

Paying Lip Service?

The Effects of Vocal Determinants on Perceived Service Quality

Yigal David, Shenkar College of Engineering and Design, Israel

Elad Harison, Shenkar College of Engineering and Design, Israel*

ABSTRACT

Literature has mainly analyzed the technical attributes of voice for enterprise technical applications, such as voice signature and speech recognition. This paper aims at identifying voice and speech attributes that reflect sentiment and affect (positively or negatively) customer satisfaction levels in voice interactions. The paper used method triangulation that utilizes multiple data sources to gain comprehensive understanding of the domain, including auditory observations, focus group interviews, customer survey, and a review of recent academic studies. The findings indicate that customer experience and satisfaction are influenced by the relative values of voice pitch between the CSR (customer service representative) and the customer. The major conclusion of the study suggests that voice fundamental pitch, speech rate, voice amplitude, and other communication parameters might deploy hidden power and affect service interaction's results. The study opens a new venue for research on social interaction adjustment from the CSR's perspective and from the customer's standpoint.

KEYWORDS

Call Centers, Communication, Customer Satisfaction, Customer Service Representative, Vocal Attributes, Voice Chatbots, Voice Frequency, Voice Pitch, Voice-Based Interactions

INTRODUCTION

In recent years, the application of academic models aiming at deciphering consumer behavior via psychological and neurological frames of reference has grown exponentially, both in advanced marketing research as well as studies conducted by retailers. This paper aims at examining the different aspects underlying customer behavior in voice-based service interactions. Further, the study identifies how these types of social interaction can be improved based on vocal properties and provides a model that assists in aligning the attributes of vocal interaction by Customer Service Representative (CSR) and the resulting customer satisfaction.

The links between enterprise information systems and voice sentiment technologies continuously evolve. Enterprise information systems have been traditionally orchestrating most of the business processes (BP) in the organization. Core applications, such as ERP and CRM, demonstrate very well how more efficiently the organization functions. As data turned more accessible and available for use, and data analytics tools became more effective and dominant (Yousfi et al., 2019; Leon et al., 2020), enterprise BPs can be consistently improved, so data-driven IT is a key factor in Business Processes Improvement (BPI) (Levykin and Chala, 2018). There is a direct positive correlation between advanced

DOI: 10.4018/IJEIS.313049

*Corresponding Author

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data analytics and designing BPIs (Cetindamar et al., 2021; Hallikas et al., 2021). Analytics-based BPI approaches include three stages: a) “What happened?”: Classic Business Intelligence (BI) monitoring dashboards demonstrate this stage. For example: how many customers churned last week? b) “What will happen?”: predictive analytics statistical tools such as Data Mining (DM) demonstrate this stage very well. For example: which customers are about to churn soon? c) “What to do next?” is a set of alternative actions and decisions in complex environment based on advanced data-driven algorithms that indicate what to do (Aydiner et al., 2019). Our research supports the third stage approach, where voice sentiment analysis is determined as a newly evolving knowledge domain that can help steering voice interactions optimally.

Current CRMs consistently extend themselves. For example, CRMs today can deploy text-based chatbots to correspond with potential customers to generate “leads” (customer details for sales purposes). The next generation is expected to utilize chatbots based on voice. In this case, the quality of voice response, which relies on speech recognition and voice sentiment analysis, will be crucial for better understanding of the customer’s feelings and state of mind. Moreover, Meta-Facebook, Google, Apple and Amazon have already deployed technologies of voice sentiment analysis in their core products and applications to add the important dimensions of customer’s voice, as described in our paper, in order to improve customer experience.

Further, voice sentiment is becoming one of the most important technologies implemented by enterprises worldwide, enabling them new capabilities that improve their organizational competitiveness and their interaction with customers. It started with basic CRM features, such as call center telephony and IVR. In recent years, it has been developed into the world of voice based personal assistants such as Amazon’s Alexa. The adoption of human-machine conversations accelerates with 40% of Internet users in the U.S. using voice assistants. The use of voice-based personal assistants is expected to reach 200 million users in 2023 (as reported by the industry research website <https://blog.hubspot.com/website/voice-search-optimization>). Thereupon, increasing number of firms adjust their websites to support voice-based input (speech to text) and output (text to speech). In this respect, voice analysis has become crucial in order to understand the context sentiment beyond the content itself. Following the technological advances, as well as any improvement in matching the “right” voice to a specific customer might improve customer satisfaction rate and conversion rates in sales and marketing as well as customer care support.

While prior literature has mainly analyzed the technical attributes of voice for enterprise technical applications, such as voice signature and speech recognition, this paper aims at identifying voice and speech attributes that reflect sentiment and affect (positively or negatively) customer satisfaction levels in voice interactions.

The research aims at identifying the match or mismatch between voice attributes of CSRs and customers and the resulting customer experience from those voice-based interactions. As voice sentiment analysis technologies and applications are utilized by a growing body of enterprises, the study can serve as a basis for further understanding of commercial voice interactions within the domain of call center services and beyond it.

Section 2 of the paper presents the literature review and research hypotheses. Section 3 elaborates the Methodology. Section 4 presents the results. Section 5 discusses the findings. Section 6 presents possible real-world implementation in a voice matching architecture for call centers. Finally, conclusions and research limitations are provided.

REVIEW OF LITERATURE AND HYPOTHESES DEVELOPMENT

The functioning of call centers, their work processes and procedures were studied and broadly applied by multiple organizations who implemented the findings of these studies in practice via elements of caring, knowledge, methodology, accuracy, positivity, politeness, creativity, active listening, and others, to improve customer satisfaction (Fernández-Sabiote and Román 2016; Ilkhanizadeh and Karatepe

2017; Gao et al., 2020). This research is inspired by the notion that in varying human interactions, the different use of voice suggests that “it would be surprising if people did not use their voices to project a culturally desirable image” (Graddol and Swan, 1991). Further, the inter-influence between the brains of persons during interactional sessions facilitates hidden social forces and dynamics that voice and speech impose on dyadic interactions (Wilkinson et al., 2021). Therefore, we aim at discovering the attributes that affect customer satisfaction through the inter-influence of fundamental voice frequency and other voice attributes between CSRs and customers during voice-based interactions.

In this respect, the discussion surrounding issues of the fundamental frequency range of the voice and its average levels is highlighted by Freud et al. (2018), Tendra et al. (2019) and Ambarita and Mulaydi (2020), *inter alia*. Insights from this literature suggest that the most common values for the average fundamental frequency pitch of male speakers are around 110-115 Hz, while those of female speakers are approximately 190-210 Hz.

The anatomical and physiological structures that lead to an enormous number of variations in vocal harmonies create an individual vocal identity and personality, which are unique to each person. The social contexts of the voice, i.e., voice frequencies that are connected to social positions and human perception, are derived from these vocal identities, as they constantly transmit information about the speaker, especially in different social contexts, beyond the textual contents and the context of the social encounter (Karagkouni, 2021; Nguyen et al., 2022). Other studies confirm that voice triggers a signal for human attractiveness and social dominance. Ohala, Hinton, and Nichols (1994) describe this phenomenon as the *frequency code*, in which a low-pitched voice sounds confident and dominant, whereas a high-pitched voice is associated with submissive and subordinate individuals. In recent years, a growing body of evidence suggests that voice frequencies also influence the attractiveness levels of partners. Pisansky and Feinberg (2017) studied the relation between vocal attractiveness in women as judged by men. Puts (2004) tested the hypothesis that “female choice for good genes influenced the evolution of male voice pitch.” Puts, Gaulin and Verdolini (2006) examined the relationship between voice pitch, dominance, and male mating success. Stern et al. (2021) examined the effects of attractiveness, maturity of face, and voice on interpersonal impressions. Cussigh et al. (2020) showed that women with low-pitched voices are perceived more dominant by men. Meanwhile, women with high-pitched voices are perceived more attractive by men than those with low-pitched voices. Additionally, the pitch of women’s own voice is raised when a woman is attracted to men with low voice pitch (Vukovic et al., 2010). Klostad, Anderson, and Peters (2012) and Tigue, Borak, O’Connor, Schandl, and Feinberg (2012) indicated that men and women prefer leaders with a low-pitched voice. Low-pitched male leaders are largely perceived by women as attractive and by men as competent and strong.

High-quality customer service has a positive impact on customer satisfaction (Al-Adwan et al., 2020; Campbell, 2020), and customer satisfaction is one of the crucial parameters in ensuring organization growth through customer engagement and loyalty (Hsiao, 2019; Mosa et al., 2020). Moreover, the majority of the service delivery and resources involved in customer service are based on human vocal interactions between CSRs and clients.

The aim of the research is to identify how attributes and patterns in voice-based interactions can contribute to the positive dynamics between customers and CSRs. The main research questions are as follows:

- How do voice and speech dynamics influence the relationship between customers and call center’s CSRs?
- Which aspects of voice dynamics of customers and CSRs (i.e., voice fundamental frequency pitch, resonance frequency, voice clarity, voice amplitude/intensity, speech rate, call possession rate) have impact – positive or negative – on customer satisfaction?
- In what ways can call centers change the way they function to respond to these findings and what managerial and organizational implications emerge from the findings of this research?

Based on our literature survey, we predict that customer satisfaction is affected by differences in voice attributes between male CSRs and female customers, and *vice versa*, and test the following hypotheses:

Hypothesis 1. Voice-based interactions between low-pitch male CSRs and high-pitch female customers result in improved customer satisfaction.

Hypothesis 2. Voice-based interactions between high-pitched male CSRs and low-pitched female customers result in poor customer satisfaction.

Hypothesis 3. Does the speech rate affect customer satisfaction in any way?

Hypothesis 4. Does call possession rate affect customer satisfaction in any way?

Hypothesis 5. Do voice amplitude and voice clarity affect customer satisfaction in any way?

METHODOLOGY

The methodology was using triangulation in qualitative research through which it mixed four data sources in order to gain comprehensive understanding of the domain:

- 1) Auditory observations of real-world records retrieved from a call center (see Table 1).
- 2) Focus group interviews with the call center representatives to gain their interpretation.
- 3) Sample survey amongst the customers sampled for this study to get their customer experience (CX) impressions.
- 4) A survey of recent and relevant academic literature in order to cross and synthesize insights.

Table 1. Exemplary samples of auditory observations and their measured attributes in M-M, M-F, F-M and F-F categories

Type of interaction:		CSR=M, Customer=M	CSR=M, Customer=F	CSR=F, Customer=M	CSR=F, Customer=F
CSR	Dominant voice pitch (Hz)	110	120	190	180
	Resonance frequency (Hz)	2200	2500	2500	1800
	Pitch clarity (clear / semi / rough)	Semi	Rough	Semi	Clear
	Amplitude / Voice intensity (low / mid / high)	Mid	Mid	Low	Low
	Speech rate (+/-110w/m) (slow / average / fast)	Average	Average	Fast	Slow
	Call possession rate	34%	44%	31%	31%
Customer	Dominant voice pitch (Hz)	100	200	150	160
	Resonance frequency (Hz)	700	1800	2500	2300
	Pitch clarity (clear / semi / rough)	Semi	Clear	Clear	Rough
	Amplitude / Voice intensity (low / mid / high)	Low	Low	High	High
	Speech rate (+/-110w/m) (slow / average / fast)	Slow	Slow	Average	Slow
	Call possession rate	40%	32%	50%	49%

Table 1 continued on next page

Table 1 continued

Type of interaction:		CSR=M, Customer=M	CSR=M, Customer=F	CSR=F, Customer=M	CSR=F, Customer=F
Additional details	Time of the day	09:59	10:09	11:22	08:32
	Silence rate	26%	24%	19%	20%
	Call duration (minutes)	3.45	3.13	3.4	4.16
	Conversation subject	Internet reception	Billing	Call forward	Roaming info
Interaction results	Problem solved	Yes	No	Yes	Partially
	Customer satisfaction (1 poor, 2 fair, 3 excellent)	3	2	3	1
	Correlation (Problem solving / Satisfaction)	Correlated	Over-rated	Correlated	Under-rated

This type of triangulation is known as Method Triangulation. It involves data collection sourced from several methods dealing with the same phenomenon (Gibson, 2014). which can enhance our insights as “a researcher’s conceptual sophistication and analytic skills can be increased by serious and sustained engagement with alternative positions and methods” (Wooffitt, 2005).

Moon (2019) investigated the effect of method triangulation on clinical research. By his view, the combination of observations, interviews and raw data, provides more complete picture and contribute to the validity, reliability and legitimation of the research.

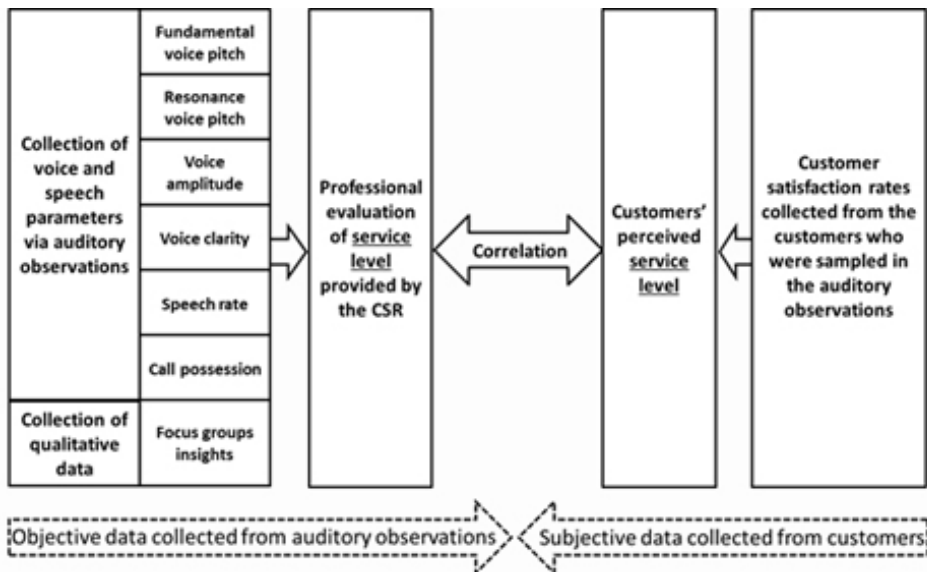
The method triangulation is especially efficient when it comes to CX evaluation, as the application of multiple methods can better reflect and express CX by its gradual analysis, i.e. “piece by piece” (Pettersson et al., 2018).

In its empirical part, processed and reassured between September 2018 and January 2019, the auditory observations were carried out in a call center that is part of the customer care division in one of five Mobile Network Operators (MNO) in Israel. The MNO holds around 15% market share (about 1.5 million customers), and the researched recordings sampled only mass-market customers. Other segments were excluded. The call center employs around 300 CSRs spread in a few locations throughout Israel. The research was coordinated with the MNO’s legal counsel and involved several ethical measures, as follows; For confidentiality and respect reasons, all the auditory observations were made directly from the CRM system rather than downloading them to a storage device. Additionally, the names of the participants were not documented to sustain their privacy. For integrity and responsibility reasons, potential bias was avoided by isolating parameters, such as participant’s segment, gender, age, accent, and dialects. Indirect biases caused by unknown factors were eliminated by selecting call records with similar service attributes, e.g. call duration, waiting time until the call was taken, the time of day, etc. For transparency reasons, each sampled interaction had a prompt ‘this call is recorded for study and training purposes’ played prior to the interaction. In addition, all the involved CSRs in the triangulating focus group were pre-informed about the research background and aims.

In the first phase of the study, a survey of auditory observations based on recent, archived audio-recordings of customer interactions was conducted. The attributes of voice-based interactions of both CSRs and customers (voice pitch, voice intensity, voice clarity, speech rate, call duration, possession rates) and their dynamics over time were recorded. Following, an analysis was conducted to identify significant variations through patterns of speech that indicate particular customer behaviors. The study was carried out with special attention to ethical considerations that came into practice in access

approval by the system manager, data protection, confidentiality, and avoidance of information misuse (see the methodological process of the study in Fig. 1).

Figure 1. Methodological process of the research

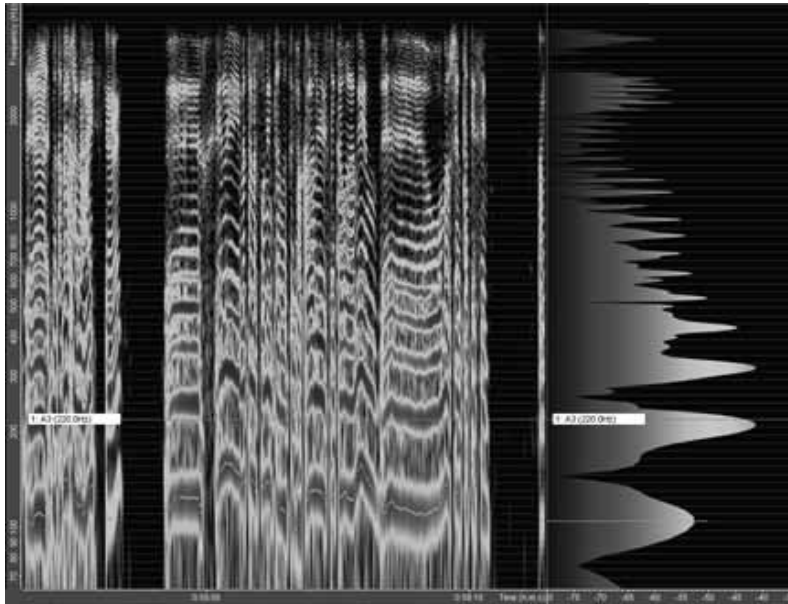


The call center from which recordings were collected handles around 70,000 calls per month. The mass market segment contributes around 30,000 calls per month; consequently, our target population (N) included 60,000 recorded calls over two months. During the first phase, we sampled forty voice-based interactions between CSRs and customers, distinguishing between male-to-male, male-to-female, female-to-male, and female-to-female conversations. The recordings were randomly selected from the mass market segment, avoiding conversations with foreign accents and dialects. The recordings were drawn from two specific months to avoid bias. The sampled calls (n) were selected as follows: one sampled call every 1,500 calls ($N/n = 60,000/40$), following the simple random sample rationale. Voice frequency (fundamental and resonance) were measured and documented for each sample (see Fig. 2 for a representation of the vocal attributes during one of the sampled interactions).

In order to analyze streaming voice recording, we used Overtone Analyzer Live with a sampling rate of 44 KHz (16 bit) on a single channel (mono) and a frequency resolution of 5.4 Hz (At this accuracy level, differences in terms of Hz between two frequencies are shown and can be distinguished by the Overtone Analyzer). This tool provided accurate results and was able to overcome background noise and cancel echo while isolating the speech stream in order to obtain clear, unbiased results. The telephone codec (an embedded telephone element that decodes analogue voice streams into digital audio through various compression algorithms), which was expected to deliver voice frequencies only in the spectral range of 300 Hz to 3400 Hz, unexpectedly managed to trace frequencies between 75 Hz and 300 Hz, which overlaps with an extremely dominant spectrum for male and female voice pitch, i.e. approximately 75 Hz – 240 Hz for males and approximately 125 Hz – 350 Hz for females. The technical explanation for this surprising development is that original telephone standards limited the audio coding to the spectral range 300 Hz – 3400 Hz. However, blocking electromagnetic direct current (DC) and filtering frequencies below 300 Hz prevented interference. Since the telephone has become mobile and the criticality of electromagnetic induction has become marginal, the audio coding

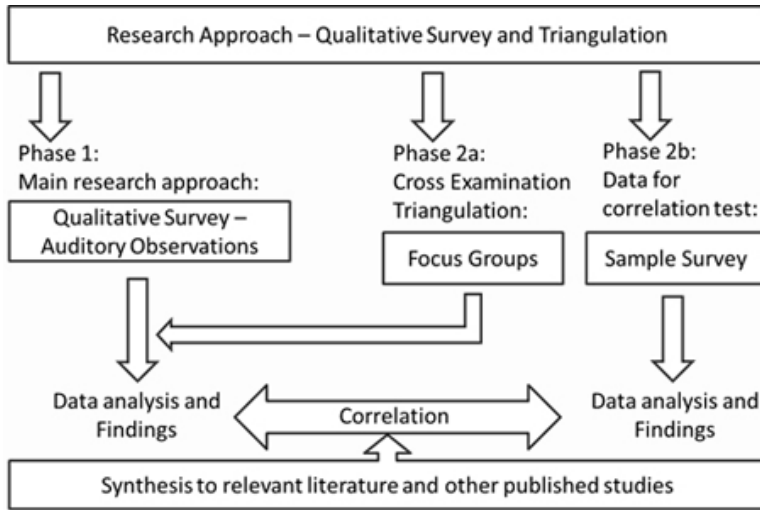
spectral range began to vary. In our specific case, the codec's official specifications showed that the supported spectral range is 200 Hz – 3400 Hz. Moreover, 200 Hz was not the minimum rate that can be practically measured, since the filtering mechanism does not cut off sounds at a specific value (200 Hz) all at once, but gradually; thus, sounds below 200 Hz can be still traced (as demonstrated in Figure 2). Further, the new telecommunication standard focuses on transmitting complete information above 200 Hz, but it does not prevent the transmission of frequencies below 200 Hz. It also depends on the equipment installed in the core network; in our case, the Nokia-Siemens Media Gateway enables the leaking of sounds below 200 Hz.

Figure 2. Real recording screenshot demonstrating a fundamental frequency of around 120 Hz



In the second phase of the study, we followed the prior auditory observations with a focus group session for additional evidence, cross-examination, reliability testing, and finding confirmation and subjectivity reduction regarding the properties of the recordings to generate a comprehensive understanding of the complex aspects of human behavior reflected by the vocal interactions (Cohen and Manion, 2017). The focus group, which included CSRs who were sampled in the auditory observations, listened to the recorded conversations that they had had and interpreted the conversation outcomes, in order to cross-examine the findings of the first phase of the study. This activity was followed by a sample survey that was distributed to the customers who took part in the sampled conversations. They indicated their *de facto* satisfaction levels after listening to the recordings of their conversations (the different phases of the methodology are illustrated in Fig. 3).

Figure 3. Overarching methodology for the research



The sample survey included the question, “Following your service call yesterday, how satisfied were you with the service you received from the customer service representative?” This question was distributed to the forty customers who were sampled in the auditory observations up to 24 hours after their interaction with the customer service. For the sake of simplicity, the customer could grade it as “Very satisfied,” “Partially satisfied,” or “Not satisfied.” In order to avoid bias, we isolated the following factors in advance: gender (splitting into four groups: M-M, M-F, F-M, F-F), customer segment (focusing only on mass market), accents and dialects (sampling only Jewish-Israelis), customer age (excluding kids, youth, and the elderly). Other factors were also controlled (selecting call records with similar service attributes, such as waiting time and the time of day).

Statistical analysis was conducted, where the causal variable was the fundamental voice frequencies (of both CSRs and customers), and the resulting variable was the measure of service perception gap, i.e., the difference between the actual level of service (evaluated by us in the first phase) and the level of customer satisfaction (rated by customers in the second phase). A focus group session with CSRs (in the second phase) provided cross-examination for our evaluation of the actual level of service, in order to validate the findings from different angles and to reduce subjectivity and bias.

The correlation between customer satisfaction rate and the actual results of the conversation, determined during phase 2 of the study, is presented in Table 2.

Table 2. Correlation between interaction results and customer satisfaction rate

Conversation results: <i>Problem solved?</i>	Customer satisfaction grade: <i>How satisfied?</i>	Correlation
Full solution	Very satisfied	Correlated
Full solution	Partially satisfied	Under-rated
Full solution	Not satisfied	Under-rated
Partial solution	Very satisfied	Over-rated
Partial solution	Partially satisfied	Correlated
Partial solution	Not satisfied	Under-rated

Table 2 continued on next page

Table 2 continued

Conversation results: <i>Problem solved?</i>	Customer satisfaction grade: <i>How satisfied?</i>	Correlation
No solution	Very satisfied	Over-rated
No solution	Partially satisfied	Over-rated
No solution	Not satisfied	Correlated

RESULTS

The sampled recordings obtained from the call center were divided into four different groups according to the gender combination of the CSRs and customers. Consequently, conversations between male CSRs and male customers, male CSRs and female customers, female CSRs and male customers, and female CSRs and female customers were analyzed separately.

The research findings indicate that voice-based interactions between male CSRs and female customers characterized by a difference of at least 80 Hz between high-pitched female customers (fundamental pitch of 200 Hz or higher) and the male CSR's voice pitch correlate with improved customer satisfaction. Hence, Hypothesis 1, by which voice-based interactions between low-pitch male CSRs and high-pitch female customers result in higher level of customer satisfaction in comparison to other interactions, is affirmed.

Formally,

If $(F0Fcs - F0Mcu) \geq 80 \text{ Hz}$ and $F0Fcu \geq 200 \text{ Hz}$, then $SRFcu = \text{over-rated}$

where

$F0Mcs$ is the Fundamental voice pitch of the Male CSR

$F0Fcu$ is the Fundamental voice pitch of the Female Customer

$SRFcu$ is the Satisfaction Rate of the Female Customer

Voice-based interactions between male CSRs and female customers with high-pitched male CSRs (fundamental pitch of 120 Hz or higher) and low-pitched female customers (fundamental pitch of 190 Hz or lower) typically resulted in poor customer satisfaction. Hence, Hypothesis 2, suggesting that voice-based interactions between high-pitched male CSRs and low-pitched female customers result in lower level of customer satisfaction, is affirmed.

Formally,

If $F0Fcu \leq 190 \text{ Hz}$ and $F0Mcs \geq 120 \text{ Hz}$, then $SRFcu = \text{under-rated}$

where

$F0Mcs$ is the Fundamental voice pitch of the Male CSR

$F0Fcu$ is the Fundamental voice pitch of the Female Customer

$SRFcu$ is the Satisfaction Rate of the Female Customer

Speech rates also contributed to customer service perception. Voice-based interactions between male CSRs with rapid speech rates and female customers with lower speech rates led to dissatisfaction amongst female customers. Therefore, Hypothesis 3, by which speech rate affects customer satisfaction, is affirmed.

Formally,

If $SRFcu < SR$ and $SRMcs \geq SR$, then the probability of under-rated $SRFcu$ increases

where

$SRFcu$ is the Speech Rate of the Female Customer

SRMcs is the Speech Rate of the Male CSR

SR is the Average Speech Rate

SRFcu is the Satisfaction Rate of the Female Customer

In voice-based interactions between female CSRs and female customers, the average silence rate was lower than other gender combinations (17.9% compared to 24.9%), and the average duration of interactions was shorter than in other combinations (3.21 minutes per call compared to 3.36 minutes). This information might indicate greater efficiency in female-to-female interactions (see results in Table 3). Nonetheless, no conclusive indications supporting improvement of customer satisfaction by call possession, as suggested by Hypothesis 4, were found.

Table 3. Silence rates in interactions by gender groups

	<i>Group A (M-M)</i>	<i>Group B (M-F)</i>	<i>Group C (F-M)</i>	<i>Group D (F-F)</i>
	30.0%	16.1%	10.9%	19.6%
	43.0%	13.5%	37.7%	20.0%
	21.0%	36.8%	55.3%	18.8%
	31.4%	33.5%	23.9%	21.0%
	6.4%	12.1%	42.1%	21.8%
	26.0%	47.9%	30.7%	27.1%
	7.4%	20.2%	19.5%	21.0%
	32.8%	1.6%	11.3%	16.3%
	8.0%	23.7%	13.5%	9.4%
	35.5%	25.4%	28.3%	3.6%
Mean	24.2%	23.1%	27.3%	17.9%
S.D.	0.130	0.135	0.146	0.067

Key (CSR-customer): M-M = Male to Male, M-F = Male to Female, F-M = Female to Male, F-F = Female to Female.

Since the sample is statistically small, groups M-M, M-F, and F-M were agglomerated and compared to group F-F. The aggregated standard deviation of the conjoined group is 0.134, where the standard deviation of group F-F is 0.067. The results of the t-test indicate that the silence rate in all-female interactions is significantly lower than all the other forms of gender interactions, as shown in Table 4.

Table 4. Standard deviation difference test between the average silence rate for Group F-F and Groups M-M, M-F, and F-M

	<i>Groups M-M, M-F, F-M</i>	<i>Group F-F</i>		<i>F</i>	<i>Two-tailed T-test</i>
Mean	24.9%	17.9%		5.890	.038
S.D.	0.134	0.067			

Key (CSR-customer): M-M = Male to Male, M-F = Male to Female, F-M = Female to Male, F-F = Female to Female.

In interactions between female CSRs and male customers, male customers provided good ratings to female CSRs who spoke in a clear or semi-clear voice, whereas female CSRs who spoke loudly using a high-amplitude voice were poorly rated. In interactions between female CSRs and female customers, female customers provided poor ratings to female CSRs who had a low-level voice amplitude combined with a low voice pitch. The findings affirm Hypothesis 5, by which voice amplitude of CSRs, as well as gender differences between them and the customers, influence satisfaction.

The focus group session that followed the auditory observation, intended as a triangulation process to cross-check the interpretation of the auditory observations and strengthen the research reliability, was rather unexpected in its results. The CSRs were usually defensive about their own professional positions, perhaps due to job security concerns. When they were asked to evaluate the quality of service that they provided to customers, they ranked their performance highly, leaving very little room for self-criticism. This might be a case of the *Johari window effect*, in which the CSRs suffer from a “blind spot” and therefore provide an imbalanced self-assessment in comparison to feedback from their official and professional surroundings (Wright, 2016: 139-143).

When the focus group turned towards a more general and open discussion, participants became more cooperative and less biased. They considered the following parameters as key attributes to positively affect conversation results: “professional attitude,” “service-oriented approach,” “well-developed service language,” and “team spirit.” They also mention verbal elements that might negatively affect the conversation results: “indifferent,” “apathetic,” “non-caring” voices, as opposed to “keeping the conversation alive.”

Therefore, the CSRs’ biased rankings of the call results were excluded from the analysis to exclude biases. Nonetheless, several important aspects were raised by the focus group participants and, to some extent, contributed to the understanding the impact of voice dynamics on interaction results.

DISCUSSION

The customers’ personal experience is an important factor to enhance customer satisfaction and loyalty, which in turn are positively correlated with the extent to which customers trust organizations (Ribeiro and Rodrigues, 2021). Recent technological trends in the field of consumer behavior have focused on intuitive judgment and perception biases by employing speech and voice technologies. Additionally, Big Data technologies and proprietary data owned by large corporations have created multiple opportunities to explore the relationships between voice and speech attributes and customer experience in the context of voice-based call center interactions.

The results of the study largely reflect the notion that “voices are socially significant... it would be strange indeed if the voice was not subject to socially motivated adaptations” (Graddol and Swann, 1991: 26-27), illuminating the important domain of the human voice within the new social aspects of customer experience.

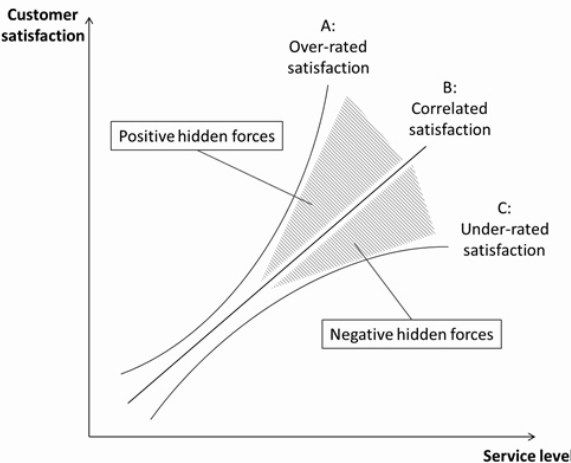
The findings of this study reveal that customer experience may be affected by the relative values of voice pitch between the CSR and the customer. Relatively high-pitched female customers have positive perceptions of male CSRs who have a fundamental voice pitch of at least 80 Hz lower than their own voice, thereby affirming Hypothesis 1, while high-pitched male CSRs are not perceived as likable by relatively low-pitched female customers. A male’s relative fundamental pitch is relevant to female perceptions of the quality of service provided to her, as relatively high-pitched male CSRs (fundamental pitch of 120Hz or higher) are not perceived as likable by relatively low-pitched female customers (fundamental pitch of 190 Hz or lower), thereupon affirming Hypothesis 2.

These findings do not only align with other studies, as mentioned above, but also provide a new and unique view on the perceived quality of services, in which differences in the fundamental voice pitches of the participants in service interactions positively or negatively affect the experience and satisfaction of customers.

The impact of a female’s fundamental voice pitch on a male perception remains questionable in our study, as in former studies. On the one hand, Weiss et al. (2021) indicate that a “dark,” low pitch is more positively accepted by males. On the other hand, Aung et al. (2021) and Siegert and Niebuhr (2021) argue that males are more attracted to a female with high voice pitch. Cussigh et al. (2020) attempt to resolve this conflict by accommodating both options: Women’s high pitch is perceived more attractive by men, but at the same time, women’s low voice pitch is perceived as being more dominant by men. This case is supported by anecdotal evidence from Margaret Thatcher’s regime, whose communication advisers testified that in her early days, they aggressively trained Thatcher’s voice pitch, managing to reduce her voice pitch by 46 Hz in order to gain an image of a powerful, competent, and more electable politician (Graddol and Swann, 1991; Klofstad et al., 2012; Wang et al., 2021; Allison et al., 2022). Either way, our research clearly shows that female customers tend to use a higher fundamental pitch when they speak with male CSRs (201 Hz on average) rather than with female CSRs (184 Hz on average). This might involve the adaptation of voice features of female customers by altering their voices when they speak to a male CSR. This assumption is consistent with Vukovic et al. (2010), who indicate that women adapt their own voice pitch, a pattern that was positively associated with their preference for low-pitched men (i.e. when women were attracted to low-pitched men, they raised their own voice pitch). Although the voice is created in a complex manner through physical and biological mechanisms that are beyond voluntary control, social adaptations can be made. With regard to voice resonance attributes, there was no pattern found between resonance frequency values and customer satisfaction rate. Moreover, as far as speech is concerned, the primary finding of our research reveals that when fast-talking male CSRs interact with slow-talking female customers, the female customers felt uncomfortable and frustrated. This finding suggests that comfort and discomfort in service interactions are not derived from absolute values of speech rate, but from relative ones, thereby affirming Hypothesis 3. Communicating around average values of speech rate usually makes the speaker feel comfortable. However, if the conversational partner does not speak in a similar speech rate, this rule is not valid and adjustments in speech rate must be made (this finding is also supported by Saberi et al., 2017). As the results of this study indicate, voice amplitude and clarity play a significant role in customer satisfaction, hereupon affirming Hypothesis 5.

In effect, all the five hypotheses were affirmed, and the research main goal - to explore significant attributes in voice-based interactions that create hidden impact between the interaction’s participants - was fully addressed and positively answered, as explained in the following proposed model.

Figure 4. A hidden forces model of customer satisfaction as a function of actual service level



Based on the insights derived from the findings of the study, a model that illustrates customer satisfaction as a function of the actual service level is proposed (see Figure 4). The model suggests that the actual service level and customer satisfaction are not always fully correlated. Hidden and irrational forces may affect this link during voice-based interactions, resulting in a curved, rather than a linear, satisfaction rate. The linear line (curve B) shows rational behavior, where customer satisfaction is fully correlated with the service level provided by the CSR. Positive hidden forces can potentially curve upwards the line and create improved customer satisfaction, even when the service level is not ideal (curve A). Negative hidden forces can potentially curve downwards the line and degrade customer satisfaction, even when the service level is good (curve C). The gray zones reflect areas of opportunity, where actions must be taken either in strengthening existing patterns or in correcting procedures.

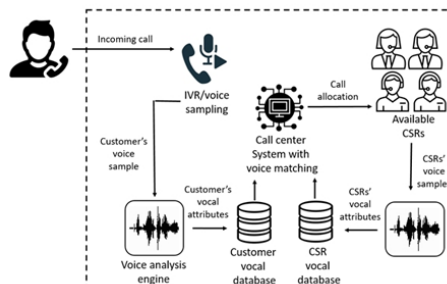
VOICE MATCHING ARCHITECTURE FOR CALL CENTERS AND SERVICE DEPARTMENTS

The results of the research indicate the significant and positive effects of voice matching between the voices of customers and those of CSRs that communicate with them. Further, the results present the attributes of customer-CSR matching that foster higher levels of perceived service quality and satisfaction among customers.

Following the findings of the research, we propose an IT architecture for call centers that forwards incoming customer calls to available CSRs based on the vocal attributes of the caller and the potential respondents (other IT architectures were introduced in the past by Al-Kharusi et al., 2018 and Masuda et al., 2021). The architecture is based on the following operations that underlie the customer-CSR voice matching process:

- 1) A database of CSR voice attributes – The voices of all CSRs will be sampled and analyzed to extract their vocal attributes.
- 2) Retrieval of a voice sample from the customer – For example, customers will be requested to pronounce their ID, use an interactive voice response (IVR), etc. The customer's voice sample will be analyzed, and its vocal attributes will be associated with the caller's phone number as an identifier.
- 3) A dynamic dataset of available CSRs is a part of the call center system and is continuously updated when a representative is engaged in a new call or disconnects it.
- 4) A voice-matching module that compares the gender and the attributes of the caller with those of available CSRs and allocates the call to the CSR with the best vocal match with the customer's voice.

Figure 5. A customer-representative voice matching architecture



Implementation of a voice-matching module that is based on the findings of this research requires use of voice analysis tools and integration to the call center's allocation system. However, similar integrations were already carried out on a larger scale where matching between the customer's data, obtained from the CRM, and the skills of CSRs, stored in the HR system, is needed for better allocation of calls and enhanced service provision. Thereupon, the vocal attributes of both customers and CSRs can be gathered and stored in a similar manner in the organization's database.

CONCLUSIONS

The study aims to identify voice and speech attributes that affect (positively or negatively) customer satisfaction levels; the results can be utilized by service providers to enhance the service quality and the performance of call center employees, as well as their level of satisfaction. The research methodology is based on a qualitative survey through which real-world data has been collected from a call center (auditory observation), with the triangulation of this data with that of a focus group session.

Former academic studies have investigated voice and speech profiles with reference to human behavior in terms of gender attractiveness and human dominance (Puts, 2004; Puts et al., 2006; and more recently Schmitt and Fuss, 2018 and Ponseti et al., 2022). While all these studies contributed to the development of the field of sociobiology, the role and effects of voice within the relatively complex contexts of service interactions have been generally overlooked.

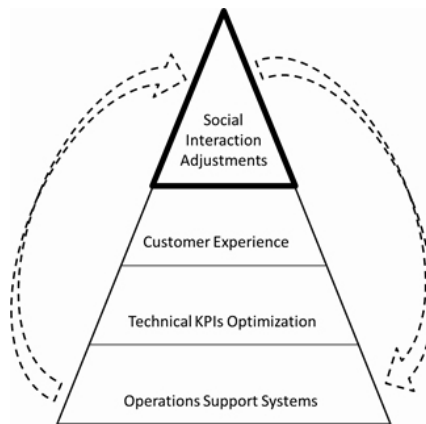
This study shows that voice fundamental pitch, speech rate, voice amplitude, and other communication parameters might deploy hidden power and affect service interaction's results. It enlightens the various effects in different gender settings, as follows: First, high-pitched female customers (fundamental pitch of 200Hz or higher) show improved customer satisfaction rate in interactions with low pitched male CSRs (with at least 80Hz difference in pitch range), hence confirming Hypothesis 1. Second, high pitched male CSRs (with fundamental pitch of 120Hz or higher) bring about poor customer satisfaction by relatively low-pitched female customers (fundamental pitch of 190Hz or lower), thereby confirming Hypothesis 2. Third, speech rate affects customer satisfaction, e.g., rapid speech rate of CSRs leads to dissatisfaction amongst female customers with a lower speech rate, hence confirming Hypothesis 3. Moreover, differences in speech rate between customers and CSRs affect customer satisfaction. Fourth, Hypothesis 4 examining how call possession rate affects customer satisfaction was found inclusive. Fifth, voice amplitude and clarity affect customer satisfaction, thereby affirming Hypothesis 5.

The theoretical and practical contribution and implications of this study are that it opens a new venue for research on the new dimension of social interaction adjustment, i.e., the social effects of voice from *both sides* of the interaction: from the CSR's perspective and from the customer's standpoint. It examines the *relative* impact on each participant in this sort of interaction. The research also contributes a new dimension to understanding the service perception of customers, i.e., the hidden information in CSR-customer interactions, related to voice and speech dynamics. This layer affects customer experience, positively or negatively, and provides an opportunity to adjust the interaction between the CSR and the customer in order to improve the customer experience and, consequently, attain better service perception rates. Some of the adjustments (such as speech rate) require updated operational guidelines coupled with CSR training. These findings support the conclusions of prior studies by Ben David and Icht (2016) and by Anand and Bottalico (2021) that recommend vocal training for CSRs to sustain their vocal properties over time, as changes in their voices and professional performance are evident over the workday. Additionally, the findings support the need for vocal CSR training to facilitate leadership among CSRs and to prevent burnout, as discussed by Luria, Gal, and Yagil (2015) and by Huang et al. (2022). Other adjustments (such as voice fundamental pitch) can be applied via voice-manipulation software applications (of course, after considering ethics implications).

Purely management wise, this research contributes a new dimension in understanding the service management domain, beyond its current three layers that play key factors for optimal customer

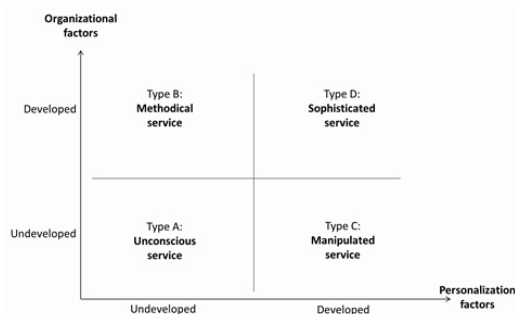
service – operations support systems, technical KPI BI, and customer experience tools – as mentioned by Böhmann et al. (2018). The new fourth dimension that this research suggests is *The Social Interaction Adjustment* layer, as described in Figure 6. This dimension contains the interactional hidden information - related to voice and speech dynamics - that might affect customer experience, positively or negatively. It provides the opportunity to make personal adjustments between the CSR and the customer in order to improve the call center perception in terms of customer satisfaction and conversion rates.

Figure 6. New dimension in customer service and the consequent customer satisfaction



Moreover, the new dimension of Social Interaction Adjustments affects all the layers of the pyramid that are below. It requires updating of customer experience procedures through training, applying new value-added services, adopting new service policies, re-optimization and re-monitoring of KPIs. Furthermore, in these times of hyper-competition, and where voice service applications are taking place massively, voice sentiment is becoming crucial as a key success factor, whether the CSR is human or a bot. The following model (see Figure 7) suggests a map of various service organizations as a function of their operative service orientation. It consists of Y axis that represents the organizational service orientation factors, involving routines, trainings, strategy and technology, and X axis that represents the service personalization level, involving awareness to voice and speech impacts.

Figure 7. Positioning map of service orientation by organization type



This model identifies four types of organizations: Type A represents an organization which is unaware of its customers' surroundings and does not develop its CSRs' professional capabilities either organizationally or individually. This kind of service might be called *Unconscious*. Type B represents organizations that manage their service 'by the book' - *Methodical*. They maintain cultural and operational procedures in order to provide a high quality of customer service through CSRs training, monitoring and technological development, i.e., knowledge management, service-oriented attitude, and language practicing. Type C is a quite rare option since the organization does not take any responsibility for the service quality, so the CSRs aim at creating an un-frustrating environment for the customers. It can be done by using their *Manipulating* personal charm in order to ease the painful process that the customer experiences. Type D is the ultimate ideal service in which both organizational operational support and customer personalization awareness are involved, and they together provide *Sophisticated* service which necessary means to make the customer experience successful. Managers must take the opportunity to become a Type D service organization, while strengthening *positive hidden forces* and mitigating *negative hidden forces* as indicated earlier.

Potential new implementations in organizations resulting from this research might be as follows:

- Real-time automatic matchup router for incoming service calls: analyzing the caller voice profile and routing the call to the most suitable CSR.
- Real-time voice pitch adjustment equalizer: after analyzing the caller voice profile. Suitable also for bots.
- Real-time speech rate rhythms which indicates to the CSR to adjust the speech rate according to the caller's speech rate.
- Real-time recommendations' popup notices for the CSRs' attention: for speech rate, voice amplitude, voice clarity, and call possession/dominance adjustments.

The benefits of applications analyzing the attributes of caller voices were recently acknowledged in healthcare (Heapy et al., 2017; Lamanna et al., 2019). The research provides managerial insights to improve the selection and allocation of CSRs and salespersons on the basis of their vocal attributes and patterns. Practices in which customers reach organizational units within companies, describe their needs or provide personal details (such as ID number) by vocal instructions that are processed by voice-identifying systems become increasingly popular. Thereupon, customer voices can be seamlessly sampled to measure their attributes. Customers will automatically be transferred to a CSR whose voice can provide the best match to the customer's voice in terms of the perceived experience and quality service, as shown in our research.

The emergence of vocal chatbots and virtual assistants, such as Apple's Siri, Google's Assistant, and Amazon's Alexa, suggests that vocal customer interactions based on Artificial Intelligence (AI) will be broadly adopted by companies, due to the scalability and cost-saving benefits that these technologies offer. Nonetheless, at present, vocal chatbots and virtual assistants interact by standard, semi-mechanical voices that negatively affect the experience of users and even foster some of them to seek interaction with human CSRs. Our study offers insights for developing the next generations of vocal chatbots and virtual assistants, in which the voice attributes of the interactive systems can be adjusted and customized to the voice of their human users to provide a satisfactory and convenient man-machine dialogue.

Further research should examine the effects of varying the spectral range of the CSR's and customer's pitch frequencies since this study only refers to average values. Varying voice intensity (volume) during voice-based interactions might provide a new understanding beyond our measured average values. The analysis of peak-fundamental frequency and off-peak-fundamental frequency during voice-based interactions may also be a potential area for future research.

In addition, former studies are in conflict regarding whether rapid speech rates of male CSRs result in the discomfort of slower female customers or contributes to the image of the CSR as reliable and truthful (Saberi et al., 2017). Thus, there is room to explain this mismatch in future studies.

A major challenge for further research and future studies is gaining access to real-world voice recordings for training purposes. Since heavy privacy limitations are involved, those bodies who own this data might concern and consider not co-operating. However, the implementation of voice analysis tools and a voice-matching module that is based on the findings of this study as a part of the call center systems in enterprises and organizations, as presented in the proposed architecture, can significantly improve the service perception and the satisfaction of their customers.

RESEARCH LIMITATIONS

The research population of CSRs and customers is based on the sample used, as the studied organization provided only a very limited access to its CRM system and to its voice recordings, due to legal constraints. Yet, the research aims to explore the broader view of voice sentiment through multiple qualitative methods from various angles, among which the survey sample is one of them, by using method triangulation. Method triangulation assists in reaching possible explanations about the ways in which voice attributes may affect customer experience. This analysis, among other methods brought in this paper, can be expanded via further research in organizations that provide access to larger samples of CRM data and voice records.

The respondents were acquired in a single country. Expanding the study to multiple countries can identify similarities or changes in the patterns of voice-based interactions that result from cultural or lingual differences.

ACKNOWLEDGMENT

Y.D.'s gratitude goes to the Middlesex University London that hosted this research in its practitioner research doctorate programme.

The authors acknowledge that the research meets the ethical guidelines stated by their institutes.

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Yigal David has been acting for more than two decades in several VP and CEO positions in various Israeli mobile telecom corporates. He is specialized in corporate strategy and product development, and well connected in the local market. Yigal holds a Doctorate degree and MBA, both from Middlesex University London, and BSc degree from Shenkar Institute for Engineering & Design in Israel. Today, he is a faculty member and a lecturer in the School of Industrial Engineering at Shenkar. His research interests include Entrepreneurial Innovation and Product Development, Emerging Technologies, Voice Sentiment Analysis and Consumer Behaviour.

Elad Harison is the former Head of the Department of Industrial Engineering and Management at the Shenkar College of Engineering and Design, Israel. He specializes in the Economics of innovation and technical change in the context of information technologies. Dr. Harison received his Ph.D. from the University of Maastricht, was a Marie Curie research fellow at the Copenhagen Business School and a faculty member at the University of Groningen, before his current affiliation in Israel. Dr. Harison published in journals such as Information and Management, Research Policy, Journal of Information Technology and Economics of Innovation and New Technology, among others.