams that describe problem-solving (e.g., "help," "assistance," or "solution") and optimism (e.g., "no problem," or "won't regret"). The sales tactics falling under the umbrella of overcoming objectives include three distinct approaches: promise, social proof, and scarcity. The dictionaries for the promise-tactic include action verbs and adverbs (e.g., "promise" or "guaranteed"), while the dictionaries for the social proof tactic mainly include bigrams consisting of action verbs along with the word "also" (e.g., "used also", or "has also"). The dictionaries for the scarcity tactic consist of words and bigrams that signal low availability (e.g., "limited" or "few available").

3.2.5 Close. The fifth component of the selling process is defined as the presentation of the final buying reason and the completion of the transaction. This phase is associated with the drivers of sales success, namely persuasiveness and drive, and is measured by several components. Initially, the extent to which the agent offered a discount was examined. Given the multifaceted nature of the SPS, an alternative measurement criterion was employed, whereby a lower discount is assigned a higher weighting in the SPS than a higher discount. Secondly, we observed which product was ultimately sold. Given the variation in specifications and price points among the bikes in the study (see Appendix Figure A3), it is acknowledged that not all bikes are equally suited to the needs of the customer. To account for this variation, a weighting scheme was employed as not all available products do perfectly align with the customer's preferences and budget. Thirdly, we examined whether the agent employed an upselling approach and whether an alternative was presented (Johnson and Friend 2015). Regarding the sales tactics, assertiveness and reciprocity have been identified as integral components of the close component. The occurrence of these tactics was measured using dictionaries containing either completion-related terms for assertiveness (e.g., "contract," "order confirmation," or "pay online") or test-related terms for reciprocity (e.g., "test drive" or "try it out").

3.2.6 Communication Skills. An additional element of the SPS that does not adhere to the conventional sales process is communication skills, which are defined as effective verbal communication. A considerable number of communicational elements are already encompassed within other SPS components, thereby precluding their measurement on multiple occasions. In this study, we opted to assess the frequency of "I" pronouns and the expression of gratitude, as these elements have the potential to positively influence customer relations (Packard et al. 2018; You et al. 2020) and the degree of positivity in the agent transcripts. To this end, we employed the Syuzhet package in R to quantitatively analyze the positive sentiment present in the transcripts.

3.2.7 Overall. The final component of the SPS is designated as "overall" and is defined as the salesperson's enthusiasm and self-confidence. To assess these dimensions, a linguistic approach was employed, utilizing two dictionaries. The first dictionary comprised phrases that denote enthusiasm, such as "great" or "fantastic," while the second dictionary encompassed self-confidence terms, including "I know" and "for sure."

3.3 Part 2: Collect Character Features from Video Interviews

In the experimental setting, an application for a sales position as a sales agent for bicycles was presented (see the graphic job advertisement that the students saw in Appendix Figure A1). The application was submitted by students enrolled in a course that focused on sales and marketing. The decision to utilize a student sample as candidates for sales positions was guided by the fact that sales students are not yet trained, and our methods allow us to detect the SPS *before* a sales job employment. Secondly, we sought to demonstrate that the SPS is not strongly dependent on experience and knowledge, and that student job candidates can attain a top-level score. The students were motivated to dedicate effort to the application process, as only complete and valid applications would result in course credit. The application comprised three components. As sensitive data of the students are collected, the study was previously approved by the ethics committee of the university faculty (see Appendix Figure A2 for the official confirmation).

Collecting sales job candidate characteristics: In the initial phase of the study, participants completed a survey that collected demographic control variables, including age, gender, and work experience. This is analogous to the information provided in a CV. Table 4 presents the descriptive statistics of the survey.

In the subsequent stage, the students were tasked with recording a video of approximately one minute in duration at home. This requirement is in alignment with the increasing prevalence of video-based applications in sales positions, as highlighted in the expert interviews conducted for this study (Indeed 2024). In this video, students were tasked with providing a concise introduction of themselves, articulating their motivations and interests for the position, and explaining why they believed themselves to be a suitable sales job candidate. They were also instructed to describe their initial approach to customer interactions. To identify the character of the candidates using the three dimensions (personality traits, emotions, and paralanguage as well as some controls) previously discussed, we first used the text transcript of the video to draw the personality traits included in the Big 5 model using LIWC 2015 (Pennebaker et al. 2015). The results of this analysis are presented In Table 5, which includes descriptive statistics for the extraction of the five personality traits.

Thirdly, we extracted the emotion data of Ekman's (1999) seven basic emotions, including neutral, from these videos using Py-Feat (Cheong et al. 2023). Py-Feat is an AI-driven video analysis package running in Python that determines emotions in facial expressions on a scale from 0 (no emotion expression in face) to 1 (perfect emotion expression in face). The emotions are detected in pre-defined frames (in our setting, each 10th frame, which is equal to six emotion measurements per second in a 60 frame per second video). In videos with a frame rate of 30 frames per second, the frame detection rate was adjusted to three. For a one-minute video, this results in 360 observations for each basic emotion. Consequently, the mean of the basic emotions for each participant over the entire video has been calculated. Table 5 presents the descriptive statistics of the means in the face emotion analysis. Additionally, we have calculated the descriptive statistics of the range of the emotions, which are shown in Appendix Table A1.

Fourth, we extracted audio data from the video to measure paralinguistic attributes. We used the Librosa package in Python (McFee et al. 2015) to extract the average pitch of the applicants' voice, the pitch range in which they talked and the tempo in BPM (beats per minute). Summary statistics of the extracted audio data are shown in Table 5. Additionally, Table 6 provides an overview over the dimensions, measurements and tools we use in this part.

Table 4: Descriptive Statistics of Sales Job Candidate Survey

	Mean	SD	Min	Q 25	Median	Q 75	Max
Age	20.736	2.570	17	19	20	21.250	45
Gender	0.528	0.510	0	0	1	1	1
Semester count	3.222	1.772	2	2	2	4	10
# Job application interviews	2.132	2.436	0	1	2	3	20
Job experience	0.783	0.413	0	1	1	1	1
Sales job experience	0.241	0.428	0	0	0	0	1

Table 5: Descriptive Statistics of Sales Job Candidate Character Measures

	Mean	SD	Min	Q 25	Median	Q 75	Max
Big 5 personality traits							
Openness	3.731	.773	1.677	3.195	3.725	4.205	6.073
Conscientiousness	4.636	.776	2.646	4.130	4.660	5.142	6.754
Extraversion	6.754	1.629	2.870	5.620	6.767	7.763	11.573
Agreeableness	6.023	1.240	3.092	5.215	6.098	6.741	9.277
Neuroticism	.355	.214	.000	.211	.310	.476	1.250
Basic emotions							
Surprise	.225	.191	.001	.079	.167	.314	.863
Sadness	.033	.045	.001	.007	.015	.035	.275
Neutral	.478	.239	.019	.287	.456	.658	.981
Happiness	.175	.189	.000	.028	.106	.267	.891
Fear	.040	.061	.000	.006	.015	.045	.489
Disgust	.024	.045	.000	.001	.004	.030	.239
Anger	.026	.047	.000	.004	.010	.027	.459
Paralanguage							
Average pitch (Hz)	167	58	79	113	172	215	357
Pitch range (kHz)	3.70	348	1.34	3.75	3.83	3.85	3.85
Tempo (BPM)	121	20	83	108	117	136	172
Demographics and controls							
Age	20.736	2.570	17	19	20	21.250	45
Gender	.528	.510	0	0	1	1	1
Semester count	3.222	1.772	2	2	2	4	10
# Job application interviews	2.132	2.436	0	1	2	3	20
Job experience	.783	.413	0	1	1	1	1
Sales job experience	.241	.428	0	0	0	0	1
Chat length (words)	177.5	155.127	29.0	99.5	147.0	211.5	1865.0

Notes: SD = standard deviation, Q = quantile, Hz = Hertz, BPM = beats per minute

Table 6: Overview of Dimensions, Measures, and Tools for Character Identification

Dimension	Measure	Reference	Tool
Text	Big 5	McCrae & Costa (1987) Goldberg (1990)	LIWC 2015 Pennebaker et al. (2015)
Audio	Paralanguage	Aronovitch (1976) van Zant & Berger (2020)	Python Librosa McFee et al. (2015)
Video	Basic emotions	Ekman (1999)	Python Py-Feat Cheong et al. (2023)
Controls	Age, gender, semesters, chat length		Survey

3.4 Part 3: Chatbot Assignment

In the third part, the students completed a chatbot sales assessment, which involved selling a bike to a bot-programmed customer. In this simulation, three different kinds of bicycles, either a city bike, a mountain bike, or an electric bike could be sold. We provided sales job candidates a short list with some specifications directly in the chat, together with instructions how to play the simulation (see the specifications and instructions in Appendix Figures A3 and A4). The chatbot is programmed from scratch, runs in Python via the Telegram API and was doable in the Telegram app. It consists of more than 3,500 lines of code mainly including else-if statements to trigger answers. The chat-bot is programmed dictionary-based to ensure similar customer responses for similar agent input. The chatbot has a block structure, meaning that certain words or sentences activate different blocks: e.g., if the student writes “I recommend you the city bike”, the city bike block gets activated and responses can be traced back to this product. The SPS was then measured by analyzing the transcripts, provided information and final price negotiation in this bot assignment. In total, 224 sales job candidates participated in the experiment. We had to eliminate 16 responses due to incompleteness, resulting to an n = 208 complete surveys, videos, and chat bot assignments. The distribution of the SPS of the sales job candidates follows a normal distribution (see Appendix Figure A5 for a histogram).

In order to be able to classify and validate the results of the student SPS, we acquired a professional sales call center from a big German B2B company that primary sells their products personally. We asked experienced sales agents (n = 30, on average more than 10 years of sales experience) to also conduct the same chatbot assignment and measured their SPS in the same way as for the student sample. We expect the professional salesforce to have a significantly higher SPS compared to the student sample for chatbot validation. For further statistical analyses, we use the obtained SPS from the professional salesforce as a reference point for “successful” agents.

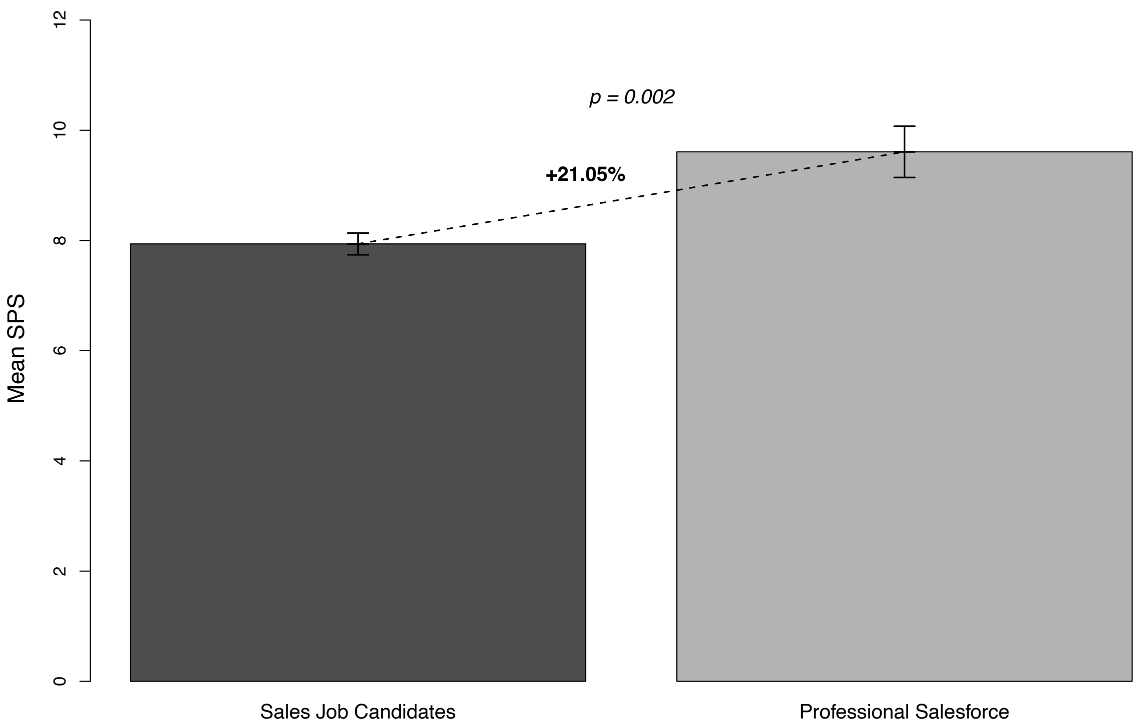
The final SPS is the weighted sum of the previous seven components of sales performance and shown in the equation below. As not all sub-variables are equally distributed, we adjusted the specific weighting of these sub-variables in order to determine a homogeneous and comparable SPS.

$$SPS = .05 * \sum Approach + .25 * \sum Need\ Identification + .25 * \sum Product\ Demonstration + .15 * \sum Overcoming\ Objectives + .10 * \sum Close + .15 * \sum Communication\ Skills + .05 * \sum Overall$$

As illustrated in Figure 2 below, the mean values of the sales job candidate sample (M = 7.938, SD = 2.852) and the professional salesforce sample (M = 9.608, SD = 2.549) are presented. The percentage difference between the two groups is 21.05%, and the SPS of the professional salesforce is significantly higher compared to the sales job candidate sample (p = .002, t = -3.304). This finding indicates that the professional salesforce utilizes a higher level of success drivers and influence tactics, which is consistent with their experience in the job and is therefore to be expected.

If the mean SPS value of the professional salesforce is used as a reference for suitable salespeople, 52 sales job candidates from the student sample would be suitable, as their SPS is greater than or equal to the reference. Accordingly, 156 sales job candidates fall below this threshold and would therefore be considered as non-suitable. The reference SPS now refers to one specific professional sample, and the results may vary when the experiment is repeated with other samples or varying sample sizes of professionals. The thresholds for suitable and unsuitable samples shift accordingly due to the influence of other referenced elements. In the initial attempt, the professional sample comprised less salespeople, and the reference SPS was elevated by a mere 14.7%. Notably, this variation did not lead to a significant alteration in the outcomes of the subsequent classifiers, thereby validating the robustness of the reference SPS as a reliable metric.

Figure 2: Comparison between Sales Job Candidate and Professional Sales Force SPS



3.5 Part 4: Support Vector Machine (SVM) Classifier

In the fourth part, we employ a classifier to identify suitable candidates for sales positions based on the personality traits, emotions, paralanguage, and control variables revealed. The support vector machine (SVM) is employed for this purpose, as it is a highly effective classification model frequently utilized in sales and marketing contexts when a substantial number of variables (features) are available for the classification process (e.g., Singh et al. 2020). A salient benefit of the SVM is its resilience to overfitting, a phenomenon in which the number of features used is disproportionately large relative to the sample size. This characteristic enables a high degree of flexibility in the optimization of model parameters (Lantz 2013). The following equation illustrates the features employed in the classification process with a linear kernel.

$$f(x) = w_1 openness_T + w_2 conscientiousness_T + w_3 extraversion_T + w_4 agreeableness_T + w_5 neuroticism_T + w_6 happiness_V + w_7 surprise_V + w_8 anger_V + w_9 disgust_V + w_{10} sadness_V + w_{11} fear_V + w_{12} neutral_V + w_{13} average\_pitch_A + w_{14} pitch\_range_A + w_{15} tempo_A + w_{16} age + w_{17} gender + w_{18} job\_experience + w_{19} sales\_job\_experience + w_{20} semester\_count + w_{21} chat\_length + b$$

with w1…w21 indicating the vectors of the features personality traits, facial emotions, paralanguage, and control variables and T/V/A indicating if the feature was collected from text, video, or audio data. The parameter b is the bias of the scalars of vectors and features. The objective of an SVM classification is to derive a matrix that enumerates the actual and predicted suitable and non-suitable salespeople. The accuracy of the SVM model is maximized when the number of correctly predicted and actually suitable and non-suitable salespeople is closely similar. Precision measures how many of the predicted positive instances are true positive; recall determines how many actually positives are correctly predicted, and specificity measures how many negatives were correctly classified.

The data set was partitioned into a training set and a test set, with the former comprising 70% of the data and the latter constituting the remaining 30%. The classification process involved the utilization of a linear kernel and scaled data. We also used a 5-times cross validation to avoid overfitting. The output of the SVM classification is presented in Table 7.

Table 7: Results of the SVM Classification with Linear Kernel

	Non-suitable (predicted)	**Suitable (predicted)**
Non-suitable (actual)	43	3
Suitable (actual)	4	11
Accuracy	(43 + 11) / (43 + 3 + 4 + 11) = .8852	
Precision	11 / (3 + 11) = .7857	
Recall	11 / (11 + 4) = .7333	
Specificity	43 / (43 +3) = .9348	
Cost parameter	.001	
Training error	.2517	

The results show precise results with an accuracy of .8852, indicating that 88.52% of the salespeople are classified correctly using the feature variables of emotions, personality traits, paralanguage, and controls from audio, video, text, and survey data. From 14 sales job candidates that fall into the suitable section based on their SPS and the reference SPS of professional salesforce, the SVM model was able to correctly classify 11 of them as suitable, resulting in a precision of .7857. The degree of the correctly classified suitable sales job candidates in total is 11 out of 15 and resulted in a recall of .7333. The amount of non-suitable sales job candidates is .9348, indicated by the specificity.

For a linear kernel SVM classification, we can extract the weights of the vectors to generate an impression which features are more likely to predict suitable sales job candidates (positive signs), and which are more likely to predict non-suitable sales job candidates (negative signs). We observe that conscientiousness, disgust, anger and happiness as well as the paralanguage attribute pitch range predict suitable sales job candidates the most. Table 8 shows the weights for all personality trait, emotion, and paralanguage features. It is important to note that the length of the chat of the participants which we included as a proxy of effort also has a high degree of explanation for the suitability of sales job candidates.

Table 8: Weights for SVM Classification Features

Feature	Weight	Feature	Weight
Openness	-1.9565	Agreeableness	-1.3361
Conscientiousness	3.4433	Extraversion	-2.3807
Neuroticism	-4.3543	Happiness	3.2313
Disgust	4.7367	Fear	-3.6309
Anger	5.1407	Surprise	-3.1227
Sadness	-10.0321	Neutral	.9194
Average pitch	1.8684	Pitch range	5.7986
Tempo	.2208		

However, we set-up a second SVM classifier and employing a radial, non-linear kernel and also scaled data as we have continuous variables (the emotion, personality trait, and audio parameters) and binary variables (gender, job experience) as features in the data set. The results of the non-linear SVM classification are displayed in Table 9 below.

Table 9: Results of the SVM Classification with Non-Linear Kernel

	Non-Suitable (predicted)	Suitable (predicted)
Non-suitable (actual)	45	1
Suitable (actual)	2	13
Accuracy	(45 + 13) / (45 + 1 + 2 + 13) = .9508	
Precision	13 / (1 + 13) = .9286	
Recall	13 / (13 + 2) = .8667	
Specificity	45 / (45 +1) = .9783	
Cost parameter	.25	
Sigma parameter	.03	

The results show more precise results with an accuracy of .9508, indicating that 95% of the salespeople are classified correctly using the feature variables. Furthermore, the precision, i.e., the predicted positive instances which are true positive, is much higher with a coefficient of .9286, as well as the recall coefficient with .8667. Finally, the specificity is also a bit higher with a coefficient of .9783, indicating that a non-linear kernel works better for the given features. In a non-radial SVM classification, we cannot extract weightings due to the transformed feature space.

3.6 Robustness checks

First, we implemented a hyperparameter tuning for the non-linear SVM model to try to receive even more accurate results. For this, we optimize both the parameters cost and sigma (in the caret R package, otherwise gamma is used) with a grid-search method with values from 10^{-3} to 10^{2} for cost and 10^{-2} to 10^{1} for sigma. The hyperparameter tuning reveals a cost parameter of .1 and a sigma parameter of .001. The accuracy is identical to the main SVM model with .9508, indicating that the small changes within the parameter do not alter the results. The results of the tuned SVM model are displayed in Table 10.

Second, we trained a logit model with the same parameters to obtain the classification results. The accuracy of the logit model is, as displayed in Table 10, .8525 and hence less accurate compared to the SVM classification. Performing a McNemar test to compare the misclassifications of both models, the p-value is .077 and thus the models are slightly significantly different. Especially the recall, i.e., the percentage of correctly classified suitable salespeople, is .50 and significantly weaker compared to the SVM model. Therefore, the SVM classifier is the superior option when compared to the logit model.

Third, a Nearest Neighbor classifier (kNN) was employed to differentiate the data. A kNN classifier is a non-parametric classifier in which the decision of a classification depends on k data nearest that are closest within the training data. This approach is notable for its simplicity. To assess the efficacy of the kNN classification, we varied the value of k, ranging from 3 to 15, and recorded the outcomes presented in Table 10. The results indicate that the accuracy of .7869 is the lowest among all classifiers, while the precision and specificity are optimal with a value of 1. However, the kNN classified only two sales job candidates as suitable, which is also reflected in the low recall rate of .1333. Consequently, the SVM demonstrates superior performance in comparison to the kNN classification.

Table 10: Results of Robustness Checks

	Accuracy	**Precision**	**Recall**	**Specificity**
Tuned SVM	.9508	.9286	.8667	.9783
Logit Model	.8525	.6500	.8667	.8478
k-NN	.7869	1[1]	.1333	1[1]

[1] only identified 2 sales job candidates as being suitable

3.7 Interpretable Model Outputs for Assisting Human Decision-Making

The model outputs can serve as an assistant for recruiting decisions. First, the SPS is a robust metric for measuring and analyzing the performance of sales job candidates prior to a job, both as a beginner and in the hiring process prior to a hire. As illustrated in Figure 3, the SPS can be compared between sales job candidates and be broken down between its single components to distinguish "suitable" from "non-suitable" sales job candidates. The exemplary sales job candidate in Figure 3 is "non-suitable" according to the SPS comparison but exhibits an above-average positive sentiment and greeting/direct approach attributes. A comparison with the professional sales force (right column) is also possible. Here, the exemplary sales job candidate has named more product features as the professional salesforce (8 vs. the mean of 6.70 from the professional sample).

Figure 3: SPS Component Comparison between Sales Job Candidates

	Exemplary sales job candidate	Sales job candidate "suitable"	Sales job candidate "non-suitable"	Professional salesforce mean
Greeting/direct approach	2	1.62	1.01	2.80
# Questions	6	7.27	4.11	8.40
# Product features	8	13.98	6.34	6.70
Problem-solving words	2	4.10	1.86	2.63
Degree of discount given	.06	.05	.04	.02
Product offered	1	1.06	.94	1.23
Upselling	0	.08	.07	.47
Offering an alternative	1	.50	.27	.33
I-pronoun usage	3	5.58	2.94	5.03
Saying thank you	0	.27	.09	.47
Positive sentiment	9	7.96	4.10	5.1
Motivational words	0	1.58	.73	2.33
SPS	9.5	> 9.608	<= 9.608	ø 9.608

Notes: Colors of exemplary sales job candidate indicates exceeding the threshold value of the suitable, non-suitable or professional salesforce peer group.

Second, as illustrated in Table 11 below, the SVM classification provides a probability of suitability or unsuitability for each sales job candidate in the test sample with a certain percentage. In this case, sales job candidates 2, 9 and 10 are suitable based on their SPS, and the SVM classifier is able to predict the probability of being suitable with a likelihood of 92.7%, 97.4% and 96.7%. Such a percentage can be determined for each sales job candidate in the sample and thus provide an AI-based approach for a hiring decision.

Table 11: Probabilities from the Non-Linear SVM Prediction

Sales job candidate in test sample	Classification based on SPS threshold	Non-linear SVM prediction of being suitable
1	Non-suitable	.2374
2	Suitable	.9272
3	Non-suitable	.1479
4	Non-suitable	.2474
5	Non-suitable	.1002
6	Non-suitable	.0313
7	Non-suitable	.1414
8	Non-suitable	.2550
9	Suitable	.9735
10	Suitable	.9671

Third, as demonstrated in Table 12, sales and hiring managers can assess the character profile of specific sales job candidates by comparing their traits, emotions, and paralanguage with the means of sales job candidates classified as either suitable or non-suitable. The exemplary sales job candidate (the same as in Figure 3 and thus narrowly classified as non-suitable) demonstrates reduced levels of openness and extraversion, less positive emotions, and a higher pitch and tempo compared to the suitable sales job candidate section.

Table 12: Prediction Feature Comparison between Sales Job Candidates

	Exemplary sales job candidate	Sales job candidate "suitable"	Sales job candidate "non-suitable"
Big 5 personality Traits			
Openness	2.92	3.57	3.77
Conscientiousness	4.56	4.62	4.65
Extraversion	5.46	6.58	6.74
Agreeableness	5.41	5.90	6.01
Neuroticism	.23	.34	.36
Basic emotions			
Surprise	.54	.21	.23
Sadness	.03	.03	.04
Neutral	.22	.45	.49
Happiness	.09	.20	.16
Fear	.03	.05	.04
Disgust	.04	.03	.02
Anger	.06	.03	.02
Paralanguage			
Average pitch (Hz)	252.14	175.63	163.39
Pitch range (kHz)	3826.49	3727.07	3685.01
Tempo (BPM)	129.2	120.04	121.43
SPS	9.50		
Classification	Non-suitable		

Notes: Big 5 personality traits and paralanguage are discrete variables; the basic emotion variables range between 0 and 1.

4 Discussion

The overarching research question guiding this study is how to efficiently detect suitable salespersons during the hiring process. Our research is particularly focused on the management challenges associated with uncertainty in identifying suitable sales candidates and the significant time and financial expenditures involved in the search and evaluation of sales job candidates. We developed a Sales Performance Score (SPS) derived from a literature-based analysis of salespeople success drivers as well as a set of influence and selling tactics. This score was then calculated for each candidate in a chatbot assignment with a sample of more than 200 sales job candidates. Using a comprehensive set of character attributes, encompassing traits, emotions, paralanguage, and demographic variables, extracted from text, audio, and video files of a framed sales application, we developed an SVM classifier capable of accurately distinguishing suitable from non-suitable sales job candidates with an accuracy exceeding 95% based on these attributes and the SPS. This distinction was grounded on a professional salesforce and their SPS, which they successfully attained in the identical chatbot assignment. This outcome demonstrates the efficacy of employing the chatbot assignment to efficiently detect the suitability of candidates for sales professions prior to their formal employment. The interpretable model outputs deliver additional value of the AI-driven and automated pre-selection of sales job candidates.

5 Managerial Implications

This study carries significant implications for managers by solving the initial management problems and assist in finding suitable candidates for a vacant sales job. The application video can be captured expeditiously by the sales job candidate, and the automated and AI-driven analyses deliver the results in the most efficient timeframe – important if the company received a huge number of applications for a single vacancy. The chatbot assignment is also time-efficient, expediting the overall process for the candidate and mitigating potential dissatisfaction with protracted application procedures. Concurrently, the company can reduce recruiting expenditures by automating the pre-selection of sales job candidates and furnishing decision-makers with precise information regarding sales performance and character composition.

Furthermore, the individual results and procedures of this study offer widespread possibilities for recruiters and sales managers to optimize their hiring process and increase the quality of their internal salesforce. First, they can efficiently evaluate sales job candidates in terms of the composition of specific traits, emotions and paralanguage a candidate exhibits in his or her application video. The derived information cannot be made objectively by human recruiters (Paulhus and Vazire 2007) and AI as well as automated methods are capable of solving higher-value tasks (Huang and Rust 2018). The values of the exemplary sales job candidate in Table 12 above signal a relatively low level of sales-related attributes, including being open-minded, extraverted, happy, and with a deeper and slower voice. This, in combination with the "non-suitable" classification, may negatively influence the decision to hire the candidate. In addition, the individual values of the character components determined by AI and automated methods can help to find the most suitable salespeople with regard to the customer base or corporate identity (CI), which can vary greatly from company to company.

Second, the SPS signals strengths and weaknesses of different sales performance dimensions the candidate has applied in the chatbot assignment. The classifier output of either categorizing a candidate as being suitable for a sales job or not aids recruiters and sales managers in their decision making. Importantly, as extracted from the expert interviews, an AI-hybrid decision-making is seen as the best of both worlds and the final decision of giving final commitment to a candidate should be the responsibility of human recruiters and sales managers (Chakraborty et al. 2024; Longoni et al. 2019).

Moreover, the information from the SPS can also be used for sales trainings to analyze a company's existing salesforce in terms of their neutrally measured performance, independent of company-specific target requirements. Subsequently, agents with a below-level SPS can undergo evaluation and training with respect to their specific dimensions that are deemed to be enhanced. For instance, sales personnel can be encouraged to cultivate enhanced product knowledge during interactions with customers or to exhibit augmented negotiating behavior when proposing discounts and promoting additional products or services. The chatbot, which has been designed here for generic comparability with bicycles, can also be customized for specific industries and companies in order to optimally analyze and train the internal sales force. The implementation of particular sales and influence tactics can also be cultivated through continuous training in the context of the chatbot assignment. In addition, salespeople who have already been hired can be assigned to specific departments and tasks depending on the composition of their SPS. The example sales job candidate from Figure 3 above is slightly classified as “non suitable” but exhibits an above-average positive sentiment and greeting/direct approach attributes. He or she might primarily be suitable for service-inquiries.

6 Theoretical Implications

This study also offers significant implications for sales and marketing researchers. First, the study introduces a novel, multi-dimensional framework for assessing sales candidate suitability by combining text, audio, and video data with AI and underlines the importance of multiple data sources. This extends traditional models of salesperson evaluation that have typically focused on manual CV screenings in hiring-related contexts or observation and self-reflecting interview data in job-related contexts. Researchers who have access to unstructured data such as text, audio, or video material can scrutinize these methods for gaining innovative insights, not only in terms of salespeople evaluation, but also for customer profile identification or corporate identity evaluations.

Second, with the SPS, we enrich the understanding of sales performance as we are moving away from the strict differentiation between behavioral-based and outcome-based measurements (Anderson and. Oliver 1987; Bolander et al. 2021). Our nuanced operationalization reflects an evolution in performance measurement by combining these outcomes with linguistic and emotional expressions. Researchers can thus context-specific adjust their operationalization of sales performance. E.g., for relationship building, prospecting and lead generation of salespeople, elements from the approach and need identification combined with communication skills can be measured. For adaptive selling situations, sales tactics might be taken into account. And for after-sales service, objection handling might be a suitable performance measurement.

Third, sales and marketing researchers can further explore the path of AI-hybrid instruments for solving marketing problems (Longoni et al. 2019). Our results show that AI can partially replicate human judgement and may serve as a powerful tool for recruiters and sales managers in early-stage hiring. SVM classifiers can hence be used by researchers for, e.g., detect the sales success (like a binary contract completion as present in Paper I) based on salespeople attributes or customer churn prediction based on CRM data, measurements of customer sentiment and language characteristics.

7 Limitations

Our study is accompanied by some limitations that can be addressed in future research. Firstly, our sales job candidate sample consists of students. Although they come from a sales and marketing-related course, it would be interesting to repeat the experiment with “real” sales agents to observe how they perform and how their character attributes are. However, we chose a student sample to obtain sales job candidates prior to a real sales profession not biased with past performance outcomes, so future research with real sales agents needs to strongly control for this issue. In order to employ the SPS for training purposes with greater frequency, the experiment could be executed within the workplace with sales agents, as opposed to pre-selection, and linked to authentic performance metrics such as net sales, generated revenue, or customer satisfaction scores.

Secondly, the chatbot assignment only includes one product (bicycle). Future research could enrich the assignment of the SPS with other products or services in order to make the results more generally valid. The dictionary-based chatbot with block structure is flexibly adjustable to other products and industries. The integration of artificial intelligence (AI) holds considerable potential for the development of conversation-based assignments. This can be achieved by analyzing the voice of sales job candidates and subsequently responding with AI-generated voice. Another avenue for future research could involve the utilization of learning algorithms (e.g., Siri, Alexa, or employing the NLP model of ChatGPT or other AI applications) instead of dictionary-based bots. These algorithms generate responses contingent on the input, with the capacity to adapt their answers accordingly. For instance, if the sales job candidate is more affable and extroverted, the AI could output replies according to this character profile. This approach aligns more closely with real-world scenarios; however, it hinders the comparability of the input of sales job candidates that we sought to ensure.

Thirdly, the effects of AI-supported emotion analysis are not particularly decisive. Here, emotions could be analyzed in other ways in future research, e.g. as Chakraborty et al. (2024) do with the help of body posture or by measuring emotional intelligence (Kidwell et al. 2011) or emotional control (Kidwell et al. 2021).

8 References

Aggarwal, P., Castleberry, S. B., Ridnour, R., & Shepherd, C. D. (2005). Salesperson Empathy and Listening: Impact on Relationship Outcomes. Journal of Marketing Theory and Practice, 16–30.

Ahearne, M., Hughes, D. E., & Schillewaert, N. (2007). Why sales reps should welcome information technology: Measuring the impact of CRM-based IT on sales effectiveness. International Journal of Research in Marketing, 24, 336–349.

Anderson, E., & Oliver, R. L. (1987). Perspectives on Behavior-Based Versus Outcome-Based Salesforce Control Systems. Journal of Marketing, 51, 76–88.

Aronovitch, C. D. (1976). The Voice of Personality: Stereotyped Judgements and their Relation to Voice Quality and Sex of Speaker. The Journal of Social Psychology, 99 (2), 207–220.

Arora, N., Chakraborty, I., & Nishimura, Y. (2025). AI-Human Hybrids for Marketing Research: Leveraging Large Language Models (LLMs) as Collaborators. Journal of Marketing, 89 (2), 43–70.

Baier, D. E., & Sugan, R. D. (1957). Factors in Sales Success. Journal of Applied Psychology, 41 (1), 37–40.

Bande, B., Pilar, F.-F., Varela, J. A., & Jaramillo, F. (2015). Emotions and salesperson propensity to leave: The effects of emotional intelligence and resilience. Industrial Marketing Management, 44, 142–153.

Barrick, M. R., & Mount, M. K. (1991). The Big Five Personality Dimensions and Job Performance: A Meta-Analysis. Personnel Psychology, 44, 1–26.

Barrick, M. R., Steward, G. K., & Piotrowski, M. (2002). Personality and Job Performance: Test of the Mediating Effects of Motivation Among Sales Representatives. Journal of Applied Psychology, 87 (1), 43–51.

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? Business Horizons, 63, 215–226.

Bolander, W., Chaker, N. N., Pappas, A., & Bradbury, D. R. (2021). Operationalizing salesperson performance with secondary data: aligning practice, scholarship, and theory. Journal of the Academy of Marketing Science, 49, 462–481.

Bozkurt, S., & Gligor, D. (2019). Scarcity (versus popularity) cues for rejected customers: The impact of social exclusion on cue types through need for uniqueness. Journal of Business Research, 99, 275–281.

Brown, S. P., & Peterson, R. A. (1994). The Effect of Effort on Sales Performance and Job Satisfaction. Journal of Marketing, 58 (2), 70–80.

Brown, S. P., Cron, W. L., & Slocum Jr., J. W. (1997). Effects of Goal-Directed Emotions on Salesperson Volitions, Behavior, and Performance: A Longitudinal Study. Journal of Marketing, 61, 39–50.

Capelli, P., Tambe, P., & Yakubovich (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. California Management Review, 61 (4), 1–34.

Chaker, N. N., Nowling, E. L., Pivonka, M. T., Itani, O. S., & Agnihotri, R. (2022). Inside sales social media use and its strategic implications for salesperson-customer digital engagement and performance. Industrial Marketing Management, 100, 127–144.

Chakraborty, I., Chiong, K., Dover, H., & Sudhir, K. (2024). Can AI and AI-Hybrids Detect Persuasion Skills? Salesforce Hiring with Conversational Video Interviews. Marketing Science, 44 (1), 30–53.

Cheong, J. H., Jolly, E., Xie, T., Byrne, S., Kenney, M., & Chang, L. J. (2023). Py-Feat: Python Facial Expression Analysis Toolbox. Affective Science, 4, 781–796.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. Human Resource Management Review, 33, 1–21.

Churchill, G, A., Ford, N. M., Hartley, S. W., & Walker, O. C. (1985). The Determinants of Salesperson Performance: A Meta-Analysis. Journal of Marketing Research, 22, 103–118.

Cialdini, R. (2013). Influence: Science and Practice. 5th Edition, London, UK: Pearson.

Claro, D. P., Ramos, C., & Palmatier, R. W. (2024). Dynamic and global drivers of salesperson effectiveness. Journal of the Academy of Marketing Science, 52, 399–425.

Crolic, C., Thomaz, F., Hadi, R., & Stephen, A. T. (2022). Blame the Bot: Anthropomorphism and Anger in Customer-Chatbot Interactions. Journal of Marketing, 86 (1), 132–148.

Cronofy (2023). Interview Scheduling: Candidate expectations, frustrations, and preferences. Retrieved July 12, 2024 from https://www.cronofy.com/reports/candidate-expectations-report-2023

Dawson, L. E., Soper, B., & Pettijohn, C. E. (1992). The Effects of Empathy on Salesperson Effectiveness. Psychology & Marketing, 9 (4), 297–310.

Downing, J. R. (2011). Linking Communication Competence with Call Center Agents' Sales Effectiveness. Journal of Business Communication, 48 (4), 409–425.

Ekman, P. (1999). Basic Emotions. In T. Dalgleish & M. J. Power (Eds.), Handbook of cognition and emotion (pp. 45-60). Hoboken, NJ: John Wiley & Sons.

Flair (2024). 200 Recruitment Statistics: Trends, Problems, and Strategies. Retrieved July 12, 2024 from https://flair.hr/en/blog/recruitment-statistics/

Fotheringham, D., & Wiles, M. A. (2023). The effect of implementing chatbot customer service on stock returns: an event study analysis. Journal of the Academy of Marketing Science, 51, 802–822.

Frazier, G. L., & Summers, J. O. (1984). Interfirm Influence Strategies and Their Application within Distribution Channels. Journal of Marketing, 48, 43–55.

Fried, M. (2023). The Importance of Video Introductions for Job Applications. Retrieved March 7, 2025 from https://www.linkedin.com/pulse/importance-video-introductions-job-applications-matthew-fried/

Goldberg, L. R. (1990). An Alternative "Description of Personality": The Big-Five Factor Structure. Journal of Personality and Applied Psychology, 59 (6), 1216–1229.

Good, V., Hughes, D. E., Kirca, A. H., & McGrath, S. (2022). A self-determination theory-based meta-analysis on the differential effects of intrinsic and extrinsic motivation on salesperson performance. Journal of the Academy of Marketing Science, 50, 586–614.

Greenacre, L., Tung, N. M., & Chapman, T. (2014). Self-Confidence and the Ability to Influence. In C. R. Bateman (Ed.), Academy of Marketing Studies Journal, 18 (2) (pp. 169–180). Weaverville, NC: Whitney Enterprises, Inc.

Gupta, N., Ganster, D. C., & Kepes, S. (2013). Assessing the validity of sales self-efficacy: A cautionary tale. Journal of Applied Psychology, 98 (4), 690–700.

Hecht, M. A., & LaFrance, M. (1995). How (Fast) Can I Help You? Tone of Voice and Telephone Operator Efficiency in Interactions. Journal of Applied Social Psychology, 25 (23), 2086–2098.

Heiman, A., McWilliams, B., Shen, Z., & Zilberman, D. (2001). Learning and Forgetting: Modeling Optimal product Sampling over Time. Management Science, 47 (4), 532–546.

HireVue (2025). We put the human back into human resources. Retrieved January 29, 2025 from https://www.hirevue.com/about

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21 (2), 155–172.

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda. Journal of Business Ethics, 178, 977–1007.

Hurtz, G. M., & Donovan, J. J. (2000). Personality and Job Performance: The Big Five Revisited. Journal of Applied Psychology, 85 (6), 869–879.

Indeed (2024). How to Make a Video Job Application in 5 Steps. Retrieved July 24, 2024 from https://www.indeed.com/career-advice/interviewing/how-to-make-video-job-application

Johnson, J. S., & Friend, S. B. (2015). Contingent cross-selling and up-selling relationships with performance and job satisfaction: an MOA-theoretic examination. Journal of Personal Selling and Sales Management, 35 (1), 51–71.

Kidwell, B., Hardesty, D. M., Murtha, B. R., & Sheng, S. (2011). Emotional Intelligence in Marketing Exchanges. Journal of Marketing, 75 (1), 78–95.

Kidwell, B., Hasford, J., Turner, B., Hardesty, D. M., & Zablah, A. R. (2021). Emotional Calibration and Salesperson Performance. Journal of Marketing, 85 (6), 141–161.

Kim, M., Sudhir, K., Uetake, K., & Canales, R. When Salespeople Manage Customer Relationships: Multidimensional Incentives and Private Information. Journal of Marketing Research, 65 (5), 749–766.

Lantz, B. (2013). Machine Learning with R. Third Edition, Packt Publishing. Birmingham, UK.

LinkedIn (2024). The Costs and Challenges of Recruiting Sales Professionals. Retrieved from July 9, 2024 from https://www.linkedin.com/pulse/costs-challenges-recruiting-sales-professionals-neal-tricarico-22v7c/

Lockeman, B. D., & Hallaq, J. H. (1982). Who are your successful Salespeople? Journal of the Academy of Marketing Science, 10 (4), 457–472.

Loe, T. W., & Chonko, L. B. (2000). Promoting Sales Programs: The National Collegiate Sales Competition. Journal of Personal Selling and Sales Management, 20 (1), 11–13.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. Journal of Consumer Research, 46, 629–650.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases. Marketing Science, 38 (6), 937–947.

Luo, X., Qin, M. S., Fang, Z., & Qu, Ze (2021). Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions. Journal of Marketing, 85 (2), 14–32.

Mayer, D., & Greenberg, H. M. (2006). What makes a good salesman. Harvard Business Review, 84, 164–171.

McCrae, R. R., & Costa Jr., P. T. (1987). Validation of the Five-Factor Model of Personality Across Instruments and Observers. Journal of Personality and Applied Psychology, 52 (1), 81–90.

McFarland, R. G., Challagalla, G. N., & Shervani, T. A. (2006). Influence Tactics for Effective Adaptive Selling. Journal of Marketing, 70, 103–117.

McFee, B., Raffel, C., Liang, D., Ellis, D. P. W., McVicar, M., Battenberg, E., & Nieto, O. (2015), librosa: Audio and Music Signal Analysis in Python. Proc. of the 14th Python in Science Conference, 18–25.

Miao, C. F., & Evans, K. R. (2007). The Impact of Salesperson Motivation on Role Perceptions and Job Performance – A Cognitive and Affective Perspective. Journal of Personal Selling and Sales Management, 27 (1), 89–101.

Miner, J. B. (1962). Personality and Ability Factors in Sales Performance. Journal of Applied Psychology, 46 (1), 6–13.

Packard, G., Moore, S. G., & McFerran, B. (2018). (I'm) Happy to Help (You): The Impact of Personal Pronoun Use in Customer–Firm Interactions. Journal of Marketing Research, 55 (4), 541–555.

Packard, G., & Berger, J. (2021). How Concrete Language Shapes Customer Satisfaction. Journal of Consumer Research, 47 (5), 787–806.

Packard, G., Li, Y., & Berger, J. (2024). When Language Matters. Journal of Consumer Research, 51 (3), 634–653.

Paulhus, D. L., & Vazire, S. (2007). The Self-Report method. In R. W. Robins, R. C. Fraley, & R. F. Krueger (Eds.), Handbook of Research Methods in Personality Psychology (pp. 224–239). New York, NY: The Guilford Press.

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The Development and Psychometric Properties of LIWC2015. Retrieved July 9, 2024 from https://www.liwc.app/static/documents/LIWC2015%20Manual%20-%20Development%20and%20Psychometrics.pdf

Pentland, S. J., Wang, X., & Twyman, N. W. (2025). Better job application systems: Objectively assessing measures of job performance from asynchronous video interviews. Information & Management, 62, 1–20.

Peterson, R. A., Cannito, M. P., & Brown, S. P. (1995). An Exploratory Investigation of Voice Characteristics and Selling Effectiveness. Journal of Personal Selling & Sales Management, 15 (1), 1–15.

Pettijohn, C. E., Pettijohn, L. S., & Taylor, A. J. (2002). The Influence of Salesperson Skill, Motivation, and Training on the Practice of Customer Oriented Selling. Psychology & Marketing, 19 (9), 743–757.

Plotkin, H. M. (1987). What makes a successful salesperson? Training and Development Journal, 54–56.

Plouffe, C. R., Bolander, W., & Cote, J. A. (2014). Which influence tactics lead to sales performance? It is a matter of style. Journal of Personal Selling and Sales Management, 34 (2), 141–159.

Pöyry, E., Parvinen, P., & McFarland, R. G. (2017). Generating leads with sequential persuasion. Journal of Personal Selling and Sales Management, 37 (2), 89–99.

Regan, D. T. (1971). Effects of a favor and liking on compliance. Journal of Experimental Social Psychology, 7 (6), 627–639.

Sampat, S. (2023). 20 Statistics You Need to Know Before Hiring Your First Salesperson. Retrieved July 9, 2024 from https://smith.ai/blog/20-statistics-you-need-to-know-before-hiring-your-first-salesperson

Sartori, L., & Theodorou, A. (2022). A sociotechnical perspective for the future of AI: Narratives, inequalities, and human control. Ethics and Information Technology, 24 (4), 1–11.

Shannahan, K. L. J., Bush, A. J., & Shannahan, R. J. (2013). Are your salespeople coachable? How salesperson coachability, trait competitiveness, and transformational leadership enhance sales performance. Journal of the Academy of Marketing Science, 41, 40–54.

Singh, S. K., Marinova, D., & Singh, J. (2020). Business-to-Business E-Negotiations and Influence Tactics. Journal of Marketing, 46, 837-856.

Sonnentag, S. (2003). Recovery, Work Engagement, and Proactive Behavior: A New Look at the Interface Between Nonwork and Work, Journal of Applied Psychology, 88 (3), 518–528.

Sujan, H., Sujan, M., & Bettman, J. R. (1988). Knowledge Structure Differences Between More Effective and Less Effective Salespeople. Journal of Marketing Research, 25, 81–86.

Tanner Jr., J. E., Ahearne, M., Leigh, T. W., Mason, C. H., & Moncrief, W. C. (2005). CRM in Sales-Intensive Organizations: A Review and Future Directions. Journal of Personal Selling and Sales Management, 25 (2), 169–180.

Terho, H., Eggert, A., Haas, A., & Ulaga, W. (2015). How sales strategy translates into performance: The role of salesperson customer orientation and value-based selling. Industrial Marketing Management, 45, 21–21.

Thoresen, C. J., Bradley, J. C., Bliese, P. D., & Thoresen, J. D. (2004). The Big Five Personality Traits and Individual Job Performance Growth Trajectories in Maintenance and Transitional Job Stages, Journal of Applied Psychology, 89 (5), 835–853.

Van Zant, A. B., & Berger, J. (2020). How the Voice Persuades. Journal of Personality and Social Psychology: Interpersonal Relations and Group Processes, 118 (4), 661–682.

Verbeke, W., Dietz, B., & Verwaal, E. (2011). Drivers of sales performance: a contemporary meta-analysis. Have salespeople become knowledge brokers? Journal of the Academy of Marketing Science, 39, 407–428.

Vinchur, A. J., Schippmann, J. S., Switzer, III, F. S., & Roth, P. L. (1998). A Meta-Analytic Review of Predictors of Job Performance for Salespeople. Journal of Applied Psychology, 83 (4), 586–597.

Wang, X., Jiang, M., Han, W., & Qiu, L. (2022). Do Emotions Sell? The Impact of Emotional Expressions on Sales in the Space-Sharing Economy. Production and Operations Management, 31 (1), 65–82.

Williams, K. C., & Spiro, R. L. (1985). Communication Style in the Salesperson Customer Dyad. Journal of Marketing Research, 22, 434–442.

Wooten, D. B., & Reed, A. (1998). Informational Influence and the Ambiguity of Product Experience: Order Effects on the Weighting of Evidence. Journal of Consumer Psychology, 71 (1), 79–99.

York, J. (2022). The jobseekers boosting their applications with video CVs. Retrieved March 7, 2025 from https://www.bbc.com/worklife/article/20220121-the-jobseekers-boosting-their-applications-with-video-cvs

You, Y., Yang, X., Wang, L., & Deng, X. (2020). When and Why Saying “Thank You” Is Better Than Saying “Sorry” in Redressing Service Failures: The Role of Self-Esteem, Journal of Marketing, 84 (2), 133–150.

Appendix

Table A1: Descriptive Statistics of Emotion Ranges

Range	Mean	SD	Min	Q 25	Median	Q 75	Max
Surprise	.893	.173	.075	.883	.961	.985	1.000
Sadness	.363	.284	.012	.108	.276	.583	.988
Neutral	.949	.078	.298	.942	.971	.987	.999
Happiness	.802	.286	.005	.670	.969	.994	.999
Fear	.540	.328	.0005	.243	.578	.880	.993
Disgust	.417	.381	.001	.048	.288	.842	.999
Anger	.338	.284	.003	.091	.279	.549	.989

Figure A1: Framed Job Advertisement

Notes: Text is translated from German to English.

Figure A2: Confirmation for the Experiment by the Ethic Commission

University of Cologne • CMR • Albertus-Magnus-Platz • 50923 Köln

Herrn
Robert Münster, M.Sc.
Chair of Retailing and Customer Management
Prof. Dr. Reinartz
Sibille-Hartmann-Straße 2-8
50969 Cologne

FACULTY OF MANAGEMENT, ECONOMICS AND SOCIAL SCIENCES
Today's ideas. Tomorrow's impact.

Ethical Review Board

Prof. Dr. Johannes Wohlfart

wohlfart@wiso.uni-koeln.de
www.wiso.uni-koeln.de

Cologne, 06/05/24

Advice of the Ethics Committee regarding your ERB application "Automated Pre-Selection of Sales Job Candidates" (Reference: 240026RM)

Dear Rober Münster,

Many thanks for sending your project proposal. We discussed your project proposal and are happy to approve it without any concerns.

We wish you a successful project!

Sincerely,

Prof. Dr. Johannes Wohlfart
(ERB Chairman)

This document requires no signature and is valid without a signature.

Postal address
Albertus-Magnus-Platz
50923 Köln

UNIVERSITY OF COLOGNE

Figure A3: Product Specifications of the Bike Models

1. Men's Mountain Bike "Bergrad"

- 12-speed derailleur gear
- Disk brakes front and rear
- Aluminum frame, 13 kg weight

Price: 999 Euros

2. Men's City Bike "Stadtrad"

- 21-speed derailleur gear
- Includes 880-lux headlight
- Innovative sports saddle with suspension
- Aluminum frame, 11 kg weight

Price: 799 Euros

3. Men's E-Bike "Stromrad"

- Powerful 250-watt motor with a range up to 100km
- 7-speed gear system
- Aluminum frame, 24 kg weight

Price: 1599 Euros

Figure A4: Chatbot Introduction and Instructions

Welcome to the sales simulation game!

Please enter the identification number in the chat. If you do not receive a message after a few seconds, click here on /hints

Hi, I would like to give you a few tips about the game below:

- Please put yourself in the shoes of a salesperson and have a virtual sales conversation in the chat with a potential customer.

- The customer is simulated by a chat bot.

- Please keep your individual messages as short as possible (one aspect, one argument or one statement per message is ideal) and send several messages. This increases the likelihood that the bot will understand you correctly!

- If it does not understand you correctly, try rephrasing your message!

- The simulation is over when you have agreed on a price: you can negotiate as you see fit! However, please do not offer a price that is ABOVE the selling price (you can see the prices in the next step)

- Thank you very much for participating! If you have understood everything, then click here on /continue!

In the following situation, potential customers are interested in men's bicycles. Your company has 3 different bikes in stock, which you can view by clicking on /products.

You can find some information about the bikes in the PDF above.

Everything clear? One more time before we start:

Please keep your messages as short as possible and write several messages.

If you don't receive a reply, make the message simpler or rephrase it!

The simulation is over when you have agreed on a price (you may negotiate at your own discretion, but please do not offer anything ABOVE the stated selling price)!

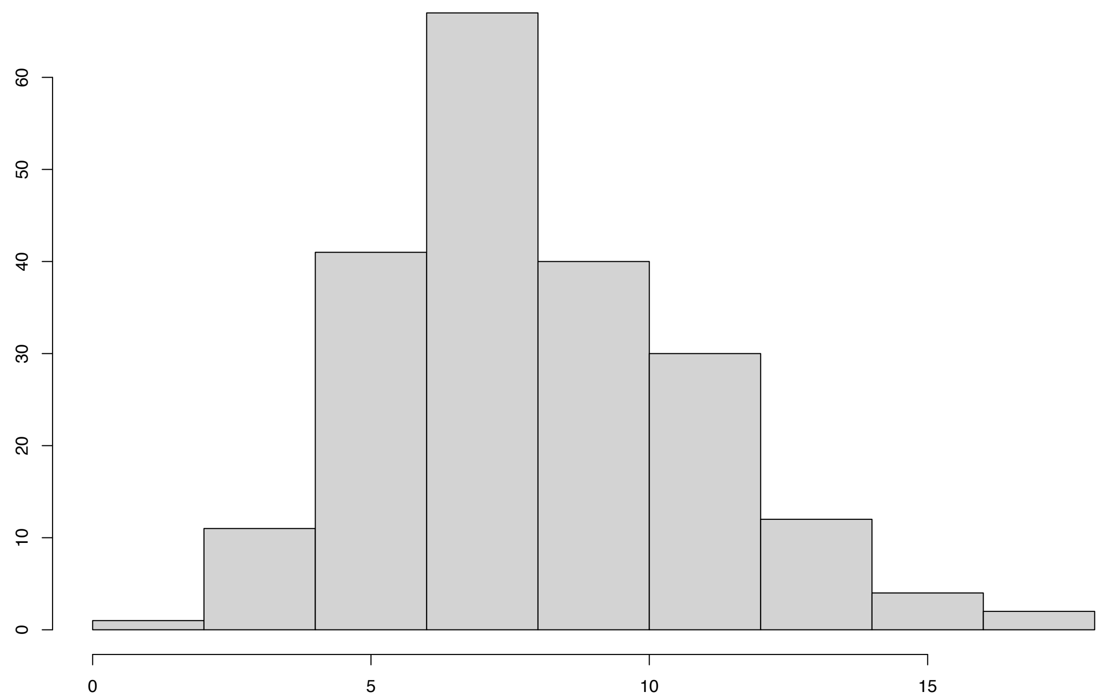
When you are ready, click on /go!

- Christian enters the chat -

Hello, I'm interested in a new bike. Can you help me with that?

Note: These messages are translated from German to English.

Figure A5: Histogram of the Sales Job Candidate SPS



Paper III: Success Factors of Salespeople: A Topic Modeling Approach

Author: Robert Muenster

Abstract

Sales force effectiveness is a topic of significant importance in both academic and practitioner literature. Factors that enhance the performance of sales personnel are of paramount importance for the accomplishment of personal objectives, for sales and hiring managers, and for the entire organization, as salespeople are primarily responsible for generating revenue. In this study, I employ human- and AI-based classification and topic modeling approaches through BERT and LDA in two literature datasets consisting of 224 academic papers and 139 practitioner articles that encompass salesperson success factors. My analyses reveal that the success factors of salespeople can be classified into three core dimensions: knowledge, experience, and character. The study also examines the differences in priorities between academic and practitioner literature. The analysis involves collecting citations and access metrics for academic articles and downloading, viewing, and social media sharing measurements for practitioner texts. The findings reveal that the priorities of these two types of literature do not fully align. While academic research prioritizes character-related success drivers of salespeople, the practitioner side predominantly focuses on knowledge-related success drivers. Finally, I discuss these findings and provide implications for managers and organizations.

Keywords *Salespeople, Sales performance, Success factors, Topic modeling, Text analysis*

1 Introduction

Sales are the primary source of revenue for businesses. Without sales, there is no cash flow, and without cash flow, businesses cannot operate. For decades (even centuries), companies have used salespeople to build and maintain customer relationships and increase revenue through personal selling (Darmon 1993; Kim et al. 2019). Given the pivotal role of sales in generating revenue, it stands to reason that companies seek to recruit and retain the most adept and successful salespeople. This strategic effort is driven by the understanding that sales talent is a critical factor in achieving competitive advantage and maximizing profits (Claro et al. 2024).

In recent years, salespeople who embody the essential success factors have assumed an increasingly importance, as evidenced by current *Salesforce* statistics. A substantial proportion of salespeople acknowledge the imperative to swiftly adapt to evolving market dynamics: 82% of respondents report this as a key challenge. Moreover, a significant majority, 84%, encountered difficulties in attaining their targeted goals during the previous year. A further 53% assert that the act of selling has become more arduous in comparison to the previous year (Salesforce Blog 2024). Besides this, the evolving landscape of customer needs, characterized by a heightened demand for customized products, a diminution in information asymmetry, and the advancements in artificial intelligence (AI), has not concomitantly facilitated the role of the salesperson (Ahearne et al. 2022; Huang and Rust 2018; Scholdra et al. 2023).

Consequently, it is unsurprising that academic literature has historically concentrated on the core success factors of salespeople. For instance, as early as 1941, Harry R. Tosdal published an essay in the *Journal of Marketing* entitled "Significant Trends in Sales Management," which detailed the successful behaviors of salespeople. In 1964, Mayer and Greenberg sought to address this question in their *Harvard Business Review* article "What Makes a Good Salesman" which is cited 283 times according to Google Scholar (2025). This article is considered one of the most influential works in the field of practical sales management, and its analyses of empathy and ego drive among salespeople have consistently garnered attention and impact. Subsequent individual studies on various characteristics and success factors of salespeople led to the publication of the first multi-item studies and meta-analyses from the 1980s onwards. For instance, Churchill et al. (1985) distinguished between sales performance factors of role variables, skill, motivation, personal factors, aptitude, and organizational/environmental factors. This classification was afterwards corroborated by Verbeke et al. (2011). With the progressive development of the Big 5 personality model by McCrae and Costa (1987) and Goldberg (1990), more and more analyses emerged that linked traits of salespeople to performance (e.g., Barrick and Mount 1991; Hurtz and Donovan 2000; Vinchur et al. 1998). The enduring relevance of this subject is evidenced by the meta-analysis published by Claro et al. (2024), who examined dynamic factors of salespeople performance.

These findings are of immense value to managers and companies. However, two managerial problems occur. The first challenge lies in the complexity of the factors, dimensions, and characteristics, which often leads to ambiguity and inconsistencies in terminology and specification across articles. Furthermore, studies on the factors contributing to the success of salespeople frequently utilize complex frameworks that examine multiple individual dimensions and establish connections between them and performance outcomes (e.g., Claro et al. 2024; Rapp et al. 2006; Szymanski 1988; Weitz et al. 1986). It is therefore imperative to ascertain the key factors contributing to the success of salespeople and to subsequently categorize these factors in a meaningful manner to increase practical relevance.

The second challenge arises from the ambiguity surrounding the correspondence between the priorities derived from academic sources and those originating from practical literature streams (Jedidi et al. 2021). Substantial managerial implications are of particular importance in marketing and sales literature (Jaworski 2011; Kohli and Jaworski 1990). Consequently, it is elemental to ascertain whether the sales success drivers of academic research align with practical interests. The present study thus seeks to answer the following two research questions:

1. **What are the core categories of salesperson success drivers?**
2. **Do the priorities of salesperson success drivers match between academic and practitioner literature?**

The present study utilizes a multifaceted approach encompassing manual human evaluation of the articles, AI-based classification, and two topic modelling approaches, the Bidirectional Encoder Representations from Transformers (BERT) and the Latent Dirichlet Allocation (LDA) to elucidate the key success drivers of salespeople performance. The analysis reveals the identification of three overarching dimensions: 1) *Knowledge*, 2) *Experience*, and 3) *Character*. To this end, a comprehensive data set comprising 224 academic research papers and 139 practitioner articles addressing the success drivers of salespeople and their impact on performance outcomes has been compiled. Given the assumption that all these drivers should be directly relatable to salespeople, organizational and environmental factors have been ignored in this study (see Verbeke et al. [2011] for a discussion of these factors). Across the classification methods, it is demonstrated that a division in these three categories is valid for academic as well as practitioner articles. Exploiting the means across the four methods, presenting the number of articles published over time and conducting popularity analyses (citations for academic papers and views or social media shares for practitioner articles, respectively), I find that the priorities of the articles do not perfectly match, with the academic literature prioritizing character-related articles and the practitioner literature focusing more on knowledge-related articles. Using a BERT semantic similarity analysis and assessing the sentiment of the articles, I detected a low similarity between the articles, with, however, the closest match observed for academic character and practical knowledge articles, which are the respective highest prioritized categories.

With these findings, this study makes both an important managerial as well as a theoretical contribution. From a managerial perspective, the study's findings enable a more nuanced understanding of the critical factors influencing the performance of sales personnel and provide an overview of which core categories should play a major role in the hiring and training of salespeople. This enhanced understanding facilitates the identification of agents who demonstrate superior performance and distinguishes those who exhibit less successful outcomes (Lockeman and Hallaq 1982). Furthermore, these findings may serve as a catalyst for future research, opening new avenues for researchers to align their research more closely with the needs and interests of managers and practitioners (Jaworski 2011; Jedidi et al. 2021; Kohli and Jaworski 1990). Methodologically, this study also demonstrates the effectiveness of text mining topic modeling approaches such as BERT that can be used for text classification in many areas of marketing and sales research (Arora et al. 2025; Jedidi et al. 2021).

2 Derivation of Sales Success Drivers

2.1 First Category: Knowledge

The Greek philosopher Plato formulates the definition of knowledge as a belief or observation that is justified and proven to be true (Bolisani and Bratianu 2018). From a managerial perspective, knowledge is considered to be dynamic and requires continuous acquisition to bridge the gap between existing knowledge and future learning which is necessary to gain a competitive advantage (Mabe 2012). In the context of sales, knowledge is defined as the accumulation of information pertaining to products, markets, customer needs and behaviors, as well as various selling strategies. This multifaceted nature of knowledge serves as a foundational element in determining sales performance. Moreover, knowledge is recognized as a pivotal component of experience and personal skills, particularly in the context of the generation of practical know-how. In this section, however, the focus is on explicit knowledge, defined as knowledge that can be acquired through knowledge transfer and thereby constitutes a self-contained factor in sales performance. In the following, I present the most-relevant components of knowledge that are associated with sales performance according to the definition above.

2.2.1 Product Knowledge. Product knowledge stands as a paramount skill in the realm of business intelligence (Elhajjar et al. 2023) and is regarded as one of the most enduring factors contributing to the success of sales professionals (Baier and Dugan 1957). It involves the possession and dissemination of pertinent information concerning products and services to customers, thereby influencing sales performance (Singh et al. 2020). In their work, Verbeke et al. (2011) characterizes salespeople as "knowledge brokers," underscoring their key role in transferring product knowledge to customers. The possession of profound product knowledge has been shown to enhance the performance of salespeople when confronted with social anxiety during customer interactions (Verbeke and Bagozzi 2000). This is due to the fact that it conveys expertise and credibility. In the context of customer interactions characterized by limited information asymmetries, customers often possess substantial knowledge about product functions and benefits from publicly available sources such as social media or news blogs, as well as firm-provided information including reviews and descriptions. In such settings, the possession of extensive product knowledge becomes particularly salient for salespeople (Ahearne et al. 2022; Hochstein et al. 2019).

2.1.2 Market Knowledge. The unique characteristics inherent in each industry necessitate a profound market knowledge (Stremersch and van Dyck 2009). Market knowledge is referred to the comprehensive understanding of the competitive landscape, novel product developments, and trends, which has been shown to positively influence sales performance by reducing individual error-proneness of salespeople in complex market scenarios (Ahearne and Schillewaert 2000). Moreover, market knowledge exerts a twofold influence on sales performance. First, it directly impacts the performance of individual salespeople as market knowledge leads to a mature sense of what customers are willing to spend their money on (Chateau 2022). Second, market knowledge of salespeople serves as a crucial source of information for the company and its employees. The sales force stays in direct contact with suppliers, customers, and industry members and is well-positioned at the front line of the company to provide it with valuable insights of issues that are prevalent outside the company (Rapp et al. 2006; 2011).

2.1.3 Customer Knowledge. Successful salespeople must also possess a comprehensive understanding of their customers. This knowledge encompasses not only a rudimentary understanding of customer description (Leong et al. 1989), but also more profound insights into customer traits and behaviors, facilitating a more nuanced understanding of their needs (Sujan et al. 1988). The utilization of customer information is a critical factor in enhancing sales performance (Spiro and Weitz 1990; Weitz 1978). Customer knowledge encompasses the understanding of shifting customer and behavioral patterns. For instance, the ongoing shift in consumer behavior, largely influenced by the global pandemic, has led to an increased demand for hybrid services, i.e., services that are offered both online and offline. Consequently, sales personnel must develop competencies in the realm of digital communication to effectively engage with customers via online channels (Elhajjar et al. 2023; Singh et al. 2019).

2.1.4 Selling Knowledge. Successful salespeople conceptualize selling as a process that necessitates diverse techniques and skills at varying stages (attention gaining, product presentation, negotiation, etc.). The knowledge of the techniques and skills necessary for success at various stages is referred to as selling knowledge, a significant driver of sales performance (Verbeke et al. 2011). This knowledge is often also termed "declarative knowledge," signifying its function as the repository of information necessary to successfully navigate the distinct phases of the sales process (Szymanski 1988). However, it is important to note that selling knowledge cannot be completely separated from the other three areas of knowledge in sales. In fact, an understanding of the entire sales process often also includes knowledge of products, markets, and customers (Verbeke et al. 2011).

2.2 Second Category: Experience

According to the Cambridge Dictionary, experience is defined as "the process of getting knowledge or skill from doing, seeing, or feeling things." As the definition indicates, experience is contingent on knowledge, with salespeople often acquiring more experience, which is associated with greater knowledge of products, markets, customers, and general sales practices (Mintu-Wimsatt and Gassenheimer 2004). The comprehensive understanding of these components by salespeople can be encapsulated as working experience.

The temporal aspect of salespeople's professional trajectory is frequently assessed by measuring the duration of their employment as sales representatives (e.g., Rapp et al. 2006) or within specific firms, a concept referred to as tenure (Dixon et al. 2003). As in many other professions, job tenure and prior experience (either in the same firm or at other firms) have a positive influence on the performance of salespeople (Feng et al. 2021; Ko and Dennis 2011). However, in contrast to these findings, early studies have examined the relationship between the age of salespeople and sales performance and have found contradictory results, i.e., negative associations with age on performance (Baier and Dugan 1957; Lamont and Lundstrom 1977). This discrepancy may be attributed to the discovery of an inverted U-shaped relationship between tenure and performance by Minsu-Wimsatt and Gassenheimer (2004). Caution is therefore advised when attempting to equalize the experience and age of salespeople, as these two factors are not inherently equivalent.

Research has further demonstrated that expert and experienced salespeople rely more on their memory of previous selling situations than less-skilled salespeople do, effectively leveraging their experience in subsequent selling scenarios (Shepherd et al. 2006). In general, Leong et al. (1989) describe the experience of past events and sales situations as "script structures" and underline that these experiences are important factors in successful sales interactions. From a psychological perspective, accumulated work experience fosters enhanced role clarity and a more profound comprehension of one's job, thereby directly influencing performance (Bartkus et al. 1989). Furthermore, the ability to adapt to diverse sales scenarios is also shaped by prior working experiences (Banin et al. 2016). Additionally, intrinsic salesperson motivation positively moderates the effect of experience on performance (Good et al. 2022) and it also harms salespeople in inappropriate behavioral responses in case that a customer-interaction leads to undesired outcomes, e.g., a loosed sale (Dixon et al. 2003).

Furthermore, work experience is also needed to adopt technological innovations, such as artificial intelligence (AI), which in turn fosters future performance outcomes. This is due to their ability to handle evolving customer demands and adapt to novel market scenarios (Pappas et al. 2023). Consequently, proficiency in technical solutions and experience with these tools emerges as a pivotal factor in determining the performance of sales personnel.

2.3 Third Category: Character

The third category of salespeople's success drivers is described as character and encompasses all individual and personal, non-demographic attributes of salespeople that are associated with sales performance. The character dimension is comprised of three sub-categories, namely personality traits, behaviors, and soft skills, including influencing and selling tactics (McFarland et al. 2006). The character success driver has garnered significant attention from the academic sales literature, primarily due to the extensive array of components encompassed within the three sub-characteristics. Empirical evidence indicates that individual drivers of salespeople have stronger correlations with sales performance compared to other drivers such as environmental and organizational factors (Claro et al. 2024). In the following review, the most relevant components of the three subcategories of traits, behaviors, and soft skills that are positively associated with sales performance will be examined.

2.3.1 Traits. McCrae and Costa (2003, p. 18) define traits as "dimensions of individual differences in tendencies to show consistent patterns of thoughts, feelings, and actions." In the sales literature, the relationship between different traits and performance was a subject of early research, given that salespeople engage in constant human interactions and their traits can influence their performance more than in other jobs (Lamont and Lundstrom 1977; Miner 1962; Pruden and Peterson 1962). Within the Big 5 personality model, which is frequently linked to job performance, the personality component conscientiousness has the strongest association with sales performance, followed by extraversion (Barrick and Mount 1991; Vinchur et al. 1998). Furthermore, competitiveness (Plotkin 1987) and machiavellianism (Satornino et al. 2023) have been shown to lead to long-term sales performance gains. However, the findings on the trait of empathy are mixed. While the general assumption is that empathy is sales-promoting, some researchers argue that empathy alone is not connected to sales performance due to missing tenacity and ego-drive (Dawson et al. 1992; Mayer and Greenberg 1964).

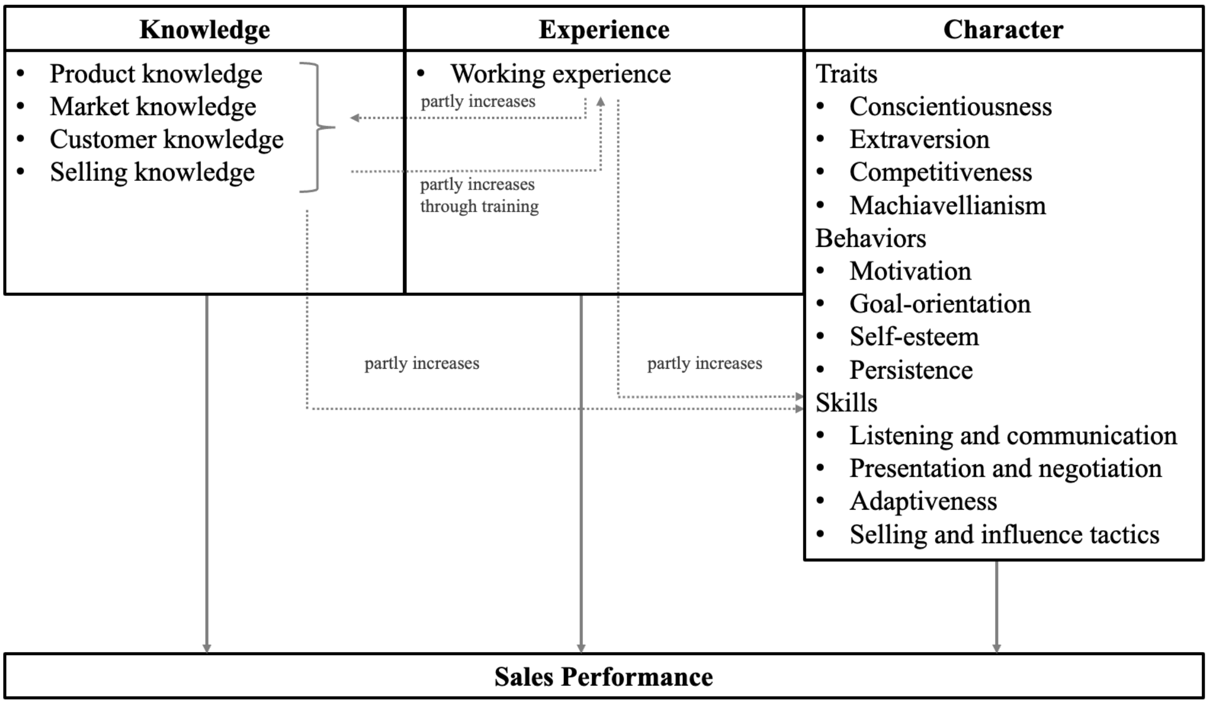
2.3.2 Behaviors. Behavioral attributes constitute an additional sub-category of character, denoting beliefs, patterns or actions that are externally stimulated but not directly reflected in personality traits (Parincu 2023). Firstly, motivation is identified as one of the primary influencing factors of salesperson behavior, denoting the extent of effort salespeople allocate to specific activities. This motivation can be categorized as either intrinsic, based on self-fulfillment, or extrinsic, based on the avoidance of punishment or the receipt of rewards (Barrick et al. 2002; Churchill et al. 1985; Good et al. 2022). Intrinsic motivation has been found to be positively associated with sales performance, with a stronger effect compared to extrinsic motivation (Good et al. 2022). Secondly, goal-orientation is a behavior often referred to well-performing salespeople (e.g., Brown et al. 1998; VandeWalle et al. 1999). It is defined as a self-regulated activity to fulfill certain goals and is divided into learning goal-orientation (i.e., goals set to increase individual competence) and performance goal-orientation (i.e., goals set to avoid negative judgements) (Elliott and Dweck 1988; VandeWalle et al. 1999). Thirdly, the positive or negative perception individuals have of themselves, termed self-esteem, and the steadfast determination to continue pursuing a course of action, termed persistence, are two behaviors of salespeople which are also positively related to sales performance (e.g., Bagozzi 1978; Chaker et al. 2018; Ferris et al. 2010).

2.3.3 Soft Skills. In addition to personality traits and behavioral tendencies, a range of soft skills have been demonstrated to be effective for salespeople. These soft skills are defined as generic intrapersonal and interpersonal capabilities and are frequently used interchangeably with the term "competencies" (Marin-Zapata et al. 2022). For salespeople, a number of soft skills have been shown to be conducive to success. Firstly, the capacity to listen and communicate effectively is paramount, as the ability to understand and appropriately respond to customer interactions is demonstrably associated with enhanced sales performance (Aggarwal et al. 2005; Williams and Spiro 1985). In addition, changes to nuances in the language can also increase the performance of salespeople, e.g., by using certain pronouns, words or language styles (Packard et al. 2018; You et al. 2020; see also Paper I of this dissertation). Secondly, the ability to present and negotiate, i.e., the ability to convey the added value of the product and successfully sell it to the customer, is a key competency of successful salespeople (Alavi et al. 2018; Johlke 2006). Thirdly, the degree to which salespeople are able to modify their sales behaviors either within a single customer interaction or across multiple interactions foster sales performance (Homburg et al. 2024). The modification of behavior to gain customer favor is also known as adaptive selling (Weitz et al. 1986).

Furthermore, a substantial number of sales and influencing tactics are pertinent to successful adaptive selling, and these also fall into the category of soft skills as a success factor.

These include information exchange, recommendations, threats, promises, inspirational appeals and assertiveness (Frazier and Summers 1984; McFarland 2006; Singh et al. 2020). I displayed the above discussed drivers of sales performance in Figure 1 below. The three categories of core success drivers are also summarized in Appendix Table A1.

Figure 1: Overview of Sales Performance Success Drivers



2.4 Connections between the Categories

As demonstrated in Figure 1, it is evident that certain components exert an influence on one another, thereby indicating that the three categories cannot be regarded as being entirely isolated entities. Firstly, it can be posited that the skills component of the character category is susceptible to being influenced by the acquired knowledge and experience of salespeople. The more salespeople learn and train on their product knowledge, market situation management, customer interactions, and improved selling knowledge, the more they know how to successfully apply selling-related skills (Boorom et al. 1998). Furthermore, it has been demonstrated that work experience has a direct impact on the enhancement of confidence and ease of use with regard to specific selling skills and influence tactics (Rapp et al. 2006). For instance, salespeople who boost their comprehension of customer behaviors, requirements and attributes they express, and who also possess greater experience in interacting with diverse customers, are better equipped to accurately discern customer needs, communicate and negotiate with customers in an appropriate manner, and realize sales through the implementation of influence tactics that optimally align with the specific selling situation (Davenport et al. 2011).

Secondly, it is important to note that the categories of knowledge and experience are not completely isolated from each other, as they are interactions between these two categories: Sujan et al. (1988) report a strong correlation ($r = .59$) between knowledge and experience. To illustrate this, training, which can be defined as an augmentation in knowledge through the acquisition of specific abilities, has the capacity to heighten experience if certain situations have been assimilated and are recognizable to salespeople. Conversely, knowledge can also be acquired through experience, as the sales area, in particular with its high degree of practical relevance and implementation, can also generate knowledge through the experience of certain situations and contexts (Sharma et al. 2000). According to this literature review, these three categories comprehensively address the fundamental drivers of sales performance, encompassing all the attributes necessary for salespeople to thrive in their profession. However, it should be noted that some overlap exists among these categories, which will become more evident as the papers are categorized subsequently, as certain papers may be methodologically assigned to more than one category.

3 Classification of Academic Articles

Based on the number of subcategories in Figure 1, the previous literature review implies that there may be a preponderance of academic publications in the character category, followed by knowledge-based and experience-based articles. To empirically group the articles in the three number of categories and to make statements about the importance of the individual categories in the literature, I conducted four distinct topic classification methods using a dataset comprising n=224 empirical articles. These articles examine various attributes of salespeople and their influence on sales performance. A comprehensive list of these articles can be found in Appendix Table A2. I sourced these articles from A+/A journals, including the *Journal of Marketing*, *Journal of Marketing Research*, *Journal of the Academy of Marketing Science*, *International Journal of Research in Marketing*, *Journal of Applied Psychology*, and *Marketing Science*. Additionally, I included selected B journals with a strong emphasis on sales research, such as the *Journal of Personal Selling and Sales Management*, *Industrial Marketing Management*, and the *Journal of Business Research*. Within the dataset, A/A+ journal articles constitute 64.16%, articles from the *Journal of Personal Selling and Sales Management* account for 18.58%, and the remaining B journals contribute 17.26%. To identify articles addressing agent-specific success factors of sales performance, I utilized journal-specific search tools, platform searches on *Google Scholar* and *EBSCO Host*, and forward and backward citation search procedures.

I classified the articles in the dataset through a combination of methods. First, I personally reviewed the articles and abstracts to categorize them (human classification). Second, I employed ChatGPT prompts (see Appendix Figure A1 for examples) to assist in the classification process. Finally, I applied BERT and LDA topic modeling approaches to classify the articles. In my manual classification, I assigned a total of 162 articles to the character dimension, 53 articles to the knowledge dimension, and 22 articles to the experience dimension.

To ensure accuracy, I gave a sample of articles other marketing-involved people who agreed with my classifications. Since some articles explore multiple drivers of sales success, certain articles were allocated to more than one dimension where applicable. However, a classification in at least one of the three dimensions was possible for all articles without exception and concerns.

For the second classification approach, I follow Arora et al. (2025) that used GPT 4.0 for data classification and utilized Open AI's ChatGPT 4.0 to categorize the articles. I individually uploaded each article and applied a consistent task formulation ("prompt") across all articles, asking ChatGPT to determine whether each article could be classified into at least one of the three dimensions. To ensure clarity and consistency, I provided examples of attributes belonging to each dimension. ChatGPT successfully classified all articles into one of the three dimensions. Notably, in 86.18% of cases, the classifications generated by ChatGPT aligned with the human classifications.

For the third classification approach, I employed a BERT topic modeling method. BERT is a machine learning-based text analysis algorithm that not only identifies words and sentences from left to right but also analyzes sentence structures and contextual relationships. This approach allows for a deeper understanding of topics within large text datasets, such as the 224 articles analyzed in this study (Alaparthi and Mishra 2021; Devlin et al. 2019). In marketing and sales research, BERT has been utilized to derive valuable insights from unstructured text data (Arora et al. 2025). However, its application to sales-specific text analysis and classification remains underexplored. For this classification, I focused on the conclusion and managerial implications sections of the articles for three primary reasons. First, these sections explicitly outline the core attributes of sales performance, offering managers actionable guidance on fostering, training, or leveraging these attributes within their organizations. Second, the text length in these sections is suitable for BERT to accurately analyze content and word structures. Third, using these sections facilitates comparison with practitioner articles discussed in the next chapter, as their content closely aligns with the managerial implications presented in empirical studies.

Before conducting the BERT classification, I prepared and cleaned the texts to ensure accurate analysis. First, I removed common and industry-specific stop words, augmented with a custom list of additional terms that were not directly relevant to sales topics. For instance, words such as "information," "price," and "brand" were excluded, as they do not provide meaningful insights into salespeople's success factors. To generate text embeddings, I utilized a Count Vectorizer, followed by dimensionality reduction using UMAP with a cosine similarity metric. Subsequently, I applied the BERTopic package in Python to identify topics within the articles, setting a minimum cluster size of three documents to account for smaller yet meaningful topics.

The analysis identified six distinct topics, with a total of 44 articles classified as noise, indicating that these articles could not be clearly allocated to a specific topic. However, BERTopic attempted to categorize these articles, forming a cluster associated with the terms "training, skills, knowledge, and learning" which could clearly allocated to the knowledge category. The other topics and classifications are detailed in Table 1. As a robustness check, I repeated the BERT topic modeling several times, but the results were always roughly the same.

Table 1: BERT Topics and Applied Classification Categories

BERT topic	Classification
training, skills, knowledge, learning	Knowledge and Character
training, effort, relationship, motivation	Character
personality, conscientiousness, polychronicity, big	Character
training, knowledge, experienced, experience	Knowledge and Experience
learning, self-efficacy, training, goal	Knowledge and Character
technology, digital, readiness, leaders	Knowledge
success, characteristics, happiness, confidence	Character

Additionally, Table 4 below illustrates that the concurrence between the BERT topic modeling classification and the human classification is 84.96%, while the agreement with the ChatGPT classification stands at 78.32%. These results indicate strong performance of the topic modeling approach and provide further validation for the previous classifications.

For the fourth and final classification, I analyzed the key topics of the papers using Latent Dirichlet Allocation (LDA), a generative probabilistic model for text analysis (Blei et al. 2003). Unlike BERT, LDA is not neural network-based and does not account for the meaning or context of words. Instead, it focuses solely on word occurrences within the text. Despite these limitations, LDA remains a widely used method in marketing research due to its simplicity and ease of interpretation (e.g., Tirunillai and Tellis 2014).

To identify latent topics within the articles, I first removed the aforementioned set of stop words. Using a Count Vectorizer, I transformed the texts into a bag-of-words representation, excluding words that appeared in more than 95% or fewer than 2 documents to reduce noise and eliminate non-meaningful patterns. The analysis extracted five topics, as the results for a three-topic solution proved to be inaccurate. Each topic represents a probabilistic distribution of the most relevant terms, which are detailed in Table 2 below. I also performed multiple LDA analyses, which always led to roughly the same output.

Table 2: LDA Topics and Applied Classification Categories

Topic words from LDA	Classification
goal, learning, effort, personality, self-efficacy, behavior, ability, agent	Character
listening, information, positive, effort, behaviors, trust, relationship, emotions	Character
knowledge, relationship, motivation, personal, adaptive, behavior, communication	Character and Knowledge
information, knowledge, social, individual, effect, technology, positive, business	Knowledge
relationship, turnover, behavior, effect, factors, self-esteem, experience, organizational, success	Character and Experience

The concurrence between my individual classification and the LDA algorithm is 76.11%, while the alignment with the ChatGPT classification is 71.68%, and with the BERT topic modeling, 75.66%. Although the agreement with LDA is somewhat lower compared to the AI-based methods, it still demonstrates a high degree of consistency and reinforces the validity of the classifications.

Overall, the classification of the article dataset into the three major categories—knowledge, experience, and character—appears valid, supported by the comprehensive literature review presented in the previous chapter and the application of multiple classification methods. As summarized in Table 3, an average across methods of 74.78% of the articles are classified into the character dimension of sales success drivers, 37.5% into the knowledge dimension, and 12.06% into the experience dimension. Furthermore, the relative shares of articles across these dimensions are consistent across most methods, with the exception of the LDA classification, which yielded the most divergent results. This confirms that character-related articles represent the majority of academic articles and have priority in sales research.

Table 3: Shares of Article Affiliation across the Classification Methods

	Character	Knowledge	Experience
Own classification	74.11%	25.89%	9.82%
ChatGPT classification	63.84%	38.39%	9.38%
BERT topic modeling	87.95%	38.39%	9.38%
LDA topic modeling	73.21%	47.32%	19.64%
Span	24.11%	21.43%	10.26%
ø	74.78%	37.50%	12.06%

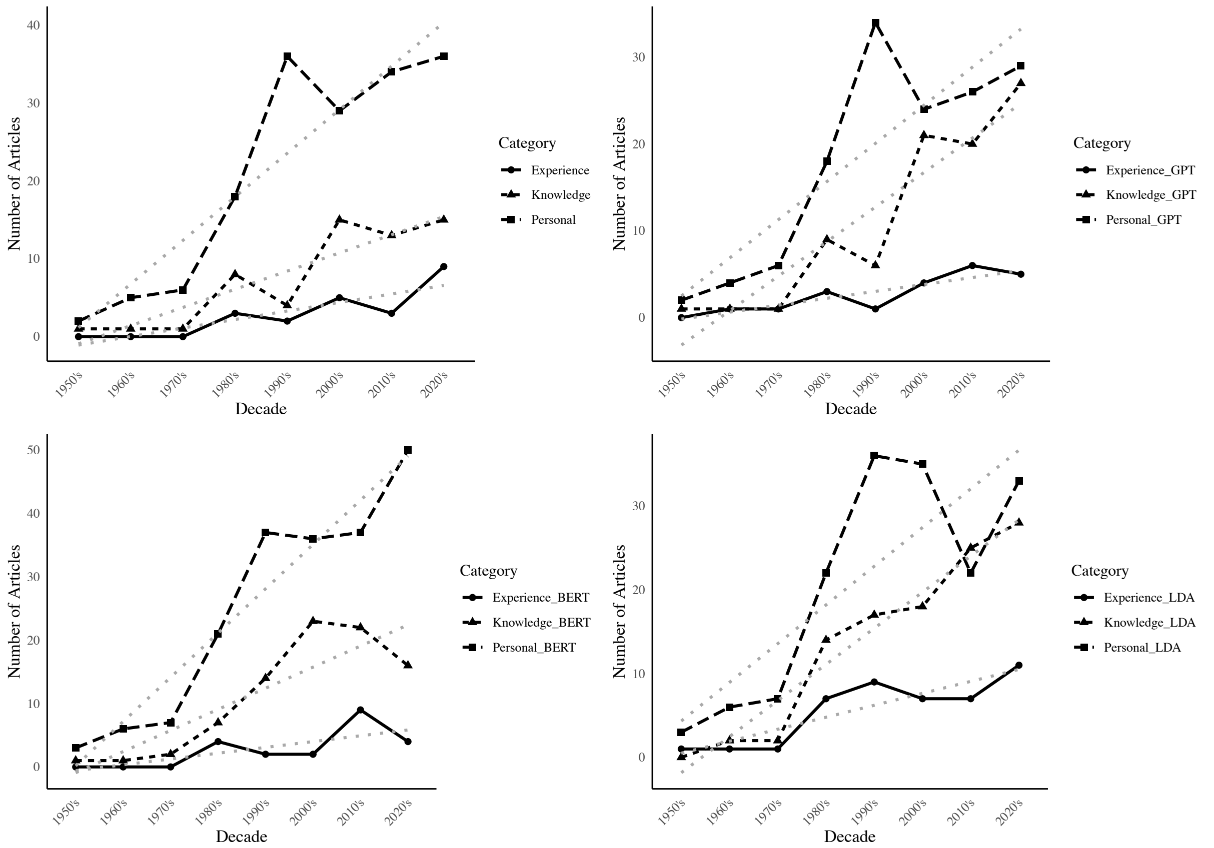
Table 4: Share of Academic Papers across Different Classification Methods

	Own	ChatGPT	BERT Topic	LDA Topic
Own	1	86.28%	84.96%	76.11%
ChatGPT	86.28%	1	78.32%	71.68%
BERT Topic	84.96%	78.32%	1	75.66%
LDA Topic	76.11%	71.68%	75.66%	**1**

3.1 Publications of Academic Articles over Time and Frequently Occurring Words

After completing the classification, I organized the articles by decade according to their assigned categories and plotted their distribution over time, as illustrated in Figure 2 below. The temporal development of the articles is consistent across all classification methods, showing a predominance of articles classified in the character category, followed by knowledge and experience. Only the LDA classification distributes a majority of knowledge-related articles in the 2010s decade. The figure also includes a linear trend line for each category (gray lines), highlighting that the growth rate is steepest for character articles across all classifications, followed by knowledge and experience.

Figure 2: Publications of Academic Articles by Category and Classification over Time



For an overview of frequently occurring words in each category, I first created word clouds by category. As illustrated in Appendix Figure A2, the most frequent terms align well with the assigned categories: In the character category, words like “skill”, “ability”, “trait”, “behavior” and “personality” are frequently appearing. In the knowledge category, “knowledge”, “process”, or “strategy” are frequently appearing. And in the experience category, words like “process” or “age” are frequently appearing.

3.2 Popularity of Categories in Academic Articles

To gain insights into the popularity of the categories identified in the classified articles, I analyzed citation counts using two separate measures. First, I extracted the total citations for each article from *Google Scholar*. Second, I retrieved cumulative citation counts from the past five years (2020–2024) using the *Web of Science* API, which provides year-specific data for a more up-to-date measure of an article's impact. For this analysis, I focused on subsets of the dataset based on my human classifications, as these are likely the most accurate due to the thorough reading and evaluation of the articles.

To calculate the mean Google Scholar citations per year, I used the oldest article in the dataset (Baier and Dugan 1956) as a reference point, assigning an increasing numerical value for each subsequent year (e.g., value 1 for 1956, value 2 for 1957, ..., value 69 for 2024). The results, shown in Table 5, indicate that academic articles classified under the character dimension have the highest average citation counts for both Google Scholar and Web of Science measures. Specifically, the character articles show a higher average citation rate of 23.56% (Google Scholar) and 31.23% (Web of Science) compared to "knowledge" articles. However, these differences are not statistically significant, as indicated by two-sample t-tests with p-values of .18 (Google Scholar) and .15 (Web of Science). In contrast, other comparisons reveal statistically significant differences: the difference in citation rates between "character" and "experience" articles yields p-values of .00 (Google Scholar) and .00 (Web of Science), while the difference between "knowledge" and "experience" articles results in p-values of .02 (Google Scholar) and .05 (Web of Science).

A different trend emerges when analyzing access to the articles. I examined the absolute access rates—specifically views and downloads—from publisher websites and calculated the averages per year. Unlike citations, which are typically generated by researchers for own publications, article access can also reflect practitioner engagement through downloads and views. The results reveal that knowledge-related articles have higher access rates compared to character-related articles, with averages of 468.29 and 356.52 accesses per year, respectively.

As a robustness check, I repeated all popularity analyses using only the articles that were consistently classified across all four classification methods, rather than relying solely on the human classification. The results, detailed in Appendix Table A3, demonstrate no change in the direction of the findings, further validating the robustness of the conclusions.

Table 5: Citations and Accesses per Year for Academic Articles by Category

	Google citations/year	WoS citations 2020 - 2024	Accesses/year
Character	15.89 (18.81)	44.42 (53.42)	356.52 (557.69)
Knowledge	12.86 (13.20)	33.85 (38.56)	468.29 (1037.47)
Experience	7.45 (7.87)	19.07 (18.68)	450.25 (673.23)

Notes: standard deviations in brackets.

4 Classification of Practitioner Articles

Next, I applied the same four text classification procedures to practitioner articles sourced from three prestigious journals: *Business Insider*, *Forbes*, and the *Harvard Business Review (HBR)*. These journals cater to practitioners by providing insights on topics such as sales, general management, strategy, and business innovation. According to *SimilarWeb* statistics, the monthly total visits in December 2024 were 5.6 million for HBR, 76.9 million for Business Insider, and 169.7 million for Forbes. The lower number of visits to HBR and Business Insider is likely attributable to their subscription requirements for accessing full content.

To compile the dataset, I conducted a comprehensive search for relevant keywords, collecting all available articles that address success drivers for salespeople. For articles from

Forbes, I also scraped topic-related headlines (as full texts were unable to scrape due to dynamic page loading techniques) to search for relevant articles with Python. Unlike the academic articles, these practitioner pieces do not empirically test the influence of attributes on performance. Instead, authors, managers, senior salespeople, and sales trainers provide recommendations and insights on how the attributes discussed in the articles may affect performance when applied as described. In total, the practitioner dataset comprises n= 139 articles, distributed as follows: 45.33% from HBR, 7.9% from Business Insider, and 46.77% from Forbes.

The classification process for practitioner articles closely follows the approach used for academic articles. For the topic modeling approaches, I analyzed the full texts of the practitioner articles, as these texts are significantly shorter than academic publications. I also extended the stop word list to include additional terms and adjusted the model parameters slightly to optimize clustering. The results, as presented in Table 6, indicate that an average of 65.29% of the practitioner articles were classified into the character dimension, 77.34% into the knowledge dimension, and 24.46% into the experience dimension; Appendix Tables A4 and A5 show the topics of the BERT and LDA classifications. Among the methods, BERT topic modeling yielded the least accurate results compared to the overall averages. This discrepancy may be attributed to the diverse and broad range of topics discussed in practitioner texts, which could complicate clear categorization – this is also stated in the higher number of double-categorizations compared to the academic articles. Furthermore, as Table 7 shows, human and GPT classification have a congruence of 86.18% in classifying the articles into the three categories, which is the highest percentage. Human and BERT classifications show also a high congruence with 84.79%. The less accurate congruence exhibit BERT and LDA classifications with 75.83%.

Table 6: Shares of Article Affiliation across Classifications for Practitioner Articles

	Character	Knowledge	Experience
Own Classification	65.47%	71.22%	20.86%
ChatGPT Classification	75.54%	79.86%	32.37%
BERT Topic Modeling	49.64%	92.81%	4.32%
LDA Topic Modeling	70.50%	65.47%	40.29%
Span	25.90%	27.34%	35.97%
ø	65.29%	77.34%	24.46%

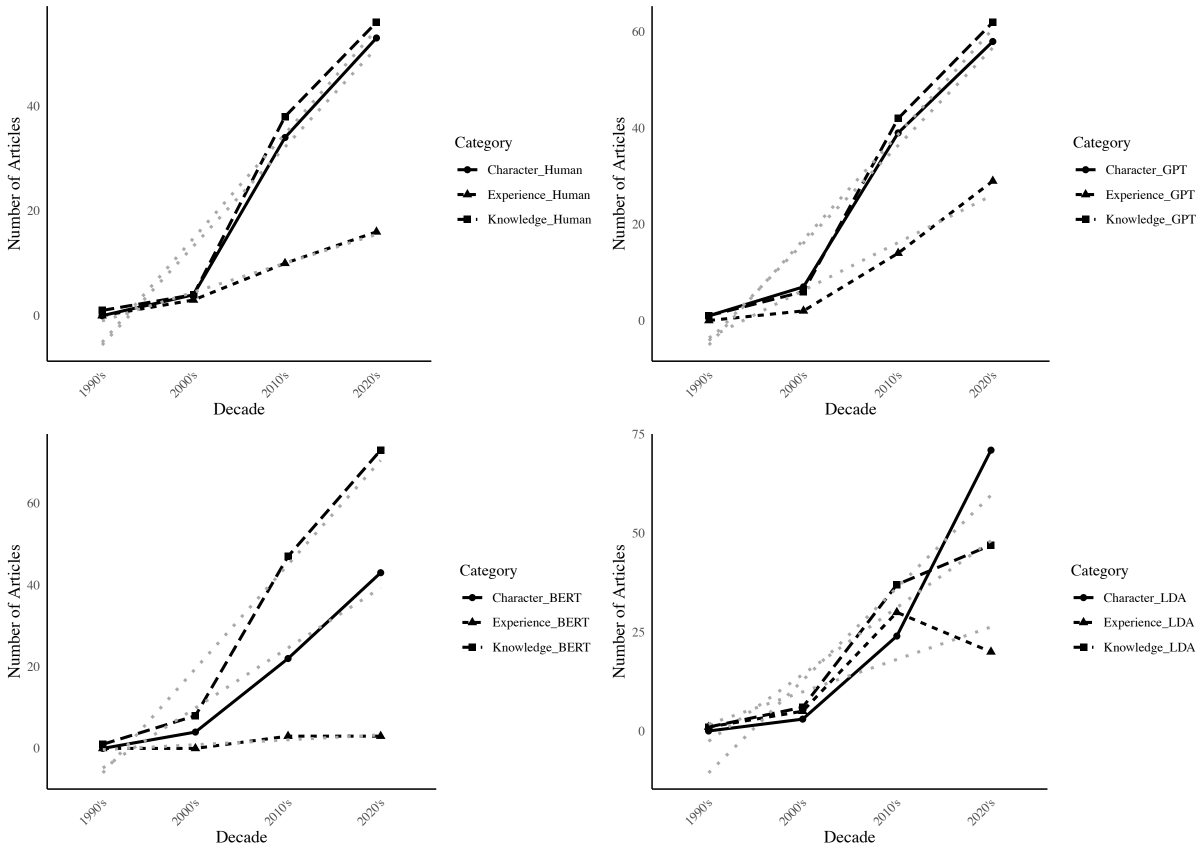
Table 7: Share of Academic Papers across Different Classification Methods

	Own	ChatGPT	BERT topic	LDA topic
Own	1	86.18%	84.79%	75.59%
ChatGPT	86.18%	1	77.88%	71.83%
BERT Topic	84.79%	77.88%	1	75.59%
LDA Topic	75.59%	71.83%	75.59%	1

4.1 Publications of Practitioner Articles over Time and Frequently Occurring Words

Similar to the academic articles, I sorted the practitioner articles by decade according to their classifications and created plots for each classification method to visualize the publication trends over time. As illustrated in Figure 4, the trends differ slightly across classification methods. The graphs of human and GPT-based classifications are almost identical and show a strong increase in character- and knowledge-related articles since the early 2000s with a slight overweight of knowledge articles. The grey-dotted linear trends of the three categories are also nearly identical, showing stronger increases for character and knowledge articles compared to experience articles. In contrast, the BERT classification indicates a predominance of knowledge-related articles and no increase in experience articles, while the LDA classification shows mixed trends, with character-related articles becoming dominant from the 2010s onward.

Figure 3: Publications of Practitioner Articles by Category and Classification over Time



As with the academic articles, I generated word clouds for the nouns within the human-classified practitioner texts in each category to visualize the most frequently occurring words (Appendix Figure A3). These word clouds confirm category alignment in the character and experience dimensions. For example, "language," "skill," and "conversation" are prominent in character-related articles, while "experience," "year," and "career" dominate the experience-related articles. However, in the knowledge category, the specific word "knowledge" is notably absent. Instead, terms such as "process," "question," "training," and "information" suggest a knowledge-focused content area. Interestingly, the terms "customer" and "people" are highly prevalent across all three dimensions, reflecting their central importance in sales-related discourse.

4.2 Popularity of Categories in Practitioner Articles

To estimate the popularity of the categories within the practitioner articles, I used two distinct measures. For articles published on Forbes, I relied on the "views" metric, which indicates the number of article visits. For articles from Harvard Business Review (HBR) and Business Insider (BI), no equivalent measure is available. Instead, I utilized the *SharedCount* API in Python to extract the number of Facebook shares as a proxy for popularity, given that LinkedIn's API restrictions prevent the retrieval of share data. As with the academic articles, I based this analysis on the human-classification results to ensure consistency.

I created three subsets of the dataset, each containing articles classified as knowledge, experience, or character, and calculated the mean views per day (for Forbes articles) and mean social media shares per day (for HBR and BI articles). Articles without available data for these measures or with no views or shares were excluded from the analysis. The results, presented in Table 7, reveal that both the average number of views and shares per day are highest for knowledge-related articles. The difference between the views per day of character-related (knowledge-related) and experience-related articles is (slightly) statistically significant with a p-value of .08 (.10). Moreover, the shares per day of character and experience-related articles is statistically significant (p-value = .06), indicating that experience-classified articles show the lowest popularity in practical domains. Despite this, the mean views per day for knowledge-related articles are 53.98% higher than for character-related articles and 216.36% higher than for experience-related articles. Similarly, the mean shares per day for knowledge-related articles are 44% higher than for character-related articles and 260% higher than for experience-related articles, indicating that knowledge-related articles have the highest popularity and relevance for practitioners.

Table 8: Views per Day and Shares per Day for Practitioner Articles by Category

	Views per Day (Forbes)	Shares per Day (HBR, BI)
Character	2.26 (3.29)	.25 (.15)
Knowledge	3.48 (8.17)	.36 (.29)
Experience	1.10 (.73)	.16 (.05)

Notes: standard deviations in brackets.

Again, as a robustness check, I also conducted these analyses only with articles that have been clearly assigned to a category by all 4 classification methods. These results are roughly comparable with those of the human classification.

5 Similarities and Sentiment between Academic and Practitioner Articles

Using BERT, I calculated semantic similarity scores between the academic and the practitioner article and between the three subsets of data frames containing only character-related, knowledge-related, or experience-related articles. For the academic articles, I again used the managerial implications sections as the basis for analysis. While I filtered out stop words, I retained all other terms previously excluded during the classification analyses to maintain semantic clarity. I then computed cosine similarity scores between the texts of the two groups and calculated the mean values, as shown in Table 8. Figure A4 in the Appendix shows graphically the BERT similarity matrix.

The results indicate that the overall similarity between academic and practitioner articles is .2029, which is a relatively low score (where 0 represents total dissimilarity and 1 represents complete similarity between two texts). While the similarity of academic articles is even lower with a mean score of .1699, the similarity of practitioner articles, in contrast, is at a medium-low level, with a mean score of .3714. It shows that academic articles differ more semantically from one another than practical articles. When comparing the category-specific subsets, experience-related texts exhibit the highest similarity score between academic and practical articles with a similarity score of .3264. Interestingly, the character-related academic articles and the knowledge-related articles show a relatively high score with .4005, which represent the most popular categories of the two article types.

Table 9: BERT Similarity Scores of Academic and Practitioner Texts

	A. Art.	P. Art.	P. Art. Char.	P. Art. Know.	P. Art. Exp.
A. Art.	.1699	.2029			
P. Art.	.2029	.3714			
A. Art. Char.			.2116	.4005	.4337
A. Art. Know.			.2516	.2527	.4337
A. Art. Exp.			.3255	.3262	.3264

I also conducted a sentiment analysis using LIWC 2015 to evaluate the emotional tone of the articles by category (Pennebaker et al. 2015). The range of the emotional tone is measured on a scale between 0 (totally negative tone) and 1 (totally positive tone). As presented in Table 9 below, the levels are all at a medium, positive level with the academic character articles showing the less positive tone (63.60) and the academic experience articles showing the most positive tone (74.73). The difference between these articles is statistically significant (p-value = .02). Furthermore, the character-related practitioner articles show a statistically higher positive emotional tone compared to the academic articles belonging to the character category (p-value = .05).

Table 10: Sentiment Scores of Academic and Practitioner Articles

	Sentiment Acad. Art.	Sentiment Prac. Art.	Two-sample t-test
Character	63.60 (25.22)	69.47 (24.66)	.05**
Knowledge	68.81 (20.60)	71.94 (21.83)	n.s.
Experience	74.73 (19.99)	72.54 (17.85)	n.s.

Notes: standard deviations in brackets.

To compare the most occurring words of both article types, I also created a dictionary consisting of all words appearing in the academic and practitioner articles (using the full articles without the references for the academic articles). Note that the full academic texts are much longer than the practitioner text which is reflected by the total frequency of words per paper. Then, I counted the most-occurring words within both dictionaries to generate an impression about the key terms of both article data sets. The results, shown in Table 10, indicate at a first glance a common focus of salespeople performance within the academic texts and also a sales-focus within the practitioner texts. The frequency divided by the total words occurring is approximately twice as high for the word "customer" within the practitioner texts, indicating a broader focus on customer-specific topics. Additionally, while academic texts focus most on research and marketing topics through studies, the most-occurring words within the practitioner texts indicate stronger practical reference, applications, and new insights through the words "people," "business," "product," and "new."

Table 11: Most-Occurring Words within Academic and Practitioner Texts

Top 10 Ac. paper words	Frequency/ paper	Frequency/ words	Top 10 Pr. texts words	Frequency/ paper	Frequency/ words
Sales	53.97	.9%	Sales	12.31	2.8%
Performance	36.53	.6%	Customer(s)	7.88	1.8%
Salespeople	24.54	.4%	Salespeople	5.91	1.4%
Salesperson	24.22	.4%	Time	3.13	.7%
Customer(s)	22.60	.4%	People	2.92	.7%
Research	20.51	.4%	Business	2.58	.6%
Selling	20.07	.3%	Company	2.45	.6%
Marketing	18.02	.3%	Salesperson	2.42	.6%
Job	15.89	.3%	New	2.39	.5%
Study	13.69	.2%	Product	2.19	.5%

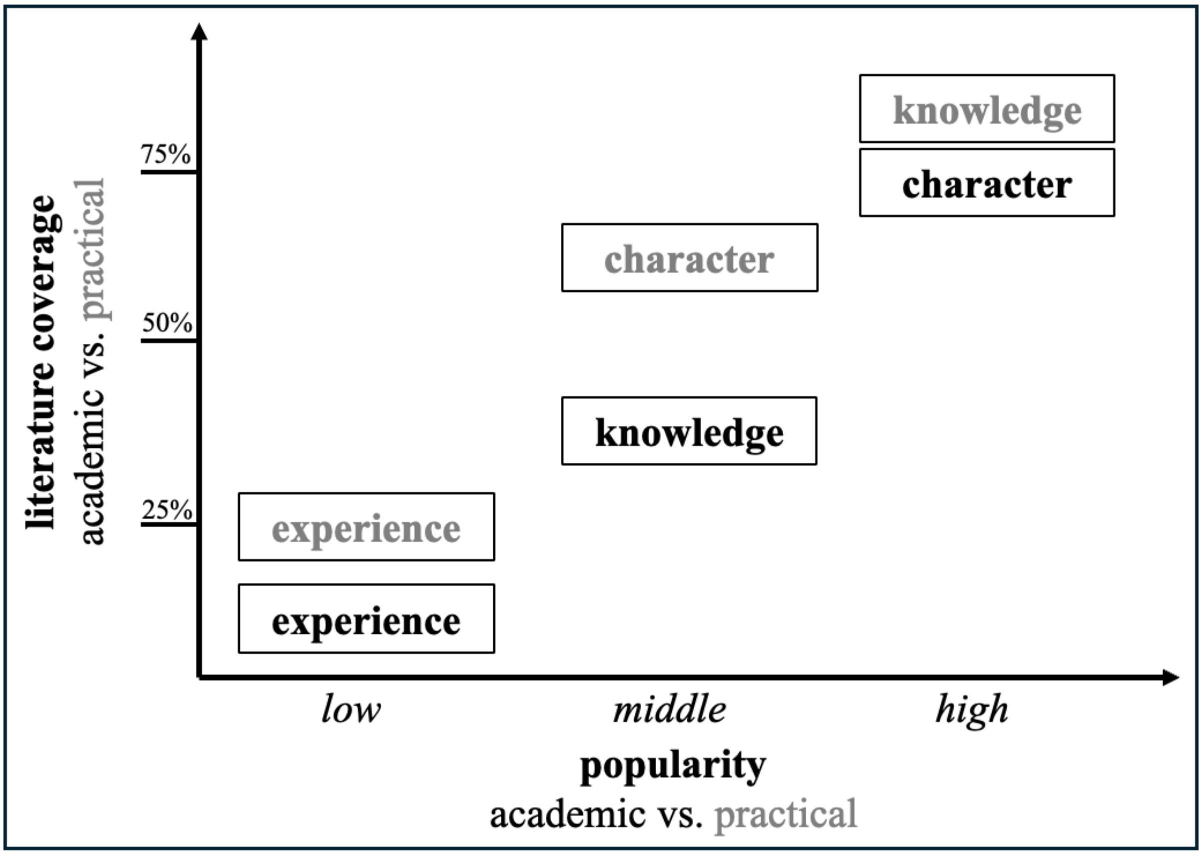
6 Discussion

The first research question focuses on the core categories of salesperson success drivers. A comprehensive review of the extant literature yielded three primary categories: 1. *Knowledge* with the sub-categories product, market, customer, and selling knowledge; 2. *Experience* which can also defined as working experience and containing tenure and technological practices; and 3. *Character*, which comprises traits, behaviors, and soft skills. The most salient success drivers of salespeople could then be categorized within these three main categories (see Appendix Table A1).

The second research question concentrates on the priorities of salesperson success drivers between academic literature and practitioner articles. First, using four different text classification methods, the findings suggest that while academic literature has a great emphasis on character-related literature, practitioner articles demonstrate a greater focus on knowledge-related articles. However, character-related articles also play a substantial role in practical texts. Experience-related articles, in contrast, exhibit the lowest number of articles in both academic and practitioner publications.

Second, popularity analyses support the finding that character-related articles are prioritized by researchers and knowledge-related articles by practitioners. Articles pertaining to character in academic literature garner higher citations on Google and Web of Science than articles related to knowledge and experience. In terms of article access, which can be done not only by researchers but also by managers and practitioners, knowledge-related articles demonstrate a higher value compared to character-related academic texts. This trend is further substantiated by the popularity analyses of practical literature, which demonstrate that knowledge-related articles exhibit higher views and shares per day compared to character-related publications. Experience-related articles show the lowest values for both academic citations and practical shares. Figure 4 below graphically demonstrates the relationship between literature coverage of the article categories and popularity in terms of citations (academic articles) and views/shares (practitioner articles). It shows that, on average, practical articles exhibit a higher proportion of shares per category. This observation suggests that practical articles encompass a more extensive array of key success drivers and frequently address multiple categories, in contrast to academic articles, which predominantly concentrate on a singular driver or domain, such as experience, knowledge, or character.

Figure 4: Literature Coverage and Popularity of Article Categories



Third, the semantic similarity analysis with BERT reveals that academic and practical articles exhibit only a low degree of semantic similarity. However, character-related academic articles and practical articles with knowledge-related themes demonstrate medium semantic similarity. While there are no substantial differences in the sentiment analysis, the most prevalent words effectively capture the research focus of academic articles and the business focus of practical articles.

7 Theoretical Implications

The findings offer significant implications for sales researchers. The study has demonstrated that academics should prioritize a more concentrated examination of fundamental subjects in sales agent performance research. Practice-oriented research, yielding innovative results, is paramount, particularly within the marketing and sales sectors. Consequently, the core topics that sales managers and companies with a robust sales force address and prioritize should be accorded greater significance.

Regarding the category of knowledge factors of salespeople which has major importance in practitioner literature (e.g., Dutton 2020; Kim 2016), researchers could, e.g., put a stronger emphasis on drivers that characterize knowledge and investigate these drivers with regard to performance to increase managerial relevance. Research has already divided sales agents into successful vs. unsuccessful actions (Dixon et al. 2001) or high-performing vs. low-performing (Luo et al. 2021), but direct differences between low and high levels of knowledge about products, markets and customers and their impact on performance could be analyzed. Furthermore, researchers could conduct studies on how the knowledge of technologies and new-tools influences salespeople's performance, e.g., with *Salesforce* or *Gong*.

For the character dimension, automated and AI-based methods have significantly contributed to the extraction of traits, behaviors and skills from unstructured data, such as texts, and the linkage of these to performance in recent years (e.g., Chakraborty et al. 2024; Packard and Berger 2021). Researchers can further use these tools in the future to identify unexpected patterns in the character category and provide valuable insights into the influence of these aspects on the performance of salespeople (Grewal et al. 2021). As the derivation for the character category has finally shown, there are ultimately also the most sub-categories and therefore the greatest research potential in this category. In addition, innovative implications would offer managers and companies added value as they are not in a position to uncover these character-based factors in daily business and are therefore dependent on scientific findings.

Experience-related articles are least common on both academic and practitioner literature on salespeople success drivers. This may be due to the fact that experience requires less change effort to be implemented by salespeople. Working experience and technical know-how often generally increases automatically over time. Sales researchers could concentrate on the mediating role of experience and identify drivers and actions that foster working experience of salespeople, which then in the second step influence sales performance (Ko and Dennis 2004).

In addition, as the semantic similarity analysis shows, the managerial implications sections could be semantically and in terms of content geared more towards managers in order to convey the results obtained in the studies in an understandable way and to clearly show managers the added value of the findings. As is frequently evidenced in the sales and marketing literature, this study has once again demonstrated the fundamental importance of incorporating current practitioner literature when generating ideas. This incorporation facilitates the identification of meaningful gaps in the literature and the subsequent generation of practical implications (Jedidi et al. 2021; Moorman et al. 2018).

8 Managerial Implications

The findings of this study also offer important implications for sales managers and practitioners related to personal selling and sales management. In general, it is crucial for practitioners to expand their perspective and acknowledge the numerous factors that contribute to the success of sales personnel based on academic research. Managerial access to research findings is a fundamentally important component for optimizing a company’s internal salesforce. Character-related articles play the biggest role in sales research. In addition to conventional and evident elements, it is essential to consider character factors when evaluating job applications and developing strategies to enhance the effectiveness of an organization's internal sales force. An analysis of relevant literature reveals that character-based core topics often include communicational elements that go “beyond the norm” (e.g., Lafreniere et al. 2021; Packard et al. 2018). In this regard, current language sales research could be utilized to dive deeper into the subject and offer novel insights, such as the influence of language styles on performance (see Paper I of this dissertation) or the use of specific language (Packard and Berger 2021). The smaller number of experience-related articles can also take away the fear of hiring inexperienced salespeople. The analyses show that the candidate's character (academic articles) and knowledge (practitioner articles) are the most relevant components and that experience often “comes naturally”.

In addition, the findings of sales research on character-based factors such as traits and behaviors can also provide added value for managers by using tools available on the market to measure these factors in their internal salesforce or to identify them during the application process. For example, tools as HireVue offer such analyses (HireVue 2025) and Paper II offers a novel 4-stage framework for the pre-selection of sales job candidates.

9 Limitations

The present study demonstrates certain limitations that may be addressed in future research. Primarily, the present study has concentrated on core success factors of salespeople that are directly attributable to the agent. The three categories of knowledge, experience and character relate directly to the agent as a person. It is acknowledged that additional factors, such as organizational or environmental elements (Verbeke et al. 2011), may influence salespeople; however, these factors do not directly align with the core success factors identified in this study. In future research, a similar theory-practice comparison could investigate these external factors.

Secondly, the popularity criteria for the practical articles were citations and accesses for academic articles, and views and social media shares for the practical articles. While these metrics offer a comprehensive overview and facilitate meaningful interpretation of the results, they do not fully address the question of what managers in practice find most interesting and important. A potential avenue for future research could involve the implementation of surveys and qualitative interviews to explore the specific interests and priorities of managers with regard to core success factors in sales.

Thirdly, the result cannot be fully generalized due to the unavoidable presence of subjectivity in human classification. Moreover, the results of the classifications are based on mean values of the four individual classifications, some of which differ significantly from one another (LDA modeling for academic article classification, BERT for practitioner article classification). In addition, the managerial implications of the academic articles were consulted for topic modeling approaches, not the full texts, for technical and content-related reasons. The data sets are modest in size, with n = 224 academic publications and n = 139 practice-oriented publications. Future analyses could, for example, examine other text fragments or expand the academic data set to include B and C journals, which could counteract the fact that some differences are not significant.

10 References

Aggarwal, P., Castleberry, S. B., Ridnour, R., & Shepherd, C. D. (2005). Salesperson Empathy and Listening: Impact on Relationship Outcomes. Journal of Marketing Theory and Practice, 16–30.

Ahearne, M., & Schillewaert, N. (2000). The Effect of Information Technology on Salesperson Performance. eBusiness Research Center Working Paper, 3–47.

Ahearne, M., Atefi, Y., Lam, S. K., & Pourmasoudi, M. (2022). The future of buyer-seller interactions: a conceptual framework and research agenda. Journal of the Academy of Marketing Science, 50, 22–45.

Alaparthi, S., & Mishra, M. (2021). BERT: a sentiment analysis odyssey. Journal of Marketing Analytics, 9, 118–126.

Alavi, S., Habel, J., Guenzi, P., & Wieseke, J. (2018). The role of leadership in salespeople's price negotiation behavior. Journal Academy of Marketing Science, 46, 703–724.

Arora, N., Chakraborty, I., & Nishimura, Y. (2025). AI-Human Hybrids for Marketing Research: Leveraging Large Language Models (LLMs) as Collaborators. Journal of Marketing, 89 (2), 43–70.

Bagozzi, R. P. (1978). Salesforce Performance and Satisfaction as a Function of Individual Difference, Interpersonal, and Situational Factors. Journal of Marketing Research, 15, 517–531.

Baier, D. E., & Sugan, R. D. (1957). Factors in Sales Success. Journal of Applied Psychology, 41 (1), 37–40.

Banin, A. Y., Boso, N., Hultman, M., Souchon, A. L., Hughes, P., & Nemkova, E. (2016). Salesperson improvisation: Antecedents, performance outcomes, and boundary conditions. Industrial Marketing Management, 59, 120–130.

Barrick, M. R., & Mount, M. K. (1991). The Big Five Personality Dimensions and Job Performance: A Meta-Analysis. Personnel Psychology, 44, 1–26.

Barrick, M. R., Steward, G. K., & Piotrowski, M. (2002). Personality and Job Performance: Test of the Mediating Effects of Motivation Among Sales Representatives. Journal of Applied Psychology, 87 (1), 43–51.

Bartkus, K. R., Peterson, M. F., & Bellenger, D. N. (1989). Type A Behavior, Experience, and Salesperson Performance. Journal of Personal Selling and Sales Management, 9, 11–18.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. Journal of Machine Learning Research, 3, 993–1022.

Bolisani, E., & Bratianu, C. (2018). Emergent Knowledge Strategies. Strategic Thinking in Knowledge Management. Cham, Switzerland: Springer.

Boorom, M. L., Goolsby, J. R., & Ramsey, R. P. (1998). Relational Communication Traits and Their Effect on Adaptiveness and Sales Performance. Journal of the Academy of Marketing Science, 26 (1), 16–30.

Brown, S. P., Cron, W. L., & Slocum Jr., J. W. (1998). Effects of Trait Competitiveness and Perceived Intraorganizational Competition on Salesperson Goal Setting and Performance. Journal of Marketing, 62 (4), 88–98.

Cambridge Dictionary (2024), “experience”. Retrieved December 1, 2024 from https://dictionary.cambridge.org/dictionary/english/experience

Chaker, N. N., Zablah, A. R., & Noble, C. H. (2018). More than one way to persist: Unpacking the nature of salesperson persistence to understand its effects on performance. Industrial Marketing Management, 71, 171–188.

Chakraborty, I., Chiong, K., Dover, H., & Sudhir, K. (2024). Can AI and AI-Hybrids Detect Persuasion Skills? Salesforce Hiring with Conversational Video Interviews. Marketing Science, 44 (1), 30–53.

Chateau, O. (2022). Startups Can’s Succeed On Ideas Alone: Why Deep Market Knowledge Is Key. Retrieved February 20, 2025 from https://www.forbes.com/councils/forbesbusinesscouncil/2022/05/1…s-cant-succeed-on-ideas-alone-why-deep-market-knowledge-is-key/

Churchill, G, A., Ford, N. M., Hartley, S. W., & Walker, O. C. (1985). The Determinants of Salesperson Performance: A Meta-Analysis. Journal of Marketing Research, 22, 103–118.

Claro, D. P., Ramos, C., & Palmatier, R. W. (2024). Dynamic and global drivers of salesperson effectiveness. Journal of the Academy of Marketing Science, 52, 399–425.

Darmon, R. Y. (1993). Where Do the Best Sales Force Profit Producers Come From? Journal of Personal Selling and Sales Management, 13 (3), 17–29.

Davenport, T. D., DalleMule, L., & Lucker, J. (2011). Know what your customers want before they do. Retriever December 30, 2024 from https://hbr.org/2011/12/know-what-your-customers-want-before-they-do

Dawson, L. E., Soper, B., & Pettijohn, C. E. (1992). The Effects of Empathy on Salesperson Effectiveness. Psychology & Marketing, 9 (4), 297–310.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Proceedings of NAACL-HLT, 4171–4186.

Dixon, A. L., Spiro, R. L., & Jamil, M. (2001). Successful and Unsuccessful Sales Calls: Measuring Salesperson Attributions and Behavioral Intentions. Journal of Marketing, 65 (3), 64–78.

Dixon, A. L., Spiro, R. L., & Forbes, L. P. (2003). Attributions and Behavioral Intentions of Inexperienced Salespersons to Failure: An Empirical Investigation. Journal of the Academy of Marketing Science, 31 (4), 459–467.

Dutton (2020). What Does A Salesperson Do When Business Is Paused? Retrieved November 10, 2024 from https://www.forbes.com/sites/forbesrealestatecouncil/2020/04/13/whatdoesasalespersondowhenbusinessispaused/

Elhajjar, S., Yacoub, L., & Ouaida, F. (2023). The present and future of the B2B sales profession. Journal of Personal Selling and Sales Management, 44 (2), 128–141.

Elliott, E. S., & Dweck, C. S. (1988). Goals: An Approach to Motivation and Achievement. Journal of Personality and Social Psychology, 54 (1), 5–12.

Feng, C., Fay, S., & Xiang, K. (2021). When do we need higher educated salespeople? The role of work experience, Review of Managerial Science, 15, 1391–1429.

Ferris, D. L., Lian, H., Pang, F. X. J., & Keeping, L. M. (2010). Self-Esteem and Job Performance: The Moderating Role of Self-Esteem Contingencies. Personnel Psychology, 63, 561–593.

Frazier, G. L., & Summers, J. O. (1984). Interfirm Influence Strategies and Their Application within Distribution Channels. Journal of Marketing, 48, 43–55.

Goldberg, L. R. (1990). An Alternative "Description of Personality": The Big-Five Factor Structure. Journal of Personality and Applied Psychology, 59 (6), 1216–1229.

Good, V., Hughes, D. E., & Kirca, A: H., & McGrath, S. (2022). A self-determination theory-based meta-analysis on the differential effects of intrinsic and extrinsic motivation on salesperson performance. Journal of the Academy of Marketing Science, 50, 586–614.

Grewal, R., Gupta, S., & Hamilton, R. (2021). Marketing Insights from Multimedia Data: Text, Image, Audio, and Video. Journal of Marketing Research, 58 (6), 1025–1033.

HireVue (2025). We put the human back into human resources. Retrieved January 29, 2025 from https://www.hirevue.com/about

Hochstein, B., Bolander, W., Goldsmith, R., & Plouffe, C. R. (2019). Adapting influence approaches to informed consumers in high-involvement purchases: are salespeople really domed? Journal of the Academy of Marketing Science, 47, 118–137.

Homburg, C., Knapp, M., & Wagner-Fabisch, R. (2024). Personality matters: how adaptive selling skills mediate the effect of personality traits on salespeople's exploited cross-selling potential. Journal of Personal Selling and Sales Management, 44 (3), 293–314.

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21 (2), 155–172.

Hurtz, G. M., & Donovan, J. J. (2000). Personality and Job Performance: The Big Five Revisited. Journal of Applied Psychology, 85 (6), 869–879.

Jaworski, B. (2011). On Managerial Relevance. Journal of Marketing, 75 (4), 211–224.

Jedidi, K., Schmitt, B. H., Sliman, M. B., & Li, Y. (2021). R2M Index 1.0. Journal of Marketing, 85 (5), 22–41.

Johlke, M. C. (2006). Sales presentation skills and salesperson job performance. Journal of Business & Industrial Marketing, 21 (5), 311–319.

Kim, E. (2016). Here's what the best salespeople do to close more deals and make tons of money. Retrieved November 12, 2024 from https://www.businessinsider.com/what-best-salespeople-do-to-close-more-deals-2016-11

Kim, M., Sudhir, K., Uetake, K., & Canales, R. (2019). When Salespeople Manage Customer Relationships: Multidimensional Incentives and Private Information. Journal of Marketing Research, 56 (5), 749–766.

Ko, D.-G., & Dennis, A. R. (2004). Sales Force Automation and Sales Performance: Do Experience and Expertise Matter? Journal of Personal Selling and Sales Management, 24 (4), 311–322.

Ko, D.-G., & Dennis, A. R. (2011). Profiting from Knowledge Management: The Impact of Time and Experience. Information Systems Research, 22 (1), 134–152.

Kohli, A. K., & Jaworski, B. (1990). Market Orientation: The Construct, Research Propositions, and Managerial Implications. Journal of Marketing, 52 (2), 1–18.

Lafreniere, K. C., Moore, S. G., & Fisher, R. J. (2022). The Power of Profanity: The Meaning and Impact of Swear Words in Word of Mouth. Journal of Marketing Research, 59 (5), 908–925.

Lamont, L. M., & Lundstrom, W. J. (1977). Identifying Successful Industrial Salesmen by Personality and Personal Characteristics. Journal of Marketing Research, 14, 517–529.

Leong, S. M., Busch, P. S., & John, D. R. (1989). Knowledge Base and Salesperson Effectiveness: A Script-Theoretic Analysis. Journal of Marketing Research, 26, 164–178.

Luo, X., Qin, M. S., Fang, Z., & Qu, Ze (2021). Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions. Journal of Marketing, 85 (2), 14–32.

Mabe, M. (2012). Does journal publishing have a future? In R. Campbell, E. Pentz & I. Borthwick (Eds.), Academic and Professional Publishing (pp. 413–440). New Delhi: Oxford Cambridge.

Marin-Zapata, S. I., Roman-Calderon, J. P., Robledo-Ardila, C., & Jaramillo-Serna, M. A. (2022). Soft skills, do we know what we are talking about? Review of Managerial Science, 16, 969–1000.

Mayer, D., & Greenberg, H. M. (1964). What makes a good salesman. Harvard Business Review, 42 (July – August), 119–125.

McCrae, R. R., & Costa Jr., P. T. (1987). Validation of the Five-Factor Model of Personality Across Instruments and Observers. Journal of Personality and Applied Psychology, 52 (1), 81–90.

McCrae, R. R., & Costa Jr., P. T. (2003). Personality in Adulthood. New York, London: The Guilford Press.

McFarland, R. G., Challagalla, G. N., & Shervani, T. A. (2006). Influence Tactics for Effective Adaptive Selling. Journal of Marketing, 70, 103–117.

Miner, J. B. (1962). Personality and Ability Factors in Sales Performance. Journal of Applied Psychology, 46 (1), 6–13.

Mintu-Wimsatt, A., & Gassenheimer, J. B. (2004). The Problem Solving Approach of International Salespeople: The Experience Effect. Journal of Personal Selling and Sales Management, 24, 19–25.

Moorman, C., van Heerde, H. J., Moreau, C. P., & Palmatier, R. W. (2019). JM as a Marketplace of Ideas. Journal of Marketing, 83 (1), 1–7.

Packard, G., Moore, S. G., & McFerran, B. (2018). (I'm) Happy to Help (You): The Impact of Personal Pronoun Use in Customer–Firm Interactions. Journal of Marketing Research, 55 (4), 541–555.

Packard, G., & Berger, J. (2021). How Concrete Language Shapes Customer Satisfaction. Journal of Consumer Research, 47 (5), 787–806.

Pappas, A., Fumagalli, E., Rouziou, M., & Bolander, W. (2023). More than Machines: The Role of the Future Retail Salesperson in Enhancing the Customer Experience. Journal of Retailing, 99, 518–531.

Parincu, Z. (2023). Behavioral Psychology: Definition, Theories, & Examples. Retrieved January 25, 2024 from https://www.berkeleywellbeing.com/behavioral-psychology.html

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The Development and Psychometric Properties of LIWC2015. Retrieved July 9, 2024 from https://www.liwc.app/static/documents/LIWC2015%20Manual%20-%20Development%20and%20Psychometrics.pdf

Plotkin, H. M. (1987). What makes a successful salesperson? Training and Development Journal, 54–56.

Pruden, H. O., & Peterson, R. A. (1971). Personality and Performance-Satisfaction of Industrial Salesmen. Journal of Marketing Research, 8, 501–504.

Rapp, A., Ahearne, M., Mathieu, J., & Schillewaert, N. (2006). The impact of knowledge and empowerment on working smart and working hard: The moderating role of experience. International Journal of Research in Marketing, 23, 279–293.

Rapp. A., Agnihotri, R., & Baker, T. (2011). Conceptualizing Salesperson Competitive Intelligence: An Individual-Level Perspective. Journal of Personal Selling and Sales Management, 31, 141–155.

Salesforce Blog (2024). 50 Vertriebsstatistiken, die zeigen, wie großartige Teams verkaufen. Retrieved January 2, 2025 from https://www.salesforce.com/de/blog/50-vertriebsstatistiken/?utm_source=chatgpt.com [in German]

Satornino, C. B., Allen, A., & Bolander, W. (2023). Understanding the Performance Effects of “Dark” Salesperson Traits: Machiavellianism, Narcissism, and Psychopathy. Journal of Marketing, 87 (2), 298–318.

Scholdra, T. P., Wichmann, J. R. K., & Reinartz, W. J. (2024). Reimagining personalization in the physical store. Journal of Retailing, 99, 563–579.

Sharma, A., Levy, M., & Kumar, A. (2000). Knowledge Structures and Retail Sales Performance: An Empirical Examination. Journal of Retailing, 76 (1), 53–69.

Shepherd, C. D., Gardial, S. F., Johnson, M. G., & Rentz, J. O. (2006). Cognitive Insights into the Highly Skilled or Expert Salesperson. Psychology & Marketing, 23 (2), 115–138.

Singh, J., Flaherty, K., Sohi, R. S., Deeter-Schmelz, D., Habel, J., Le Meunier-FitzHugh, K., Malshe, A., Mullins, R., & Onyemah, V. (2019). Sales profession and professionals in the age of digitization and artificial intelligence technologies: concepts, priorities, and questions. Journal of Personal Selling and Sales Management, 39 (1), 2–22.

Singh, S. K., Marinova, D., & Singh, J. (2020). Business-to-Business E-Negotiations and Influence Tactics. Journal of Marketing, 46, 837-856.

Spiro, R. L., & Weitz, B. A. (1990). Adaptive Selling: Conceptualization, Measurement, and Nomological Validity. Journal of Marketing Research, 27 (1), 61–69.

Stremersch, S., & van Dyck, W. (2009). Marketing of the Life Sciences: A New Framework and Research Agenda for a Nascent Field. Journal of Marketing, 73, 4–30.

Sujan, H., Sujan, M., & Bettman, J. R. (1988). Knowledge Structure Differences Between More Effective and Less Effective Salespeople. Journal of Marketing Research, 25, 81–86.

Szymanski, D. M. (1988). Determinants of Selling Effectiveness: The Importance of Declarative Knowledge to the Personal Selling Concept. Journal of Marketing, 52, 64–77.

Tirunillai, S., & Tellis, G. J. (2014). Mining Marketing Meaning from Online Chatter. Journal of Marketing Research, 51 (4), 463–479.

Tosdal, H. R. (1941). Significant Trends in Sales Management. Journal of Marketing, 5 (3), 215–218.

VandeWalle, D., & Brett, J. F. (1999). Goal orientation and goal content as predictors of performance in a training program. Journal of Applied Psychology, 84 (6), 863–873.

Verbeke, W., & Bagozzi, R. P. (2000). Sales call anxiety: Exploring what it means when fear rules a sales encounter. Journal of Marketing, 64 (3), 88–101.

Verbeke, W., Dietz, B., & Verwaal, E. (2011). Drivers of sales performance: a contemporary meta-analysis. Have salespeople become knowledge brokers? Journal of the Academy of Marketing Science, 39, 407–428.

Vinchur, A. J., Schippmann, J. S., Switzer, III, F. S., & Roth, P. L. (1998). A Meta-Analytic Review of Predictors of Job Performance for Salespeople. Journal of Applied Psychology, 83 (4), 586–597.

Weitz, B. A. (1978). Relationship Between Salesperson Performance and Understanding of Customer Decision Making. Journal of Marketing Research, 15, 501–516.

Weitz, B. A., Sujan, H., & Sujan, M. (1986). Knowledge, Motivation, and Adaptive Behavior: A Framework for Improving Selling Effectiveness. Journal of Marketing, 50 (4), 174–191.

Williams, K. C., & Spiro, R. L. (1985). Communication Style in the Salesperson Customer Dyad. Journal of Marketing Research, 22, 434–442.

You, Y., Yang, X., Wang, L., & Deng, X. (2020). When and Why Saying “Thank You” Is Better Than Saying “Sorry” in Redressing Service Failures: The Role of Self-Esteem, Journal of Marketing, 84 (2), 133–150.

Appendix

Table A1: Three Categories of Core Salespeople Success Drivers

1. Knowledge		2. Experience		3. Character	
About products	Singh et al. 2020	Tenure	Dixon et al. 2003	Conscientiousness & Extraversion	Barrick & Mount 1991
About markets	Ahearne & Schillewaert 2000	Working practice	Feng et al. 2021		Vinchur et al. 1998
			Ko & Dennis 2011	Competitiveness	Plotkin 1987
About customers	Spiro & Weitz 1990		Shepherd et al. 2006	Machiavellianism	Satornino et al. 2023
About selling	Verbeke et al. 2011			Empathy & Ego-Drive	Mayer & Greenberg 1964
		Practice with technologies	Pappas et al. 2023		
				Motivation	Good et al. 2022
				Goal-orientation	Brown et al. 1998
					VandeWalle et al. 1999
				Self-Esteem	Bagozzi 1978
				Communication & Language use	Williams & Spiro 1985
					Packard et al. 2018
					You et al. 2020
				Negatiation skills	Alavi et al. 2018
				Adaptiveness	Weitz et al. 1986
				Influence tactics	McFarland et al. 2006
					Singh et al. 2020

Table A2: Overview of Academic Articles for Classification

Title	Author(s) and Year
Salesperson Empathy and Listening: Impact on Relationship Outcomes	Aggarwal et al. 2005
Examining the impact of salesperson interpersonal mentalizing skills on performance: the role of attachment anxiety and subjective happiness	Agnihotri et al. 2016
Examining the effect of salesperson service behavior in a competitive context	Ahearne et al. 2007
High Touch Through High Tech: The Impact of Salesperson Technology Usage on Sales Performance via Mediating Mechanisms	Ahearne et al. 2008
If looks could sell: Moderation and mediation of the attractiveness effect on salesperson performance	Ahearne et al. 1999
Intrafunctional Competitive Intelligence and Sales Performance: A Social Network Perspective	Ahearne et al. 2013
Sales Performance Rankings: Examining the Impact of the Type of Information Displayed on Sales Force Outcomes	Ahearne et al. 2024
Why Are Some Salespeople Better at Adapting to Organizational Change?	Ahearne et al. 2010
Why sales reps should welcome information technology: Measuring the impact of CRM-based IT on sales effectiveness	Ahearne et al. 2007
The role of leadership in salespeople's price negotiation behavior	Alavi et al. 2017
The 30-sec sale: Using thin-slice judgments to evaluate sales effectiveness	Ambady et al.2006
The congruence of manager perception of salesperson performance and knowledge-based measures of adaptive selling	Anglin et al. 1990
Does selective sales force training work?	Atefi et al. 2018
Open negotiation: The back-end benefits of salespeople's transparency in the front end	Atefi et al. 2020
When does trust matter? Antecedents and contingent effects of supervisee trust on performance in selling new products in China and the United States	Atuahene-Gima and Li 2002
The role of emotional exhaustion in sales force attitude and behavior relationships	Babakus et al. 1999
Emotional Reactions and Salesperson Motivation: An Attributional Approach Following Inadequate Sales Performance	Badovick 1990
Prediction of Sales Success from Factorially Determined Dimensions of Personal Background Data	Baehr and Williams 1968
Culture Moderates the Self-Regulation of Shame and Its Effects on Performance: The Case of Salespersons in the Netherlands and the Philippines	Bagozzi and Verbeke 2003
Salesforce Performance and Satisfaction as a Function of Individual Difference Interpersonal and Situational Factors	Bagozzi 1978
Factors in Sales Success	Baier and Dugan 1957
Tests and Performance in a Sales Organization	Baier and Dugan 1956
Time Management and Achievement Striving Interact to Predict Car Sales Performance	Barling et al. 1996
Conscientiousness and Performance of Sales Representatives: Test of the Mediating Effects of Goal Setting	Barrick et al. 1993
Personality and Job Performance: Test of the Mediating Effects of Motivation Among Sales Representatives	Barrick et al. 2002
Type a Behavior, Experience, and Salesperson Performance	Bartkus et al. 1989
Exploring the Distinctive Nature of Work Commitments: Their Relationships with Personal Characteristics, Job Performance, and Propensity to Leave	Bashaw and Grant 1994
The Job Characteristics of Industrial Salespersons: Relationship to Motivation and Satisfaction	Becherer et al. 1982
A Role Stress Model of the Performance and Satisfaction of Industrial Salespersons	Behrman and Perreault 1984
Measuring the Performance of Industrial Salespersons	Behrman and Perreault 1982
Coping With Sales Call Anxiety: The Role of Sale Perseverance and Task Concentration Strategies	Belschak et al. 2006
Salesperson Motivation to Perform and Job Satisfaction: A Sales Contest Participant Perspective	Beltramini and Evans 1988
A New Livestream Retail Analytics Framework to Assess the Sales Impact of Emotional Displays	Bharadwaj et al. 2022
Salesperson social media use in business-to-business relationships: An empirical test of an integrative framework linking antecedents and consequences	Bill et al. 2020
Specialist competitor referrals: How salespeople can use competitor referrals for non-focal products to increase focal product sales	Blanchard et al. 2018
Predicting Sales Performance Job Satisfaction and Depression by Using the Achievement Strivings and Impatience-Irritability Dimensions of Type A Behavior	Bluen et al. 1990
Learned Helplessness Among Newly Hired Salespeople and the Influence of Leadership	Boichuk et al. 2014
Social Networks Within Sales Organizations: Their Development and Importance for Salesperson Performance	Bolander et al. 2015

Whom to hire and how to coach them: a longitudinal analysis of newly hired salesperson performance	Bolander et al. 2019
Self-selected sales incentives: Evidence of their effectiveness, persistence, durability, and underlying mechanisms	Bommaraju and Hohenberg 2018
Relational Communication Traits and Their Effect on Adaptiveness and Sales Performance	Boorom et al. 1998
Selection of Salesmen by means of an Assessment Center	Bray and Campbell 1968
A new look at psychological climate and its relationship to job involvement, effort, and performance	Brown and Leigh 1996
Do feelings of Success Mediate Sales Performance-Work Attitude Relationships?	Brown et al. 1993
Effects of Goal-Directed Emotions on Salesperson Volitions Behavior and Performance: A Longitudinal Study	Brown et al. 1997
Effects of Trait Competitiveness and Perceived Intraorganizational Competition on Salesperson Goal Setting and Performance	Brown et al. 1998
The Customer Orientation of Service Workers: Personality Trait Effects on Self-and Supervisor Performance Ratings	Brown et al. 2002
The Effect of Effort on Sales Performance and Job Satisfaction	Brown and Peterson 1994
Secondary selling: beyond the salesperson–customer dyad	Burchett et al. 2023
The Relationship of Tenure and Age to Role Clarity and Its Consequences in the Industrial Sector	Bush and Busch 1982
Effective Interpersonal Listening and Personal Selling	Castleberry and Shepherd 1993
More than one way to persist: Unpacking the nature of salesperson persistence to understand its effects on performance	Chaker et al. 2018
Learning from Peers: Knowledge Transfer and Sales Force Productivity Growth	Chan et al. 2014
How does team composition affect effort in contests? A theoretical and experimental analysis	Chen and Lim 2017
The Determinants of Salesperson Performance: A Meta-Analysis	Churchill et al. 1985
Dynamic and global drivers of salesperson effectiveness	Claro et al. 2024
Polychronicity, Big Five Personality Dimensions, and Sales Performance	Conte and Gintoft 2005
The Proactive Personality Scale and objective job performance among real estate agents	Crant 1995
No conversion, no conversation: Consequences of retail salespeople disengaging from unpromising prospects	Cron et al. 2021
Salesperson Selection Training and Development: Trends, Implications and Research Opportunities	Cron et al. 2005
The Influence of Career Stages on Components of Salesperson Motivation	Cron et al. 1988
The Effects of Empathy on Salesperson Effectiveness	Dawson et al. 1992
Performance expectations of salespeople: The role of past performance and causal attributions in independent and interdependent cultures	DeCarlo et al. 2007
Salesperson Communication Style: The Neglected Dimension in Sales Performance	Dion and Notarantonio 1992
It is better to be loved than feared: Machiavellianism and the dark side of internal networking	Dugan et al. 2019
The case for hiring neurotic salespeople: A longitudinal growth modeling T analysis	Dugan et al. 2020
The present and future of the B2B sales profession	Elhajjar et al. 2023
The moderating effect of goal-setting characteristics on the sales control systems–job performance relationship	Fang et al. 2005
When do we need higher educated salespeople? The role of work experience	Feng et al. 2021
Self-Esteem and Job Performance: The Moderating Role of Self-Esteem Contingencies	Ferris et al. 2010
Boundary spanner corruption: a potential dark side of multi-level trust in marketing relationships	Forkmann et al. 2022
Choreographing salesperson face-to-face visits with a buyer organization: a social network perspective	Forkmann et al. 2022
Polychronicity and Scheduling's Role in Reducing Role Stress and Enhancing Sales Performance	Fournier et al. 2013
Salesperson Adaptive Selling Behavior and Customer Orientation: A Meta-Analysis	Franke and Park 2006
Self-Management Training for Improving Job Performance: A Field Experiment Involving Salespeople	Frayne and Geringer 2000
Linking Job-Relevant Personality Traits Transformational Leadership and Job Performance via Perceived Meaningfulness at Work: A Moderated Mediation Model	Frieder et al. 2018
Motivating Salespeople to Sell New Products: The Relative Influence of Attitudes Subjective Norms and Self-Efficacy	Fu et al. 2010
Measuring and testing the impact of interpersonal mentalizing skills on retail sales performance	Gabler et al. 2019
Optimal Incentives for Salespeople with Learning Potential	Gao 2023
State or trait: Effects of positive mood on prosocial behaviors at work	George 1992

Modeling independent sales representative performance: application of predictive analytics in direct selling for improved outcomes	Glackin and Adivar 2023
Does your skin color matter in buyer–seller negotiations? The implications of being a Black salesperson	Gligor et al. 2021
Genes and Sales	Gong et al. 2023
A self-determination theory-based meta-analysis on the differential effects of intrinsic and extrinsic motivation on salesperson performance	Good et al. 2022
More than money: establishing the importance of a sense of purpose for salespeople	Good et al. 2022
Understanding and motivating salesperson resilience	Good et al. 2021
Psychological Adaptiveness and Sales Performance	Goolsby et al. 1992
Hunting for new customers: Assessing the drivers of effective salesperson prospecting and conversion	Gopalakrishna et al. 2022
Salesperson regulatory knowledge and sales performance	Groza and Groza 2018
Variable compensation and salesperson health	Habel et al. 2021
Antecedents of performance and satisfaction in a service sales force as compared to an industrial sales force	Hafer and McCuen 1985
The Importance of Starting Right: The Influence of Accurate Intuition on Performance in Salesperson-Customer Interactions	Hall et al. 2015
Re-examining Salesperson Goal Orientations: Personality Influencers Customer Orientation and Work Satisfaction	Harris et al. 2005
A theory of sales system shocks	Hartmann et al. 2024
How (Fast) Can I Help You? Tone of Voice and Telephone Operator Efficiency in Interactions	Hecht and LaFrance 1995
“Coopetition” in the presence of team and individual incentives: Evidence from the advice network of a sales organization	Homburg et al. 2024
Personality matters: how adaptive selling skills mediate the effect of personality traits on salespeople's exploited cross-selling potential	Homburg et al. 2024
Implementing the Marketing Concept at the Employee–Customer Interface: The Role of Customer Need Knowledge	Homburg et al. 2009
Validity versus Stereotype: Predicting Sales Performance by Ipsative Scoring of a Personality Test	Hughes and Dodd 1961
Information overload: Guidance for identifying when information becomes detrimental to sales force performance	Hunter 2004
Sales technology orientation information effectiveness and sales performance	Hunter and Perreault 2006
Personality and Job Performance: The Big Five Revisited	Hurtz and Donovan 2000
An Empirical Assessment of Salesperson Motivation Commitment and Job Outcomes	Ingram et al. 1989
Why Salespeople Fail	Ingram et al. 1992
Building customer relationships while achieving sales performance results: Is listening the holy grail of sales?	Itani et al. 2019
Effects of goal setting on performance and job satisfaction	Ivancevich 1976
Multiperiod contracting and salesperson effort profiles: The optimality of “hockey stick,”, “giving up,” and “resting on laurels”	Jerath and Long 2020
“Sorry about my manager”: Mitigating customer-facing adverse manager behaviors	Johnson 2024
Selling and Sales Management in Action: Why Do Salespeople Fail?	Johnston et al. 1989
A little competition goes a long way”: Substitutive effects of emotional intelligence and workplace competition on salesperson creative selling	Kalra et al. 2022
Customer-oriented salespeople’s value creation and claiming in price negotiations	Kassemeier et al. 2022
Unpacking the relationship between sales control and salesperson performance: a regulatory fit perspective	Katsikeas et al. 2018
Emotional Calibration and Salesperson Performance	Kidwell et al. 2021
When Salespeople Manage Customer Relationships: Multidimensional Incentives and Private Information	Kim et al. 2019
Predicting ratings of sales success with objective performance information	Kirchner 1960
Profiting from Knowledge Management: The Impact of Time and Experience	Ko and Dennis 2011
Sales force automation and sales performance: do experience and expertise matter?	Ko and Dennis 2004
Effects of Supervisory Behavior: The Role of Individual Differences Among Salespeople	Kohli 1989
Self–Efficacy Competitiveness and Effort as Antecedents of Salesperson Performance	Krishnan et al. 2022
Impact of competitiveness on salespeople's commitment and performance	Lam 2012
Salesperson ambidexterity in customer engagement: do customer base characteristics matter?	Lam et al. 2019
Identifying Successful Industrial Salesmen by Personality and Personal Characteristics	Lamont and Lundstrom 1977
Sales Productivity of Insurance Agents During the First Six Months of Employment: Differences Between Older and Younger New Hires	Landau and Werbel 1995
Salesperson dual agency in price negotiations	Lawrence et al. 2021

Mapping the Procedural Knowledge of Industrial Sales Personnel: A Script-Theoretic Investigation	Leigh and McGraw 1989
Salesperson knowledge distinctions and sales performance	Leigh et al. 2014
Knowledge Bases And Salesperson Effectiveness: A Script-Theoretic Analysis	Leong et al. 1989
Examining Salesperson Effort Allocation in Teams: A Randomized Field Experiment	Li et al. 2020
It Could Be Better" Can Make It Worse: When and Why People Mistakenly Communicate Upward Counterfactual Information	Li et al. 2023
How salesperson traits and intuitive judgments influence adaptive selling: A T sensemaking perspective	Locander et al. 2020
Who Are Your Successful Salespeople	Lockeman and Hallaq 1982
Sounds Big: The Effects of Acoustic Pitch on Product Perceptions	Lowe and Haws 2017
The Relationships Between Job Attitudes Personal Characteristics and Job Outcomes: A Study of Retail Store Managers	Lucas 1985
Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions	Luo et al. 2021
How psychological resourcefulness increases salesperson's sales performance and the satisfaction of their customers: Exploring the mediating role of customer-oriented behaviors	Lussier and Hartmann 2017
Lone wolf tendency and ethical behaviors in sales: Examining the roles of perceived supervisor support and salesperson self-efficacy	Lussier et al. 2022
Relationship Development in Selling: A Cognitive Analysis	Macintosh et al. 1992
Some Possible Antecedents and Consequences of In-Role and Extra-Role Salesperson Performance	MacKenzie et al. 1998
The joint and multilevel effects of training and incentives from upstream manufacturers on downstream salespeople's efforts	Magnotta et al. 2020
Salesperson competitive intelligence and performance: The role of product knowledge and sales force automation usage	Mariadoss et al. 2014
Frontline Problem-Solving Effectiveness: A Dynamic Analysis of Verbal and Nonverbal Cues	Marinova et al. 2018
Hiring for success at the buyer–seller interface	Marshall et al. 2003
Influence Tactics for Effective Adaptive Selling	McFarland et al. 2006
The predictive efficiency of temperament characteristics and personal history variables in determining success of life insurance agents	Merenda and Clarke 1959
The impact of salesperson motivation on role perceptions and job performance—a cognitive and affective perspective	Miao and Evans 2007
Personality and Ability Factors in Sales Performance	Miner 1962
Lone Wolf Tendencies and Salesperson Performance	Mulki et al. 2007
Regulation of emotions interpersonal conflict and job performance for salespeople	Mulki et al. 2015
Antecedents and performance outcomes of value-based selling in sales teams: a multilevel systems theory of motivation perspective	Mullins et al. 2020
Digital selling: organizational and managerial influences for frontline readiness and effectiveness	Mullins and Agnihotri 2022
Know Your Customer: How Salesperson Perceptions of Customer Relationship Quality Form and Influence Account Profitability	Mullins and Ahearne 2014
Managing Positive and Negative Trends in Sales Call Outcomes: The Role of Momentum	Nahm et al. 2022
Coping Strategy Profiles Used by Salespeople: Their Relationships with Personal Characteristics and Work Outcomes	Nonis and Sager 2003
Are good salespeople born or made? A new perspective on an age-old question: implicit theories of selling ability	Novell et al. 2016
(I'm) Happy to Help (You): The Impact of Personal Pronoun Use in Customer–Firm Interactions	Packard et al. 2018
How Concrete Language Shapes Customer Satisfaction	Packard and Berger 2021
When Language Matters	Packard et al. 2024
Salesperson Solution Involvement and Sales Performance: The Contingent Role of Supplier Firm and Customer-Supplier Relationship Characteristics	Panagopoulos et al. 2017
How do specialized personal incentives enhance sales performance? The benefits of steady sales growth	Patil and Syam 2018
The early-tenure salesperson: sales effort and sales growth during the ramp-up period	Peasley and Hochstein 2024
Hiring for sales success: The emerging importance of salesperson analytical skills	Peesker et al. 2022
An Exploratory Investigation of Voice Characteristics and Selling Effectiveness	Peterson et al. 1995
An Empirical Examination of the Impact of Salesperson Empathy and Professionalism and Merchandise Salability on Retail Buyers' Evaluations	Pilling and Eroglu 1994
Elaboration on potential outcomes (EPO) and the consultative salesperson: investigating effects on attributions and performance	Plouffe et al. 2017
Self-Regulation: From Goal Orientation to Job Performance	Porath and Bateman 2006
Sales Success as Predicted by A Process Measure of Adaptability	Predmore 1994
Personality and performance-satisfaction of industrial salesmen	Pruden and Peterson 1971

Prosocial behavior, noncompliant behavior, and work performance among commission salespeople	Puffer 1987
Listening to Your Customers: The Impact of Perceived Salesperson Listening Behavior on Relationship Outcomes	Ramsey and Sohi 1997
The impact of knowledge and empowerment on working smart and working hard: The moderating role of experience	Rapp et al. 2006
An interdisciplinary approach to assessing the characteristics and sales potential of modern salespeople	Reday et al. 2009
A Measure of Selling Skill: Scale Development and Validation	Rentz et al. 2002
The Power of Speaking Slower	Rizzo and Berger 2023
Understanding the Performance Effects of Dark" Salesperson Traits: Machiavellianism Narcissism and Psychopathy	Satornino et al. 2023
Self-Other Orientations Among Salesmen and Non-salesmen	Scheibelhut and Albaum 1973
Innovation in the frontline: Exploring the relationship between role conflict, ideas for improvement, and employee service performance	Schepers et al. 2016
Optimal Sales Force Compensation in Dynamic Settings: Commissions vs. Bonuses	Schöttner 2017
Self-oriented competitiveness in salespeople: sales management implications	Schrock et al. 2021
Applying learned optimism to increase sales productivity	Schulman 1999
Explanatory style as a predictor of productivity and quitting among life insurance sales agents	Seligman and Schulman 1986
An Empirical Investigation of Key Account Salesperson Effectiveness	Sengupta et al. 2000
Are your salespeople coachable? How salesperson coachability trait competitiveness and transformational leadership enhance sales performance	Shannahan et al. 2013
Knowledge Structures and Retail Sales Performance: An Empirical Examination	Sharma et al. 2000
The variance in sales performance explained by the knowledge structures of salespeople	Sharma et al. 2007
Learning and Performance Goal Orientation of Salespeople Revisited: The Role of Performance-Approach and Performance-Avoidance Orientations	Silver et al. 2006
Business-to-Business E-Negotiations and Influence Tactics	Singh et al. 2020
Customer query handling in sales interactions	Singh et al. 2018
Online training of salespeople: Impact, heterogeneity, and spillover effects	Singh et al. 2022
Striking a Balance in Boundary-Spanning Positions: An Investigation of Some Unconventional Influences of Role Stressors and Job Characteristics on Job Outcomes of Salespeople	Singh 1998
Relational Communication: Form Versus Content in the Sales Interaction	Soldow and Thomas 1984
Revisiting the nature and strength of the personality–job performance relations: New insights from interpretable machine learning	Song et al. 2024
Personality Characteristics and Salespeople's Choice of Coping Strategies	Strutton et al. 1985
The Relationship between Optimism and Coping Styles of Salespeople	Strutton and Lumpkin 1993
Knowledge Structure Differences between More Effective and Less Effective Salespeople	Sujan et al. 1988
Learning Orientation Working Smart and Effective Selling	Sujan et al. 1994
Optimism and Street-Smarts: Identifying and Improving Salesperson Intelligence	Sujan 1999
The Practical Know-How of Selling: Differences in Knowledge Content Between More-Effective and Less-Effective Performers	Sujan et al. 1991
Smarter Versus Harder: An Exploratory Attributional Analysis of Salespeople's Motivation	Sujan 1986
Technology use on the front line: how information technology enhances individual performance	Sundaram et al. 2007
Why do salespeople quit? An empirical examination of own and peer effects on salesperson turnover behavior	Sunder et al. 2017
Determinants of Selling Effectiveness: The Importance of Declarative Knowledge to the Personal Selling Concept	Szymanski 1988
Relative Importance of Key Job Dimensions and Leadership Behaviors in Motivating Salesperson Work Performance	Tyagi 1985
The Influence of Goal Orientation and Self-Regulation Tactics on Sales Performance: A Longitudinal Field Test	VandeWalle et al. 1999
A Situational Analysis on How Salespeople Experience and Cope with Shame and Embarrassment	Verbeke and Bagozzi
Drivers of sales performance: a contemporary meta-analysis. Have salespeople become knowledge brokers?	Verbeke et al. 2011
Sales Call Anxiety: Exploring What It Means When Fear Rules a Sales Encounter	Verbeke and Bagozzi 2000
When Intelligence is (Dys)Functional for Achieving Sales Performance	Verbeke et al. 2008
A Meta-Analytic Review of Predictors of Job Performance for Salespeople	Vinchur et al. 1998
Selling Strategies: The Effects of Suggesting a Decision Structure to Novice and Expert Buyers	Wagner et al. 2001

Motivation and Performance in Industrial Selling: Present Knowledge and Needed Research	Walker et al. 1977
The Effects of Job Autonomy Customer Demandingness and Trait Competitiveness on Salesperson Learning Self-Efficacy and Performance	Wang and Netemeyer 2002
Interpersonal Communication and Salesman Effectiveness	Webster 1968
Knowledge Motivation and Adaptive Behavior: A Framework for Improving Selling Effectiveness	Weitz et al. 1986
Relationship between Salesperson Performance and Understanding of Customer Decision Making	Weitz 1978
Communication Style in the Salesperson-Customer Dyad	Williams and Spiro 1985
Assessing the evolution of sales knowledge: A 20-year content analysis	Williams and Plouffe 2007
The stress of prospecting: Salesperson genetics and managerial remedies	Winter et al. 2024
Onboarding salespeople: Socialization approaches	Wiseman et al. 2022
The relationship of job image, performance, and job satisfaction to inactivity-proneness of direct salespeople	Wotruba 1990
Why Salespeople Avoid Big-Whale Sales Opportunities	Xu et al. 2022
Individual differences and sales Performance: a distal-proximal mediation model of self-efficacy conscientiousness and extraversion	Yang et al. 2011
When and Why Saying Thank You" Is Better Than Saying Sorry" in Redressing	You et al. 2020
How the Voice Persuades	Zant and Berger
Group or Individual Sales Incentives? What Is Best for Brand-Managed Retail Sales Operations?	Zhang et al. 2024

Table A3: Citations for Consistently Classified Articles

	Google Citations per Year	Web of Science Citations between 2020 and 2024
Character	18.81 (21.38)	49.76 (59.94)
Knowledge	12.86 (12.32)	45.05 (40.68)
Experience	3.22 (3.20)	10.67 (15.89)

Table A4: BERT Topics for Practitioner Articles

BERT topics	Classification
sell, know, success, making	Character, Knowledge
know, training, trust, skills	Knowledge
ask, decision, problem-solving	Knowledge
experience, relationships, virtual	Experience
language, competent, conversations	Character

Table A5: LDA Topics for Practitioner Articles

LDA topics	Classification
know, understand, skills, conversation, ability, learn, feal	Character, Knowledge
training, success, experience, know, understand	Knowledge, Experience
language, effective	Character
personal, skills, experience	Character, Experience
ability, language, ability, technology, person, drive	Character

Figure A1: ChatGPT Prompts for Academic Article Classification

"Does this article belong to sales knowledge, sales experience or character (i.e., personal factors) in sales?"

"Describes this article knowledge factors, experience factors or personal factors of salespeople?"

"Please classify this article according to whether it is about knowledge (about products, customer, markets, or technical innovations), experience (i.e., working experience), and/or personal aspects (such as traits, behaviors, soft skills and tactics) of salespeople."

"Multiple classifications are allowed if you think that an article belongs in more than one category."

Note: ChatGPT had difficulties in understanding the term "character", so I used the term "personal factors" instead. As I excluded articles solely dealing with demographic factors, this was not a problem at all.

Figure A2: Word Clouds with Nouns for Human-Classified Academic Articles

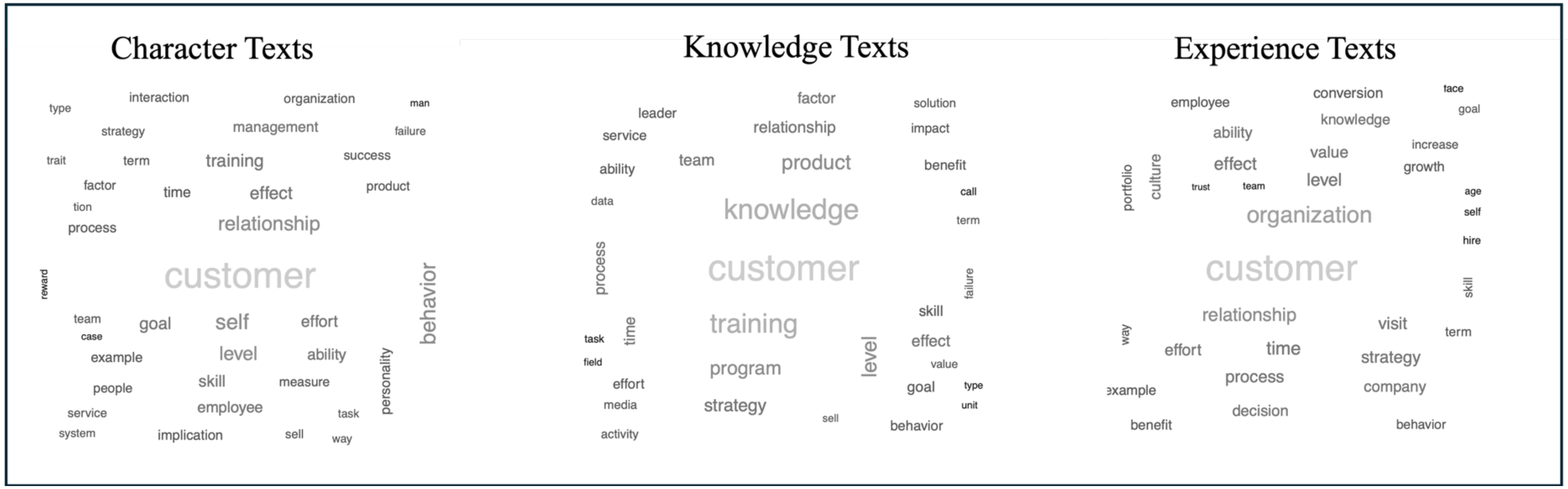


Figure A3: Word Clouds with Nouns for Human-Classified Practitioner Articles

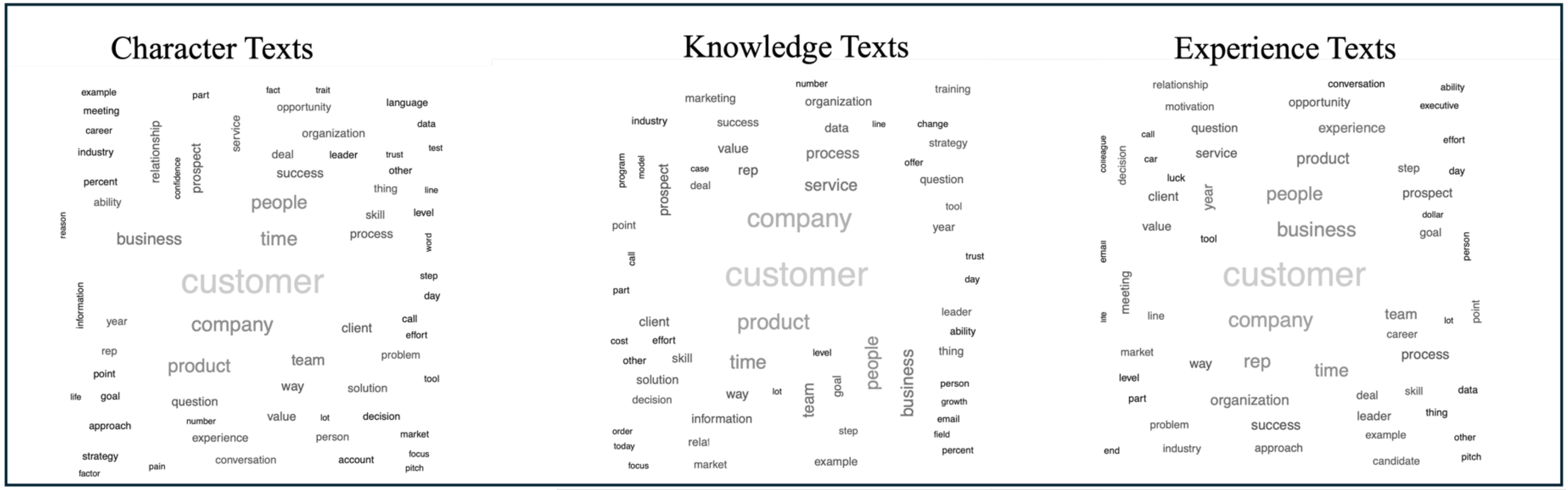


Figure A4: BERT Matrix of Similarities for Academic and Practitioner Articles