How Voice Can Change Customer Satisfaction: A Comparative Analysis between E-Commerce and Voice Commerce

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Abstract. Voice commerce is a newly evolving e-commerce channel where consumers communicate with dedicated systems on smart speakers or other devices using their voice, in order to find products. This paper comparatively investigates factors for customers' satisfaction in voice commerce and e-commerce. Being the first study to scientifically analyze customer satisfaction factors in voice commerce and compare them with e-commerce, we conducted a survey with 178 consumers and used structural equation modeling for statistical hypotheses testing. The results show, that consumers have higher expectations in convenience for voice commerce than they have for e-commerce. Transaction process efficiency significantly influences satisfaction in voice commerce, but not in e-commerce. This research provides implications for future research on voice commerce strategy and system design.

Keywords: Voice Commerce, E-Commerce, Conversational Agent, Recommender Systems, Customer Satisfaction

1 Introduction

Since their introduction in 2014, the use of intelligent virtual assistants based on smart speakers like Amazon Alexa, Apple HomePod, Microsoft Cortana and Google Home is increasing [1]. Moar [2] estimates that there are currently 450 million voice assistant devices in the US, expected to reach 870 million by 2020. These systems make it possible to conduct a "zero-click" purchase in business to consumer (B2C) commerce scenarios. Communicating with the assistant using only their voice, consumers can formulate search queries and confirm purchase actions without the need to use common visual or typing interfaces. Electronic Commerce (e-commerce) experts label this scenario "voice commerce" and expect it to be one of the most important innovations to shape the next years of e-commerce development (e.g., [3-4]). E-commerce describes commerce conducted over electronic media, such as the use of the internet to facilitate and process business transactions [5]. Voice commerce as a subset of e-commerce provides consumers with computerized voice technologies

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(e.g., speech recognition, voice identification, and text-to-speech) to execute these business transactions [6]. These systems involve natural language processing (NLP), intent recognition, speech synthesis, recommender systems and artificial intelligence (AI) technologies (e.g., [3],[5]).

Despite a long-standing research interest in customer satisfaction and loyalty factors for e-commerce applications (e.g., [6-7]) as well as on e-commerce using conversational text-based interfaces (e.g., [10]), specific research on e-commerce in a human-to-AI voice-based scenario is, however, sparse. Research related to customer satisfaction factors in voice commerce is entirely missing from current literature, as well as research aiming at possible differences in customer satisfaction factors (CSF) between e-commerce and voice commerce. Similar to mobile commerce (m-commerce) in comparison to e-commerce, voice commerce is subject to special restrictions and presents different opportunities and value proposition to customers. Therefore, it is likely that satisfactory factors for voice commerce might differ from those of e-commerce both in existence and importance.

To support voice commerce software design and implementation, managers need to know which factors influence customer satisfaction. While many CSF for e-commerce applications are known, it is difficult to ascertain factors for voice commerce from current literature. Therefore, our research question is:

RQ: *How do the influencing factors for customer satisfaction differ in voice and e-commerce?*

To identify customer satisfaction factors for voice commerce, we first review research related literature. Based on this review, we develop our research models regarding customer satisfaction and its predictors, consisting of four comparative hypotheses (cf., [11]). Following this, we describe our research design and methodology to empirically validate our models for both e-commerce and voice commerce. Afterwards, we analyze the data gathered by a survey using structural equation modeling and present our findings. Finally, the paper discusses theoretical and practical implications for management as well as presents limitations and gives directions for future research opportunities.

2 Theoretical Background and Hypotheses Development

E-commerce describes commerce conducted over electronic media. For example, Kwon and Sadeh [5] define e-commerce as the use of the internet to facilitate, execute, and process business transactions. However, in science the term is mainly used for electronic commerce conducted via computers and laptops, as opposed to mobile devices (e.g., [5]), although these devices also use the internet. Researchers label the latter scenario mobile commerce or m-commerce [12], defined as a subset of all e-commerce transactions [5].

One subset of e-commerce is conversational commerce utilizing neuro-linguistic programming (NLP) (e.g., [13]). Such interfaces can be either text-messaging or voice recognition systems [14]. One form of conversational commerce are commercial chatbots (e.g., [15]). The actual interaction is text-based, in which both human and machine generate written text to convey information [16]. Some commercial chatbots can also display product images and other visual information [17]. Animated or embodied agents (sometimes also called avatars) are conversational systems that provide a visual representation of the virtual agent in addition to a text or speech interface [13, 18]. Luger and Sellen [3] use the term conversational agent for an emergent form of dialogue system that is becoming increasingly embedded in personal technologies and devices. Galanxhi and Nah [6] define voice commerce as e-commerce involving computerized voice technologies: speech recognition, voice identification, and text-to-speech. In our context, we define voice commerce as a subset of e-commerce providing consumers with computerized voice technologies to facilitate, execute, and process business transactions (e.g. [6]).

2.1 Recommendation Complexity

Conversational recommender systems, like voice commerce and chatbots, converse with users to learn their preferences and incorporate feedback from users (e.g., [19]). Liang et al. [20] found that recommendation accuracy of these systems is positively linked to customer satisfaction. Xiao and Benbasat [21] point out that recommender systems can decrease the information overload facing consumers, as well as the complexity of online searches. For e-commerce applications, Xiao and Benbasat [21] investigate the usage of recommendation agents and created a complex interactive model of recommendation effectiveness, were product type and complexity play significant roles.

Recent research provides limitations for voice commerce using only auditory interfaces. The cognitive cost-benefit framework [22] predicts that consumers search less as media richness decreases because of higher cognitive effort for searches in low media richness environments [23]. E-commerce, due to its higher media richness and visual/text efficiency, usually presents a larger evaluation set [24]. Research by Maity and Dass [23] shows a negative impact of an "overwhelming amount of information" in low media richness channels, like voice commerce, compared to high media richness channels such as e-commerce and physical stores. This can also be applied to the presentation of recommendations, which are usually presented in the form of result lists, similar to normal search results [25]. However, to avoid exceeding user's information capacity and to reduce the time spent by a consumer to listen to recommendations, the complexity of recommendations in voice commerce can be reduced intentionally. Recommendation complexity can be subdivided into quantity of product recommendations and complexity of a single product presentation (i.e., the length and level of detail of the product description). Possibly, consumers appreciate more options than just a single one. In essence, these considerations lead to the assumption that voice commerce only supports a lower customer decision complexity. Therefore, we hypothesize:

Hypothesis 1 (H1): *Recommendation complexity has a larger effect on customer satisfaction in e-commerce than in voice commerce.*

2.2 Recommendation Personalization

In most current e-commerce platforms, search engines use recommendation features and personalize results for the consumer and also enrich them with data from social media [26]. Personalized recommendations are known to increase customer satisfaction and conversion rates, and to lower the size of the evaluation set [26-27]. The use of personalized recommendation agents generally reduces the number of products for which users want to retrieve detailed information [29]. Users of digital assistants expect a highly personalized system, as Chopra and Chivukula [4] report for Indian consumers.

If voice commerce benefits from a lower recommendation complexity, it implies a greater need for highly accurate recommendations, of which personalization is a main factor. A buying decision becomes easier if the user herself has made that same decision before, or if the system can draw upon preferences it knows about the user. Product-wise, customers are less likely to purchase high-involvement goods like a television or a dishwasher via voice commerce because of informational complexity involved. In contrast, it is more likely that customers have a tendency to purchase low involvement goods, as indicated by Maity and Dass [23] that customers are likely to undertake simple decision-making tasks on channels that incorporate low levels of media richness. Additionally, customers have a tendency to buy goods they have bought before. Personalization in recommendations can also be based on inferred or mentioned preferences from previous user-machine dialogue [30] or even based on learned body measurements (e.g., for clothing). Therefore, we hypothesize:

Hypothesis 2 (H2): *Personalized recommendations have a larger effect on customer satisfaction in voice commerce than in e-commerce.*

2.3 Convenience

Convenience is one of the most prominent CSF in e-commerce (e.g., [30-31]). Choi et al. [33] define convenience as the degree to which a person believes that navigating or engaging in transactions through e- or m-commerce is free of effort. Further they subdivide convenience into ease of use, ease of access, ease of understanding, usefulness and functionality [33].

A study by Chai et al. [34] found that most users preferred a commercial chatbot interface over a classic search interface as they liked the idea that they can express their needs in their language without being restricted to menu choices and that the computer does all the work for them [34]. For voice-based interfaces, Luger and Sellen [3] report that the principle use-case for the CA (conversational agent) was “hands free”, which was tied strongly to the theme of time-saving and convenience. This fits well to the previously mentioned idea that audio interfaces facilitate multi-tasking [35]. The efficiency and easiness of speech input is a value proposition that also plays a role. According to Luger and Sellen (2016), customers feel it is often easier and more convenient to use speech input than to type, one reason being that speech was felt to be faster. In their comparative studies, Choi et al. [33] and Cao et al. [12] found customers scored convenience higher for m-commerce than for compared to e-commerce. Since voice commerce should rank lower than e-commerce in media richness, convenience should be of greater importance. We hypothesize that customers have higher convenience expectations of voice commerce than of e-commerce:

Hypothesis 3 (H3): *Convenience has a larger effect on customer satisfaction in voice commerce than in e-commerce.*

2.4 Transaction Process Efficiency

Transaction time is a known CSF in e-commerce research (e.g., [36-37]). For example, Devaraj et al. [36] found that subjectively, excess time spent in the transaction process decreases satisfaction in e-commerce, whether it is spend on communication, searching and choosing or payment. Choi et al. [33] define the e-commerce CSF of "transaction process" as a combination of efficiency, total transaction time, clearness of the process and response time for each step. Their results show that these performance indicators very significantly in influencing satisfaction of different types of e-commerce.

Chatbot users frequently mention a high performance expectation, with subcategories of fast, efficient, and reliable [38]. Users expressed that the use of chatbot systems should reduce interaction time and increase efficiency [34]. In this context, they define efficiency as the number of clicks and the amount of time required obtaining the relevant information. By investigating task-oriented spoken dialog systems, Walker et al. [39] also found that a significant satisfaction factor is user's perception of elapsed time. According to research on users of current generation conversational agents, timesaving was a key related motivation to use these systems [3]. Therefore, we hypothesize:

Hypothesis 4 (H4): *An efficient transaction process has a larger effect on customer satisfaction in voice commerce than in e-commerce.*

3 Research Methodology

We conducted focus groups with e-commerce experts of an e-commerce consulting company in order to verify the importance of the listed constructs above (i.e., Recommendation Complexity, Recommendation Personalization, Convenience, and Transaction Process Efficiency).

To empirically test the proposed hypotheses, a survey was executed with the help of the crowd-sourcing platform Amazon Mechanical Turk (MTurk). Our questionnaire[1] consists of 39 questions, of which 13 serve demographical, 26 are related to the identified CSF and reflected both research models on e-commerce and voice commerce. Respondents have to answer the items for both types of commerce. We derived the questions for convenience from a study by Choi et al. [33] (e.g., "Ordering products **on websites**/*with my voice* is easy.", whereas the bold phrase represents the e-commerce and the italic characterizes the voice commerce construct).

[1] A comprehensive table of the measurement items can be accessed here: https://www.dropbox.com/s/ahovk0cfgcgihg5/Appendix_Studentstrack.pdf?dl=0

The measures for the construct transaction process efficiency are also adapted from Choi et al. [33] (e.g., "When ordering products on **a website**/*with my voice*, the process should take as little steps as possible."). Recommendation personalization as a construct was used by Komiak and Benbasat [28]. For example, we took items as "When ordering products on **a website**/*with my voice*, I benefit from product recommendations based on what I ordered before". Further, we adapted items for recommendation complexity (e.g., "When ordering products on **a website**/*with my voice*, I benefit from very detailed product recommendations.") based on product complexity in recommender systems [21]. Customer satisfaction was measured with items, such as "I am generally satisfied when ordering products **on websites**/*with my voice*." adapted from Chang and Chen [40]. To eliminate wording inconsistencies or comprehension problems we ran an independent pre-test with some participants, who were then excluded from the main survey [41].

The survey was restricted to only those US residents who have been consumers of both voice commerce and e-commerce systems in the previous three months. Therefore, we filtered out inappropriate participants before we conducted the main study. In a total 178 people answered the survey completely. Out of these 178, 53.9% were women and 44.9% men (1.1% did not give any information). The age distribution was: 25-44 years (70.2%), 18-24 years (17.4%), 45-64 years (9.6%), and 65 years and older (2.8%).

4 Data Analysis

In order to analyze the proposed research model and to validate the proposed hypotheses, the model has been transferred into a structural equation model [42]. For this examination the software IBM AMOS 21.0 was used to determine path influences. The suggested ratio of sample size to number of free parameters of 10:1, in order to reach trustworthiness, is fulfilled [43, 44].

4.1 Measurement Models

To begin with further data analysis, we calculated Cronbach's alpha to assess the internal consistency and reliability of the sub-scales. In the first iteration, some items showed low item-total correlation. All values calculated exceeded the recommended minimum value of 0.6, which indicated that the constructs show a high level of reliability [45, 46] (see Table 1).

We carried out a principal component analysis to identify component fit. Furthermore, we applied main component analysis as extraction method and Varimax (as our employed factors are not correlated) as rotation method (Kaiser-Normalization, convergence after 6 iterations). The model with four components fits well with an average loading of 0.82 and no cross loadings above 0.43, also indicating convergent validity. By calculation, the four factors account for 73.6 % of the total variance. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.68 and 0.69, representing a relatively good factor fit by exceeding the threshold value of 0.5 [47]. Bartlett's test of sphericity was significant ($p < .001$), indicating that correlations between items were sufficiently large for performing a factor analysis (compare table 2).

Table 1. Evidence of reliability

Model	*Construct*	*Items*	*Cronbach's alpha*
eCom	Convenience (EC)	3	0.62
	Recommendation personalization (ERP)	2	0.84
	Recommendation complexity (ERC)	2	0.72
	Transaction process efficiency (ETP)	2	0.62
vCom	Convenience (VC)	3	0.80
	Recommendation personalization (VRP)	2	0.83
	Recommendation complexity (VRC)	2	0.80
	Transaction process efficiency (VTP)	2	0.68

Table 2. KMO and Bartlett tests

Model	*Test*	*Indicator*	*Value*
eCom	KMO	Measure of sample suitability	0.68
	Bartlett	Approximate chi-square	425.461
		df	36
		Significance	< 0.001
vCom	KMO	Measure of sample suitability	0.69
	Bartlett	Approximate chi-square	634.8
		df	36
		Significance	< 0.001

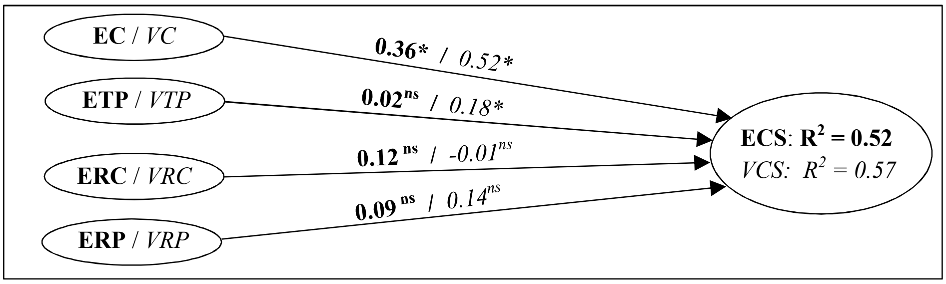
Tables 3 shows the factor correlation matrices for both models including composite reliability (CR) [48]. CR is above or near 0.7, except for transaction process efficiency. The latter achieved a CR value of 0.652 in the e-commerce model. The square root of the AVE is represented by the diagonal elements in table 3. The values show that the square root is bigger than each off-diagonal element [49]. We infer that there is an acceptable and logical extent of discriminant validity in the measurement model for all constructs.

Table 3. Factor correlation matrix

Model	*Construct*	*CR*	*ERP*	*EC*	*ERC*	*ETP*
eCom	ERP	0.835	**0.847**			
	EC	0.693	0.025	**0.659**		
	ERC	0.790	0.620	0.061	**0.816**	
	ETP	0.652	0.202	0.497	0.074	**0.699**
Model	*Construct*	*CR*	*VRP*	*VC*	*VRC*	*VTP*
vCom	VRP	0.838	**0.850**			
	VC	0.809	0.260	**0.766**		
	VRC	0.813	0.653	0.321	**0.829**	
	VTP	0.697	0.347	0.272	0.067	**0.735**

4.2 Structural Models

We created two structural models and performed an initial factor estimation using the maximum-likelihood method (see Figure 2). Straight arrows connecting each latent construct to customer satisfaction represent unidirectional effects, annotated by the standardized path coefficient. The total variance in customer satisfaction explained by the independent variables (R^2), which reflect the predictive power of the models, is above 50% in both models (0.52 in e-commerce and 0.57 in voice commerce).



^{ns}: not significant above $p < 0.05$ level, * : significant above $p < 0.05$ level; Bold = e-commerce model, Italic = voice commerce model

Figure 2. Structural model (e-commerce and voice commerce)

Table 4 shows the results for all predictors for ECS and VCS in the model. The effect of convenience is statistically significant in both e-commerce and voice commerce. Based on the convention on interpretation of correlations by Cohen [50] and Durlak [51], we classify the effect size of convenience on satisfaction as middle (0.36) for e-commerce and large (0.52) for voice commerce. Although transaction process efficiency significantly influences satisfaction in voice commerce, it does not show significance in e-commerce. The results for the rest of the constructs were not statistically significant. Recommendation complexity influences e-commerce satisfaction positively. The effect of recommendation personalization on voice commerce satisfaction has an effect size of 0.14 and a p-value of 0.13.

Table 4. Predictors for satisfaction in e-commerce and voice commerce

Path	*Estimate*	*Beta*	*p-value*
EC ↑ECS	0.52	0.36	<0.001***
ETP ↑ ECS	0.04	0.02	0.793
ERP ↑ ECS	0.10	0.09	0.355
ERC ↑ ECS	0.13	0.12	0.228
VC ↑ VCS	0.68	0.52	<0.001***
VTP ↑ VCS	0.34	0.18	0.01*
VRP ↑ VCS	0.16	0.14	0.13
VRC ↓ VCS	-0.01	-0.01	0.896

Significance levels: * p<0.05, ** p<0.01, *** p<0.001; positive effect ↑, negative effect ↓

Table 5 shows the results for the comparative hypotheses in this approach. To assess hypotheses H1-H4, we first performed a t-test to analyze statistically significant differences between datasets. The test resulted in significant difference for all constructs. We then compared the respective path coefficients (Beta) and noted the absolute numerical difference (Delta). Whenever the difference exceeded 0.10, the hypothesis is considered as supported. Convenience significantly influences both e-commerce and voice commerce satisfaction, but clearly does so more in voice commerce. Transaction process efficiency also presents a more sizable effect for voice commerce, as predicted. However, the results present the issue that this construct significantly influences satisfaction only in voice commerce. This indicates that the concept is only relevant (or only valid) in voice commerce. We also compared coefficients that were not found to be significant. The results do not support a difference between recommendation personalization for voice and e-commerce, as the numerical delta is only 0.05. The assessment of recommendation personalization shows a delta of 0.13. Thus, both effects are not significant.

Table 5. Comparative hypotheses results

Hypothesis	*Description*	*Beta*	*Delta*	*t-test*	*Conclusion*
H1	VRC < ERC	-0.01 vs. 0.12	0.13	-5.99***	Not supported
H2	VRP > ERP	0.14 vs 0.09	0.05	-5.15***	Not supported
H3	VC > EC	0.52*** vs. 0.36***	0.16	22.55***	Supported
H4	VTP > ETP	0.18* vs. 0.02	0.16	20.55***	Not supported

Significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$; Delta = numerical difference between standardized beta coefficients

5 Discussion

The first objective of this study was to identify and understand factors of customer satisfaction for e-commerce and voice commerce systems. The second objective was to compare these effects between these two channels of e-commerce. We conducted a survey to test the research models. The results confirm one out of four hypotheses and provide some support for the conceptual models. They particularly show that convenience significantly influences customer satisfaction in both e-commerce and voice commerce, and that the effect is in fact larger in voice commerce. Results also show that transaction process efficiency, in terms of overall process speed and number of process steps, significantly influences voice commerce customer satisfaction. This was explained by higher efficiency expectations through increased efficiency of the speech interface. Further the results inferred that users prefer to browse and take their time using the e-commerce channel when compared to voice commerce. According to the results, complexity, extent and degree of detail of recommendation presentation as well as personalization of recommendations do not have a significant effect on satisfaction.

When designing voice commerce applications, developers and designers should keep in mind that convenience and efficiency expectations are higher than those towards e-commerce systems. This may lead to the following design choices: 1) The voice commerce system features increased ease of use and effortlessness over comparable e-commerce systems. 2) The process of searching and buying is designed to be as quick as possible; there are neither detours nor long dialog stages. 3) The number of steps in the process is limited to a necessary minimum. Time intensive input of address or payment data should be omitted. 4) Since a significant number of my sample uses voice commerce on mobile phones, designers should think about creating voice commerce systems for these platforms. There, visual output could be added to increase media richness and usability.

This is the first study to investigate voice commerce customer satisfaction predictors and comparing these with those of e-commerce, which adds knowledge to academic literature and will improve the understanding of the relationships between these system types. It is also one of few studies to compare two structural equation models to assess comparative hypotheses. This approach should increase reliability, because the same participants provide their input on both models.

6 Limitations and Future Research

This study is subject to several limitations, such as sample selection. We collected data from Amazon MTurk, and so reached mainly young users with high IT affinity. However, it is not representative of the general population of any country [52]. Additionally, only US users participated in the survey. While this was motivated by the higher diffusion rate of voice commerce in the US and the large absolute population size, it presents a limitation when it comes to transferability and generalization of the results.

Because voice commerce is an area currently evolving, many opportunities for future research arise. A future study could try to ascertain data from voice-exclusive scenarios for clearer insights into its intricacies and avoid intermixture systems that combine voice and visual interfaces. If however the trend of these systems gains more significance, research should focus on this area.

A dedicated, detailed study to investigate how product complexity interacts with customer buying behavior and decisions, akin to Maity and Dass [23] investigations on this topic in e-commerce, m-commerce and in-store purchasing, could generate insights on how consumers handle search and experience respectively low and high involvement goods in voice commerce. A study covering detailed customer preferences for each channel could shed light to this and similar questions, for example whether repeat purchases are more likely to take place via voice commerce and whether products bought are predominantly of low-complexity as well as which factors generally influence customers in their decision to use voice commerce over other channels.

A number of assumptions concerning recommendations could be assessed more effectively with local, hands-on laboratory settings, especially those motivated by media richness and cognitive overload. For example, in an experiment where participants actually experience the difference between very long and detailed and very short product descriptions and possible cognitive overload, results may be much more distinct than in a self-administered survey. Alternatively, real-life e-commerce environments present opportunities for experiments using A-B testing.

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