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## Conversational commerce:

### Do biased choices offered by voice assistants' technology constrain its appropriation?

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## **Conversational commerce:**

### **Do biased choices offered by voice assistants' technology constrain its appropriation?**

#### **Abstract**

Conversational commerce, which relies on algorithm-based voice assistants, is still an emerging technology that changes how consumers shop. Based on natural language processing (NLP) technology and artificial intelligence (AI) systems, consumers can now purchase products and services online by making use of voice assistants such as Google Assistant, Amazon's Alexa, and Apple's Siri. However, the economic literature and international organization reports have identified some problems with conversational commerce technology that may constrain its appropriation, demonstrating that algorithm-based voice assistants can lead to exclusionary conduct and nonoptimal choices for consumers. In that context, the research explores consumers' perception of conversational commerce and product choice offers delivered by voice assistants. The paper considers how algorithm-based voice assistants can lead to perceived biased offers and identifies different strategies that could be implemented by consumers to overcome the negative side effects of algorithms and support their appropriation. The study has strong implications for policymakers and conversational commerce platform owners.

**Keywords** – conversational commerce, voice assistant, algorithm, technology appropriation, biased choice

#### **Highlights:**

- The adoption of conversational commerce is slower than expected
- From a consumer's perspective, perceived biased offers provided by voice assistants are a key factor limiting its adoption
- Different coping strategies to overcome perceived biased offers' harmfulness are identified to support the appropriation of conversational commerce
- Proactive strategies such as making the algorithm more transparent should alleviate consumers' concerns toward conversational commerce

## 1. Introduction

Conversational commerce is defined as an interface for commerce that uses natural language (i.e., voice) (Eeuwen, 2017). As e-commerce services are developing fairly quickly (Riedel & Mulcahy, 2019; Shih, 2008; Sung, 2006; Yusuf et al., 2018; Zhang, 2019), consumers can now purchase products and services by making use of artificially intelligent (AI) voice assistants such as Google Assistant, Amazon's Alexa, and Apple's Siri. Even if conversational commerce is a key sales channel in e-commerce, experts have pointed out that conversational commerce is currently experiencing a chasm between early adopters and the early majority (Miller, 2019; Shin et al., 2018), which stresses the need to understand the factors that constrain both its adoption and appropriation from the consumer's/user's perspective.

Conversational commerce produces a shift in the decision-making process by allowing consumers in data-driven ecosystems to outsource purchasing decisions to algorithms (Stucke and Ezrachi, 2018; Gal and Elkin-Koren, 2017). In line with the research analyzing the technological threats and opportunities associated with wireless data services (du Preez & Pistorius, 2003), the previous research on interactions between consumers and technology has adopted the technology acceptance model (TAM) originally developed by Davis (1989) and the unified theory of acceptance and use of technology (UTAUT) developed by (Venkatesh et al., 2003) and extended models to analyze the benefits and potential costs of algorithm-based voice assistant technology (Fernandes & Oliveira, 2021; McLean et al., 2021; McLean & Osei-Frimpong, 2019).

Algorithm-based voice assistants are understood as having both a bright side and a dark side in their influence on consumer decision processes and choices (Ezrachi & Stucke, 2016; Gal & Elkin-Koren, 2017). The bright side perspective posits that algorithms help the user make faster decisions and more rational choices and reduce search costs (Gal & Elkin-Koren,

2017; Ursu, 2018). The contrasting dark side perspective argues that algorithms can potentially cause harm to consumers. The risk of a loss of privacy due to the increasing amount of data being processed (Dinerstein et al., 2018; Stucke & Ezechai, 2018) as well as potential harm due to the collusive behavior of algorithms with regard to prices (OECD, 2017; Stucke & Ezechai, 2018) have been well documented. Nevertheless, there is a lack of understanding regarding how algorithms lead to exclusionary conduct and nonoptimal choices for consumers. By becoming a gatekeeper to access to brands, algorithm-based voice assistants may give rise to exclusionary conduct in the form of refusing to supply or degrading brands' offers and the promotion of their own or affiliated products or services (Dinerstein et al., 2018; Gal & Elkin-Koren, 2017; Stucke & Ezechai, 2016, 2018). Such concerns about exclusion might even be a stronger issue in the case of voice assistants than search engines on online platforms because queries made through voice assistants lead to only one proposal or very few items. According to a report from Digitas (Digitas Report, 2018) based on an online survey of 557 US adults who have made a purchase using a voice assistant, 85% have purchased (on at least one occasion) the first selected option proposed by the assistant instead of the specific brand requested, and only 24% ask for more options when the voice assistant selects an option other than the item they want.

Despite the increasing use of algorithm-based voice assistants (Shin et al., 2018), conversational commerce has thus far received little attention from researchers. Except for Chesney et al. (2017) and Chopra (2019), few academic papers have been published on the conversational commerce topic, focusing instead on more traditional e-commerce and e-retailing and social commerce contexts (Bugshan & Attar, 2020; Chong, 2013; M. N. Hajli, 2014; N. Hajli & Sims, 2015; Li, 2019; Tang, 2019). The sparse discussion that exists occurs in the economic literature and among international organizations such as antitrust agencies such as the Directorate General for competition at the European Commission, the U.S.

Federal Trade Commission (FTC), the Department of Justice (DoJ) and the OECD (The Organization for Economic Co-operation and Development). Recently, a sector inquiry was launched by the European Commission in July 2020 on voice assistants and IoT markets. The preliminary report on 9 June 2021 identifies potential discriminatory and exclusionary concerns via the exploitation of algorithms by voice tech giants (European Commission, 2021)

In this context, there is a need to better understand consumers'/users' expected benefits (i.e., bright side) and costs (i.e., dark side) when using voice assistants during the purchasing process. It is also necessary to complement traditional models of technology acceptance (TAM, UTAUT) (Davis, 1989; Venkatesh et al., 2003, 2012) to gain a deeper understanding of technology appropriation in voice commerce (Kirk et al., 2015; Orlikowski, 1992).

The aim of this research is to address these gaps. First, this study proposes to understand how algorithm-based voice assistant usage can lead to perceived biased offers in a two-sided framework. The theory of the two-sided markets and network effects examined in the economic literature regarding platforms, starting with the seminal articles of Rochet and Tirole (2003, 2006), has received little attention in the management science literature. This theoretical framework is particularly relevant for providing answers to our questions on algorithm-based voice assistant bright and dark side effects. Second, this research explores consumers' perception of conversational commerce and product choice offers delivered by algorithm-based voice assistants. By developing a qualitative research approach, this study contributes to the existing literature in two ways. First, it confirms that conversational commerce may lead voice assistants to make biased proposals to consumers. Second, it identifies different strategies that could be implemented by consumers to overcome the dark side effects of algorithms to sustain their appropriation. Finally, this research outlines

important implications for policymakers and managerial impacts for voice assistant platform owners and discusses limitations and suggestions for future research.

## **2. Literature review**

The prior research has recognized the benefits and limits of conversational commerce, focusing on the time-saving decisions allowed by algorithm-based voice assistants while raising privacy and trust concerns (Chopra, 2019; Eeuwen, 2017; Vassinen, 2018). Extending the nascent literature on conversational commerce, we conceptualize conversational commerce as a two-sided market (Tirole, 2017) where sellers and consumers trade through the intermediary role of voice assistant platforms. Compared with more traditional e-commerce activities, conversational commerce gives birth to a generation of algorithm-based recommender systems based on a ranking algorithm (Ursu, 2018) that also support navigation by voice (Baizal et al., 2020), which may increase the risk of exclusionary conduct. Expanding the economic literature and international organization reports on exclusionary conduct and conversational commerce (European Commission, 2021; Gal & Elkin-Koren, 2017; Katz, 2018; OECD, 2017; Stucke & Ezechia, 2018) and adopting the voice assistant's user point of view, the current research focuses on the risk of perceived bias choices proposed by the algorithm-based voice assistant as a result of discriminatory ranking and exclusionary conduct.

### *2.1. Conversational commerce in a two-sided market*

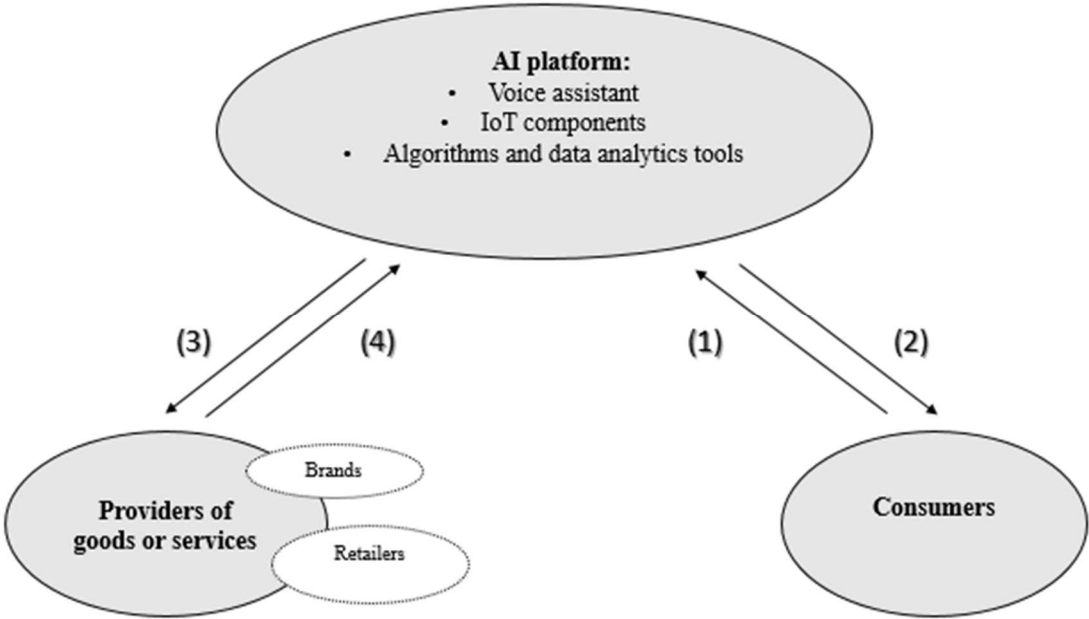
Voice assistance is a particular type of artificial intelligence (AI) platform based on machine-learning algorithms and supported by data analytics tools and the internet of things (IoT) (Cusumano et al., 2019). Voice assistants are data-based programs that require connected IoT devices or applications to implement requests (Chopra, 2019; Cremer et al.,

2017) through voice commands. IoT components are beacons, chips, and sensors that make it possible to connect home devices to smartphones or smart speakers via Bluetooth, Wi-Fi, or GPS networks (Cremer et al., 2017) (see Figure 1). Voice assistants become part of a service provisioning ecosystem defined as “the overall provision of services to users where service is defined as a set of functions offer to a user by an organization” (Farjami et al., 2000, p. 754). Branded voice assistants such as Alexa, Siri or Google Home are considered to be service providers within this environment (Baida et al., 2004). Consequently, voice assistants provide a large range of e-services (O’Grady & O’Hare, 2005). They can allow users to connect to their smart home devices or manage basic tasks such as sending or receiving email, making or receiving calls, and updating or reviewing their calendar. Voice assistants can also help consumers buy products and services as part of what is called conversational commerce (Vassinen, 2018).

Using a voice assistant as an AI platform (see Figure 1), conversational commerce opens the door to “universal accessibility of e-commerce services” (Pontelli & Son, 2003, p. 147). Conversational commerce thereby gives rise to a two-sided market (Jocevski et al., 2020) that allows consumers on the demand side and sellers (providers of goods/services/brands and/or retailers) on the supply side to meet, interact, and trade (Tirole, 2017).



**Figure 1.** Voice assistant and service provisioning in a two-sided market



Within the two-sided market, voice assistants provide real-time services for both final consumers and sellers. Building upon the information on product and service preferences, purchases and use, price sensitivity, or privacy expectations (see arrow 1 in Figure 1) provided by consumers to the AI platform, the platform delivers customized recommendations and personalized services to consumers (arrow 2) (Kwak, 2019; McCarthy et al., 2010; McLean et al., 2021). From the data-based knowledge that consumers send to sellers (arrow 3), the sellers are then able to propose to the consumers a set of products and services that fit their queries (arrow 4) (Dawar, 2018).

*2.2. Voice assistants as an algorithm-based technology*

E-commerce activities, which include conversational commerce, are built on personalized algorithm-based recommendation systems to simplify consumer purchase decisions and product sales (Soo Kim, 2011). Traditional online e-commerce buying relies on two main recommender systems: content-based filtering (CBF) (Zenebea & Norciob, 2009)

and user-collaborative filtering (CF) (Herlocker et al., 2002). CBF identifies consumer shopping preferences according to products' features that the consumer has purchased in the past to recommend similar products to the consumer (Mishra et al., 2015). To overcome the limit of recommendation nurtured by consumers' past experiences, CF, which is used by companies such as Amazon, guesses the customer's preferences by recommending products that are most likely to be purchased by a similar group (Thorat et al., 2015).

Unlike traditional e-commerce, the commodity information displayed on the conversational commerce platform is relatively limited to one or a few items. The algorithm-based voice assistant challenge is then to propose services and products of interest to customers by offering them few options. To tackle this challenge, unlike CBF and CF based on historical and similar group data behavior, conversational commerce relies on a ranking algorithm (Ursu, 2018) combined with voice command navigation through a recommender system (Baizal et al., 2020) where the consumer specifies a more or less precise query to the voice assistant. Based on this query input, the algorithm-based voice assistant calculates recommendations with ranked product proposals that may satisfy the user's personal needs (Baizal et al., 2016). As the users' queries can be generic ("find a restaurant in Paris", "buy red ballet flats"), it opens the way to product recommendations that promote affiliated brands of AI conversational platforms that may appear in the top positions in the algorithm-based voice assistant ranking (Dinerstein et al., 2018; Ursu, 2018).

### *2.3. Consumer's conversational commerce technology appropriation: the role of the bright and dark sides of algorithm-based voice assistants*

Technology appropriation is defined as the "way in which technology or technological artifacts are adopted, shaped, and then used" (Carroll et al., 2002, p. 2). Within conversational commerce usage, consumers actively interact with a voice assistant to control the technology

experience and outcomes. When users choose to use and adopt a technology, they focus not only on the technology benefits and affordances but also on the assumptions and beliefs about the potential harms the technology provides (Orlikowski, 1992). The recent literature on the use of voice assistants suggests that voice interaction has characteristics that encourage a positive consumer experience through efficiency and convenience gains (McLean & Osei-Frimpong, 2019; Stucke & Ezrachi, 2016). However, some research also suggests that negative factors, such as privacy and trust concerns (Easwara Moorthy & Vu, 2015; McLean et al., 2021), may undermine user's experience.

In our research, when using algorithm-based voice assistants during the purchasing process, consumers' expected benefits (i.e., bright side) and costs (i.e., dark side) may thus either foster or constrain conversational commerce technology appropriation.

### *2.3.1. The bright sides of the voice assistant*

Digital technologies, especially AI-enabled technologies, affect how consumers interact with sellers and retailers (Ameen et al., 2021; Grewal et al., 2018; Inman & Nikolova, 2017; Pantano et al., 2018; Teller et al., 2019). Conversational AI platforms facilitate the exchange of products and services by connecting both sides of the market – consumers/users with brands and retailers – and by allowing connections/transactions that otherwise would not occur, thereby enabling the creation of value for platform owners, brands, and retailers. AI platforms in conversational commerce create value for consumers as they help them make faster decisions, save time, and access more personalized services and products (Chopra, 2019; Eeuwen, 2017; Vassinen, 2018). This creation of value is largely due to network and data-driven effects generated by both sides of the market (Stucke & Ezrachi, 2018), which are analyzed below.

Conversational AI platforms are subject to traditional network effects that arise when either consumers or brands/retailers benefit from an increase in the number of users of a platform (Parker et al., 2016). The more popular a voice assistant, the higher the incentive will be for brands and retailers to join the platform, and *vice versa*. The more intelligent the objects or IoT components, voice apps, skills, or devices that are connected to a conversational AI platform, the greater the consumer interest will be.

In addition to these traditional network effects, conversational AI platforms are also subject to data-driven network effects, which occur when the product or the service provides personalized solutions and more targeted recommendations (Cusumano et al., 2019), as they incorporate information from the end user (i.e., present and past choices, purchases, needs and preferences, localization) through algorithms and data processing analytics tools (Parker et al., 2016; Stucke & Ezrachi, 2016, 2018).

### *2.3.2. The dark side of voice assistants and the risk to consumers of biased offers*

Network effects might also play a significant role in distorting competition, impacting rivals' products/services or brands, and harming consumers. By controlling access and becoming a potential gatekeeper, AI platforms might increase the lock-in of consumers and barriers to entry against challengers (Stucke & Ezrachi, 2018).

Voice assistant suppliers may have an incentive to engage in exclusionary conduct by promoting or pushing their affiliated products and services and, consequently, excluding or demoting unaffiliated products/services or rival firms' brands through the use of ranking algorithms. Exclusionary conduct is more likely (rather than less likely) in a two-sided market (Katz, 2018). Ranking algorithms have been particularly studied by Dinerstein et al. (2018) and Ursu (2018). These algorithms establish a touchpoint between consumers and the products and services available in the market. Ranking algorithms could potentially bias

consumers' search results by presenting a distorted view of available options and by *manipulating* the algorithms' decision parameters. Eliaz and Spiegler (2011) demonstrated how a monopoly search engine may bias its search results and its ranking of offers. Discriminatory ranking may be exacerbated if voice assistant providers are vertically integrated. Vertically integrated platforms, such as Amazon, trade their own products and brands and directly compete with rival brands on their own platform. They increase the ability to foreclose rivals' substitutes and their market power (Hagiu et al., 2020).

Discriminatory ranking might be even more problematic in conversational commerce than in traditional marketplaces and search engines. While an online search engine provides dozens of options, few users look beyond the first page. Voice assistants suggest or recommend a single item or very few items rather than presenting multiple options to the consumer.

This effect increases entry barriers and reinforces the potential exclusion of products/services and brands as it becomes more difficult and costlier for brands unaffiliated with a conversational AI platform to reach consumers through that platform.

Empirical evidence supports the risk of exclusionary behaviors. In 2016, after testing hundreds of Amazon and non-Amazon products sold on the Amazon platform, Capitol Forum, an American firm that examines business and regulation, found that *"more than 71 percent of the first 20 carousel results on Amazon private label pages were products from an Amazon clothing company"* (Capitol Forum, 2016, p. 5). In November 2017, Bain & Company carried out a study focused more specifically on conversational commerce and found evidence of exclusionary conduct (Bain & Company study, 2017). The study showed that nearly 55% of the first recommendations were Amazon's Choice products, and nearly 17% were Amazon's private labels if a search fell within a category in which Amazon offers private labels, even though those two types of products (Amazon's Choice and private labels)

make up only 2% of the total volume sold. In the same vein, the preliminary report of the inquiry into the voice assistants and IoT markets (European Commission, 2021, p. 115) acknowledged that voice assistant providers “*may be able to exploit applicable algorithms to their own advantage, e.g., by associating specific search terms to their first-party content so that it appears higher up in the ranking*”.

### **3. Methodology**

The research adopted a qualitative approach to explore consumers’ conversational commerce practices and experiences as well as the benefits and potential limits of their usage.

#### *3.1. Sample*

We adopt an interpretative phenomenological analysis that “attempts to explore personal experience and is concerned with an individual’s personal perception or account of an object or event, as opposed to an attempt to produce an objective statement of the object or event itself” (Smith & Osborne, 2012, p. 53). In line with the research adopting interpretative phenomenological analysis where the sample size of informants varies between 3 and 16 (O. C. Robinson, 2014), the interviews conducted pursue an idiographic aim with a limited size of informants to be able to obtain an in-depth and intensive analysis of each case (O. C. Robinson, 2014; Willig & Rogers, 2008).

As a result, a purposive sampling approach was adopted to select participants who can provide a rich understanding of the topic (Homburg et al., 2017). The purposive sampling approach was chosen to facilitate the adoption of an emic perspective focused on the internal viewpoints, experiences, and feelings (Morris et al., 1999) of consumers who are heavy users of voice assistants for different queries (e.g., listening to music, finding information). However, the participants could be more or less frequent users of voice assistants for

conversational commerce while they all knew that they had the opportunity to do so if they wanted. It was important to focus on voice assistants' heavy users who were more or less adept at conversational commerce to identify obstacles to its use and appropriation. Additionally, we maximized the diversity among the participants (Strauss & Corbin, 1998) in terms of consumers' occupation, country of residence, type of goods bought through conversational commerce, and type of voice assistant adopted (Table 1). The study was conducted in France and Norway. Voice assistants and especially smart speakers were introduced in both France and Norway in 2017. Approximately 34% of French users of voice assistants have already made a purchase using a smart speaker (Hadopi, 2019). The study selected informants who interact with voice assistants through different devices including smart speakers and smartphones; recent studies have demonstrated that *“46% of French people who use the Internet have interacted with a voice assistant – 39% have interacted via smartphones, 10% via smart speakers, and 6% via smart TVs”* (Hadopi, 2019, p. 40). To select the participants, we used snowball sampling from our extended personal contacts, and each contact was subsequently invited to identify potential frequent voice assistant users linked to their own contacts.

The research halted the purposive sampling when no more new insights emerged from the field data and theoretical saturation was reached (Strauss & Corbin, 1998), which resulted in a total of 22 interviews.

**Table 1.** Respondents' profiles

<b>Respondents</b>	<b>Age</b>	<b>Gender</b>	<b>Country</b>	<b>Position</b>	<b>Device on which the voice assistant is used (and brand name)</b>	<b>Frequency of shopping through conversational commerce</b>	<b>Goods or services purchased or reason for not purchasing</b>
<b>Audun</b>	17	M	Norway	Student	Smartphone (Apple Siri)	Almost every day	Transport tickets, belts
<b>Axel</b>	17	M	Norway	Student	Smartphone (Apple Siri)	First purchase	T-shirts

<b>Benoit</b>	32	M	France	Official	Smart speaker (1x Google Hub, 1x Google Home, 4x Google Mini)	0	Need to see and compare offers, Reluctance to use conversational commerce
<b>Camille</b>	23	F	France	Student	Smart speaker (Google Home Mini)	Rarely	IoT products connected to Google Home Need to see and compare offers,
<b>Cédric</b>	40	M	France	Community manager	Smart speaker (Google Home)	0	Reluctance to use conversational commerce
<b>Christer</b>	32	M	Norway	Assistant designer	Smart speaker (Google Home)	Several times a week	Cinema tickets, pizzas, jeans
<b>Christian</b>	49	M	France	Employee	Smart speaker (Google Home)	0	Need to see and compare offers, reluctance to use conversational commerce
<b>Gio</b>	35	M	France	Employee	Smart speaker (Amazon Alexa)	Rarely	IoT products
<b>Gro</b>	47	F	Norway	Director of communication	Smart speaker (Amazon Alexa) Smartphone (Apple Siri)	One a month	Books, sportswear, sweater
<b>Hugo</b>	22	M	France	Employee	Smart Speaker (Google Home Mini)	0	-
<b>Irene</b>	29	F	Norway	Chief accountant	Smart speaker (Amazon Alexa) Smartphone (Apple Siri)	Several times a week	Sushi
<b>Jan</b>	63	M	Norway	Research director	Smartphone (Apple Siri)	Several times a month	Flight tickets, flowers
<b>Jorunn</b>	38	M	Norway	IT project manager	Smart speaker (Amazon Alexa) Smartphone (Siri)	Several times a month	Culinary ingredients, books, lenses, tights
<b>Jean-Claude</b>	67	M	Norway	Retired	Smart TV (Samsung)	Several times a month	Chinese furniture, garden and table furniture
<b>Kjersti</b>	43	F	Norway	Kindergarten director	Smart speaker (Amazon Alexa) Smartphone (Samsung)	2 or 3 times per week	Bus tickets, pool tickets, scarves, sportswear, and socks
<b>Mathieu</b>	23	M	France	Student	Smart speaker (Google Home)	Rarely	IoT products connected to Google Home
<b>Nora</b>	19	F	Norway	Student		2 or 3 times	Bus tickets,



						per week	cinema tickets, clothing, skirts, shoes
<b>Oscar</b>	46	M	France	Engineer	Smart speaker (Amazon Alexa)	Rarely	IoT products
<b>Pierrick</b>	26	M	France	Executive manager	Smart speaker (Amazon Alexa)	0	Fear of conversational commerce
<b>Philippe</b>	42	M	France	Employee	Smart speaker (1x Google Home Mini, 1x Google Home, 1x Google Hub)	0	Need to compare offers, reluctance to use conversational commerce
<b>Robin</b>	21	M	France	Student	Smart speaker (Google Home)	0	Need to see offers, reluctance to use conversational commerce
<b>Stéphane</b>	46	M	France	Worker	Smart speaker (Google Home)	Rarely	IoT products connected to Google Home

### 3.2. Data collection and analysis

The study conducted face-to-face interviews that took place in March, April, May and November 2019 in Norway and in France. The interviews were arranged around three main themes: 1) the use of a voice assistant and the reasons for using or not conversational commerce and its perceived limits, 2) the consequences of the perceived limits of conversational commerce, and 3) practices to overcome the perceived limits of conversational commerce. For all interviews conducted, the interviewers' role was reflective, with generally worded questions introduced to avoid leading the participants (Thompson et al., 1989). The informants' phrasing was used to facilitate the verbalization of personal meanings. The interviews lasted between 40 and 90 minutes and were all taped without objection.

The data were analyzed using the scheme of open, axial, and selective inductive coding (Strauss & Corbin, 1998). In the open data coding, the analyses were iterative, going back and forth between reading transcripts and evaluating the conclusion to identify common themes (Thompson, 1997). With axial coding, along with the informants' interpretative frames, the

theoretical lens allowed us to identify relationships among themes and to index themes within a common set of categories (Table 2). In the selective coding process, data relating to a specific theme were selectively coded. To preserve the emic perspective, the codes were not defined by the literature but determined during the data analysis process according to the meanings of the participants' words (Arnould & Wallendorf, 1994). Narratives were submitted for triangulation among the researchers to ensure that the findings were not open to alternative interpretations. Cross-validation between each of the researchers' analyses led to a shared understanding (Goulding, 1999).

**Table 2.** Categories formed by the axial coding

<b>Themes</b>	<b>Categories</b>	<b>Subcategories</b>
<b>Reason why using or not conversational commerce and its perceived limits</b>	Different types of concern about biased offers	Primacy to voice assistant private labels
		Primacy to brands contracting with the voice assistant
		Absence of product comparison
	Factors undermining the perceived risk of voice assistant biased offer	Product expertise
		Repeat purchase
<b>Consequences of the perceived limits of conversational commerce</b>	Negative outcomes	No use or end to the use of voice commerce
		Voice assistant attitude
<b>Practices to overcome the perceived limits of conversational commerce</b>	Coping strategies	Queries' precision
		Generic product purchases
		Combination of different voice assistants

#### **4. Findings**

This study's findings provide in-depth insights into consumers' perception and experience of conversational commerce. The results are divided into three main facets: 1) consumers' concerns about biased offers from voice commerce and their negative outcomes, 2) factors undermining the perceived risks of a biased offer with voice commerce, and 3)

coping strategies implemented to overcome the perceived risks of biased offers. While the study found different usage frequencies of conversational commerce between informants from Norway and France, the informants relied on the same mechanisms to overcome the main constraints of conversational commerce. Consequently, the study did not distinguish the results according to the interviewees' country of residence.

#### *4.1. Consumers' concerns about biased offers from voice commerce and its negative outcomes*

The economic literature (Gal & Elkin-Koren, 2017; Stucke & Ezrahi, 2016, 2018) has pointed out the risk of biased offers from conversational commerce. During the interviews, the respondents expressed their perception of inappropriate proposals made by the algorithm-based voice assistant. Consumers gave different reasons and arguments to explain those inappropriate proposed choices, which consequently negatively impacted use of voice commerce and attitudes toward voice assistants.

##### *4.1.1. Concerns regarding biased offers*

The respondents stress the lack of fit between the query and the proposed offers by the voice assistant as the main obstacle to using conversational commerce. Some consumers spontaneously expressed their fear of receiving biased offers when buying products through conversational commerce. Robin confessed that he is not using his Google Home to make purchases because he does not trust the voice assistance device: *"I am not using it for voice commerce because I don't really trust it."* Different types of concerns may explain the fact that voice commerce is associated with biased offers.

*1/Primacy of voice assistant private labels.* Kjersti explained why she is using the Samsung voice assistant more often than Alexa, the Amazon voice assistant, to engage in

voice shopping. Alexa is perceived as a voice assistant that may give primacy to products and brands from the Amazon marketplace catalog: *“That’s why I use Samsung’s voice assistant more than Alexa when I don’t know the products and brands I want to buy. If I do that on Alexa, I’ll have the Amazon Choices first. That’s always what happens with Amazon. And I’m not sure I like it. If I specify on Alexa that I want a specific brand model, like Adidas, it’s OK because I know the brand.”*

Consumers notice that conversational commerce requests may lead to inappropriate product offers and brand suggestions about which they may have not heard, as Nora experienced: *“Recently, I bought a skirt. I simply asked for a skirt, and Bixby [Samsung’s virtual assistant] offered me several models of brands that I knew and others that I didn’t know.”*

*2/Primacy of the voice assistant’s contracting brands.* While using voice assistant devices to listen to music, read a book, or create an IoT ecosystem to connect the voice assistant to its smart home appliances, consumers become aware that the product choices and brands are biased. The interviewees explained how they have limited options and choices and are urged to buy specific brands or services that have a contract with the voice assistant, which can be very expensive. Camille explains that to listen to music, she needs to have a Spotify subscription, and to install a smart light bulb connected to her voice assistant device, she has to buy Philips brand bulbs, which is not the best value-for-money choice: *“So if you want to listen to music on Google Home, you need to have a subscription either on Spotify, YouTube, or Deezer. It’s a premium paid subscription to have music directly on it. Otherwise, we can listen to music on TV, but you need to have Chromecast. So I had to take out a subscription that I didn’t have before.”*

Pierrick explains how his voice assistant generates a feeling of a loss of freedom regarding the choice of products that are compatible with the voice assistant. While it has

been well documented that new technologies and the IoT can be a source of value creation (Balaji & Roy, 2017; Inman & Nikolova, 2017), even if the IoT poses significant challenges in terms of security and privacy (Mani & Chouk, 2017) and ethical issues (Cremer et al., 2017), Pierrick's testimony adds new insights on the dark side of algorithms (Gal & Elkin-Koren, 2017). This dark side can trigger a feeling of disempowerment because consumers have less decision-making power in regard to their buying choices (Bachouche & Sabri, 2019; Lincoln et al., 2002). Pierrick raises the point that some voice assistants have exclusive contracts with particular smart products and services: *"An important limitation is many objects' lack of compatibility with Alexa."*

*3/A lack of offer comparisons.* A biased offers' perception of voice commerce may also come from the impossibility of comparing different offers to finally make a final choice. Most consumers who do not use their voice assistant for conversational commerce explained that they are reluctant to do so because using the voice assistant through the smart speaker device does not allow them to compare and see the offers. This was particularly true for French informants who lamented the lack of choices and proposals made by the voice assistant. Philippe explains, *"Oh no, no, no! I don't make any purchase through my smart speaker. I like to compare."*

#### *4.1.2. The negative outcomes of perceived biased offers*

In most cases, when consumers attribute a lack of fit between voice assistant product propositions and their own expectations to an intentionally orchestrated and biased offer from the voice assistant, it may trigger negative outcomes.

*1/No use or end to the use of voice commerce.* In line with the previous research that has shown how brand experience is key to predicting relationship constructs (i.e., satisfaction, trust, and brand loyalty) (Nikhashemi et al., 2019), this negative experience can be extremely

damaging, especially if it happens during a user's first experience of voice commerce and can lead the user to stop using the voice assistant for shopping. Audun wanted to use Siri on his smartphone to buy a belt but had a bad experience. The voice assistant, which is mainly used to save time and make faster decisions (Eeuwen, 2017; Gal & Elkin-Koren, 2017), had the opposite effect and left him with a feeling of having wasted time and energy without any effective results: *"Siri offered me choices of belts that I found silly and didn't suit me. Maybe I should have asked more specifically what type of belt I wanted (e.g., men's belt, black leather), but I was lazy and didn't think about it. It has to go fast, and I shouldn't even have to say I'm looking for men's belts. Siri should know I'm a guy."* (Audun)

*2/Induced negative attitude toward the voice assistant device.* The perceived biased offers made by the voice assistant may not only limit the development of conversational commerce but also negatively contaminate the perceived value of the voice assistant as a whole, which may be used for many other activities beyond conversational commerce: *"If I wanted, I could have added music related to all the streaming sites, but it requires a subscription, and with the Google Home Mini, it only works with Deezer. I have an Apple Music subscription, so I couldn't put music on Google Home. Other voice assistants do it with all platforms. Very quickly, it cooled me a little on the item because I couldn't do what I wanted, and I was restricted regarding an application because it was... purchased by Google, in fact."* (Cédric)

#### *4.2. Factors undermining the perceived risk of biased offers with voice commerce*

Our findings highlight two main factors that seem to undermine the perceived risks of biased offers associated with conversational commerce: customers' product expertise and purchasing behaviors.

#### 4.2.1. *Relying on product expertise to evaluate voice assistant proposals*

Biased risks through voice commerce would no longer be perceived as a major problem if the consumer considered himself or herself an expert in the product category in which he or she makes a purchase. The consumer may feel knowledgeable enough to analyze and go through proposals made by the voice assistant to find the best offer that would fit his or her expectations. The consumer might then have a sense of control over the choices offered by the voice assistant (Flynn & Goldsmith, 1999) and feel more empowered (Bachouche & Sabri, 2019; Lincoln et al., 2002). For consumers who have product expertise, even if the voice assistant proposed either new and less common brands or product offers following a buying request, this situation would not be perceived as a constraint. In contrast, this apparent drawback represents a source of perceived value, as consumers can explore new choices, which may broaden their expertise as a result. Jean-Claude clearly explained how enjoyable it is to shop through the Samsung voice assistant connected to his smart TV Samsung Incurve when buying Chinese furniture: *“When it comes to buying, I used to go on the Internet via my PC. Now I much prefer using my voice assistant [but I’m careful!] to buy simple products. For example, I ask for ‘Chinese furniture.’ I have choices that appear with the corresponding videos on the screen of my smart TV. So I quickly see whether the site really offers Chinese furniture or not. Then, I select a site that actually sells Chinese furniture. I see the [offers] from all angles, as in real life. I like it very much. I can then validate my choice. Of course, we know these products well.”*

However, when consumers’ product expertise is limited, especially in regard to high-tech products, it becomes difficult to rely on the voice assistant’s choices alone. The limited number of choices can be a significant barrier for consumers who seek to make a decision. Jean-Claude confessed that he stopped buying high-tech products through his voice assistant because the choices and product information delivered by the voice assistant were not

sufficient. He added that he could find better deals through classical online searching platforms. He explained as follows: *“When it comes to more sophisticated products, such as electronics, I no longer use my voice assistant. At first, I tried. It wasn’t great because I like to have a wide range of important choices. That was not the case. It’s weird because it’s exactly the opposite when I’m buying Chinese furniture. Now I go straight to my PC. For example, I go to the CDiscount website. I can find all the technology brands at attractive prices. I can chat with a technician. This is not possible with the voice assistant.”*

#### *4.2.2. Repeat purchase behavior to limit the risk of biased offers*

Having the feeling that one is buying the right product plays an important role in conversational commerce. As previously explored by Eeuwens (2017), voice commerce offers many benefits that consumers view in a positive light. Gro, who buys books and clothes through her voice assistant, recognized the convenience offered and time savings made possible by conversational commerce: *“It’s very convenient when my hands are busy. I can make purchases without using my hands and, therefore, do different activities at the same time. It’s also a big time saver when ordering books instead of having to go to a bookstore.”*

However, for those benefits to materialize and to limit the risk of biased offers leading to a nonoptimal buying decision (Gal & Elkin-Koren, 2017; Katz, 2018), consumers may rely on repeat purchase behavior (HeeSup et al., 2018). As explained by Kjersti, who clearly states that Alexa’s proposals are biased, she relies on this Amazon product for voice commerce only for repeat purchases of products and brands she has already bought on many occasions in the past. Kjersti explained, *“I use Alexa when I want to buy products I’ve already bought on Amazon. Alexa recognizes me and can offer me identical or similar choices. So it’s convenient and very fast, and what’s more, the recommendations correspond to the products I’ve already liked and bought, like socks or scarves.”*



### 4.3. Coping strategies developed to overcome the perceived risks of biased offers

To overcome the risk of having biased offers in conversational commerce and to take advantage of all the benefits associated with voice assistants (Eeuwens, 2017), the interviewees implemented three different coping strategies. The informants may use a single coping strategy or several of them.

#### 4.3.1. Making product queries more precise

One strategy to deal with the risk of a biased offer is to make product queries more precise. Individuals explained that the more precise the product query, the higher their satisfaction with the purchase will be. Jan, for instance, asked for a specific flight with a particular airline company, and he was satisfied with this shopping experience as he could obtain the full benefits of the voice assistant during his purchase of the desired service. Jan explained, *“I requested a specific flight from Oslo to Stavanger with SAS [the Norwegian national airline] for a specific date and time. Siri found it immediately, and I was able to order it from the bus I was in. [...]. The voice assistant is very handy and really a plus for its speed at executing what I want to buy or do.”* Audun, who had a bad experience the first time he used conversational commerce to buy a belt, regretted not having been more specific in his demand. If he had changed his approach, the buying experience could have been different: *“Maybe I should have asked more specifically what type of belt I wanted (e.g., men’s belt, black leather), but I was lazy and didn’t think about it.”* To make accurate product queries in conversational commerce, the interviewees explained that they use two different tactics. On the one hand, they clearly specified the brand name and the type of product they wanted: *“I bought a specific item (a sweater from the GANT brand), and the choices offered by the voice assistant were in line with my request. So I’m very happy that I didn’t have to choose from a*

*thousand items and brands that I'm not interested in.” (Gro) On the other hand, they can take a picture of a product they want and ask the voice assistant to find it (or a similar item) for them. Nora explained how she found “the perfect shoes” with Bixby, Samsung’s voice assistant, using a photo to make the purchase. Her buying experience was very positive and enjoyable: “I bought a pair of shoes that I thought was absolutely awesome. I had taken a picture of a pair of shoes on the bus and asked Bixby to find it. He found it, and I ordered it right away! This feature on Bixby is great. This is the first time I tried to make a purchase like this with a photo.”*

#### *4.3.2. Generic product purchase*

For a low involvement product, when product brand equity is not an important choice criterion in the buying decision process (Cobb-Walgren et al., 1995), informants may rely more readily on voice assistant choices for conversational commerce because there is a low perceived risk associated with the buying. As such, Jean-Claude explained that he mainly uses conversational commerce to buy “basic” products: *“I usually make requests for simple generic products (other than Chinese furniture), like recently for ‘table sets, a room chandelier, a garden umbrella.’ I’m usually not surprised by the choices offered.”*

#### *4.3.3. Combining and using different voice assistants to access a larger range of choices*

Some informants did not want to give up the benefits of voice assistants for conversational commerce because it can make biased offers. Kjersti’s experience is particularly interesting as she uses different types of voice assistant for different types of purchase: *“With my Samsung smartphone’s voice assistant, I can shop on the go. The voice function also allows you to go fast [...] I look mostly at the first choices. If I do that on Alexa,*

*I'll have the Amazon Choices first [...]. If I specify on Alexa that I want a specific brand model, like Adidas, it's OK because I know the brand. It's also OK when I want to recommend products: Alexa recognizes me and can offer me identical or similar choices. So it's convenient and very fast, and, what's more, the recommendations correspond to the products I've already liked and bought like socks for my daughter or scarves for me.”*

## **5. General discussion**

Although the research on conversational commerce is still emerging, the existing economic literature and reports provide an important context for understanding the potential for exclusionary conduct and nonoptimal choice propositions for consumers using voice assistants (European Commission, 2021; Gal & Elkin-Koren, 2017; Katz, 2018; OECD, 2017; Stucke & Ezrachi, 2018). Although it provides an important beginning as it stresses the benefits and potential harms for the consumer, these studies and reports are limited because they do not examine conversational commerce technology from the consumer's perspective.

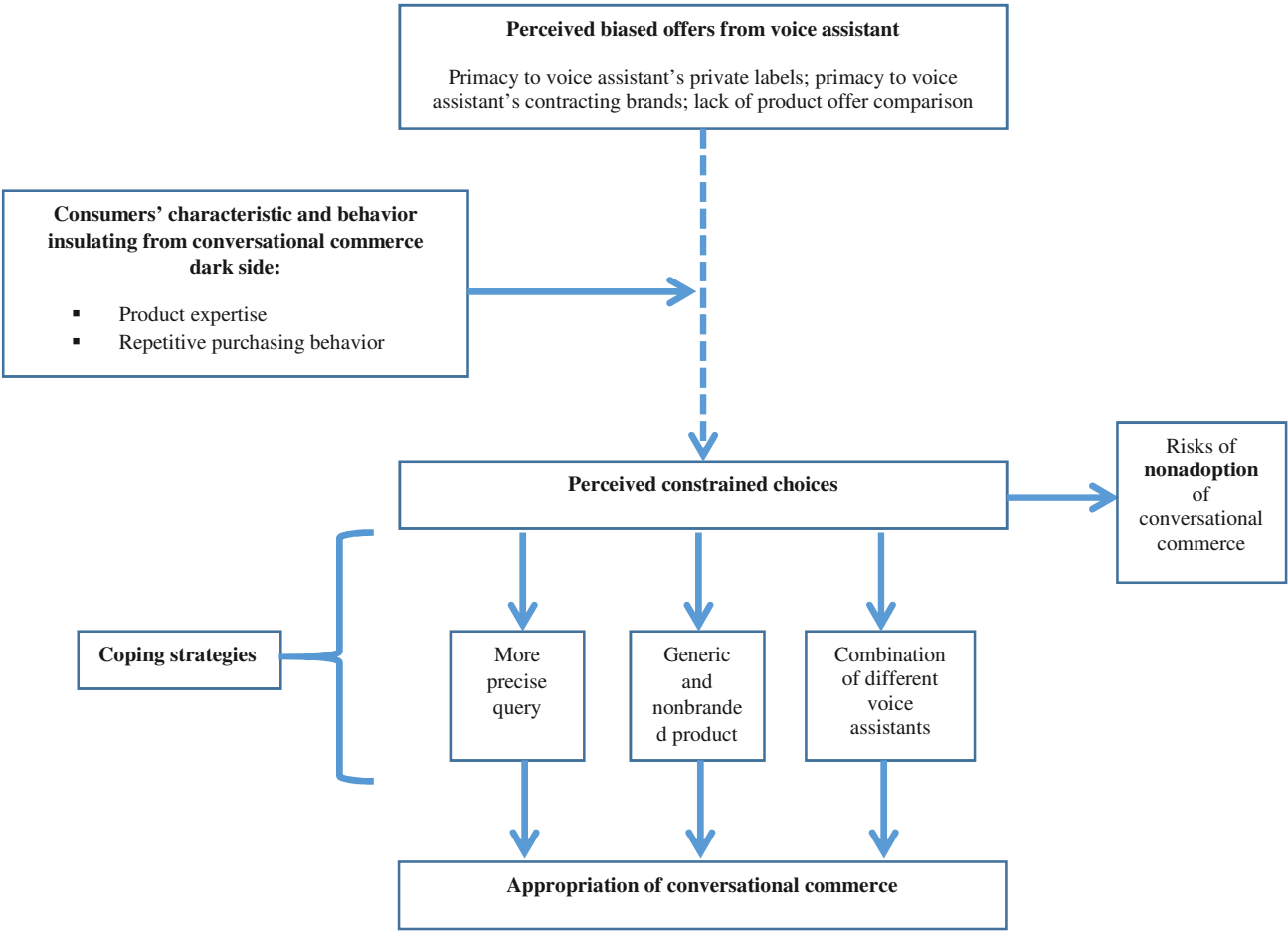
This paper fills this gap. No research to date has focused on consumers' perception of biased choices proposed by voice assistants in a conversational commerce setting. Through qualitative interviews conducted in France and Norway, this research provides empirical evidence that conversational commerce produces dark side effects that limit its appropriation. Consumers acknowledge that the choices offered by the algorithm-based voice assistant do not always match their expectations and preferences, and they sometimes feel locked in and constrained when making their final choice.

The contributions of the paper are threefold. First, by extending the research on algorithm-based commerce, which has focused on privacy and trust concerns as the two predominant negative factors that might undermine the buying experience (Easwara Moorthy & Vu, 2015; McLean et al., 2021), this research stresses the role of perceived choice bias offered by a

voice assistant as a key issue that might limit conversational commerce technology appropriation. Second, it expands the economic literature and international organization reports (European Commission, 2021; Gal & Elkin-Koren, 2017; Katz, 2018; OECD, 2017; Stucke & Ezrachi, 2018) by identifying consumers' characteristics and behavior that may insulate consumers from the dark side of the biased offers made by voice assistants. Conversational commerce may not systematically be perceived as risky from the consumers' point of view when they have some expertise regarding the purchased product or when they are engaged in more repetitive purchasing. Finally, while the existing literature on conversational commerce focuses on its main benefits and costs (Chopra, 2019; Vassinen, 2018), there is a lack of understanding of the strategies that consumers may implement to overcome its perceived costs. Expanding this literature, the current research identifies three coping strategies implemented by consumers to overcome the negative counterparts of conversational commerce (see Figure 2).

Our research, therefore, is able to provide a more comprehensive picture of the appropriation conditions of conversational commerce technology. Next, we further elaborate on the theoretical contributions, practical implications, and limitations of our findings.

**Figure 2.** The perceived biased offers from voice assistant limiting its adoption and appropriation



*5.1. Theoretical contributions*

The research makes a number of theoretical and substantive contributions.

*5.1.1. Contributions to the conversational commerce research*

This research makes substantial contributions to the emerging field of conversational commerce research (Chopra, 2019; Eeuwen, 2017; Vassinen, 2018). The literature insists on the benefits that users derive from conversational commerce as it offers more personalized and convenient choices while making it possible for consumers to make faster decisions (Chopra, 2019; Vassinen, 2018). In the service literature, these findings have been identified by Ameen et al. (2021) and Ostrom et al. (2019), who specify that AI-based technology offers

great value to consumers by enhancing, in particular, convenience, time savings, capabilities, and personalized services, e.g., in the design of personalized medical treatments in the healthcare market or personalized teaching programs in the education sector.

First, the findings extend those conclusions to a theoretical setting based on two-sided market-generating network effects. This framework is particularly relevant to examine both the bright and dark sides of conversational commerce. Second, the results show how the positive benefits of conversational commerce might be counterbalanced by the ability of an algorithm-based voice assistant to constrain consumers' choices, limiting its appropriation. The study identifies two factors that can shield the consumer from the negative effects associated with voice commerce: consumers' product expertise and repeat purchase behavior. In addition, when there is a perceived risk of the voice assistant making a biased offer, the informants sometimes implement coping strategies. In the specific case of conversational commerce, we find that only one type of coping strategy is implemented, namely, "*action coping*," which is defined as "*direct, objective attempts to manage a source of stress*" (Duhachek, 2005, p. 44). The investigation expands the understanding of the dark side of conversational commerce as the study shows how consumers may cope with this dark side to fully enjoy all the benefits of voice assistants in the context of conversational commerce while limiting the negative effects of biased offers. Finally, this research identifies one key factor (i.e., perceived biased offers made by voice assistants) that may constrain the diffusion and adoption of conversational commerce technology. By doing so, we expand our understanding of the factors that support technology adoption and diffusion (Chang et al., 2009; Shih, 2008), focusing on the underexplored e-commerce context of conversational commerce.

### *5.1.2. Contribution to consumers' empowerment research*

The research enriches the literature regarding consumers' empowerment. In the specific context of conversational commerce, consumers state that they have fewer options and fewer choices, mention a perceived risk of biased offers in the purchasing process when they use a voice assistant and feel disempowered as a result. The study's results contradict the existing literature on the role of digital technology and the internet, which is supposed to reduce consumers' perceived uncertainty and risk (Thakur & Srivastava, 2015) and develop consumer empowerment (Bachouche & Sabri, 2019) as consumers have fast access to diverse sources of information and can compare offers (Cova & Pace, 2016).

### *5.2. Implications for policymakers*

The findings stress the need for greater regulation of conversational commerce as consumers are not clearly aware of the risk of biased offers made by voice assistants. The research shows that conversational AI platforms may constrain consumers' choices by self-preferencing their own or affiliated products or services with the help of algorithms, thus leveraging such platforms' market power and regulators' and policymakers' concerns by making the marketplace less competitive. Self-preferencing by dominant players and by a vertically integrated dominant platform could distort competition. Therefore, antitrust authorities should be particularly vigilant to ensure that dominant platforms such as the big three (Apple, Amazon, and Google) do not engage in abusive self-preferencing, especially when a dominant player such as Amazon is vertically integrated with downstream firms. They should request more transparency from tech giants in regard to the contracts they have with suppliers, brands, or the private labels they own. While direct access to algorithms is not always possible to safeguard intellectual property rights and/or potential business secrets, there is a need for transparency regarding how algorithms are designed.

### *5.3. Implications for conversational AI platforms owners*

This research has implications for voice assistant players. The study showed that some consumers may feel disempowered as they must deal with biased choices and have less control over the choices than they would like. As underscored by some of the informants, there may be a risk that consumers will not use their voice assistants for conversational commerce. Worse still, they may stop using their voice assistants altogether. Action should be taken to ensure that voice assistant players develop their consumers' feelings of empowerment. Proactive customer strategies such as making the algorithm more transparent should alleviate those concerns. On the one hand, conversational AI platforms need to be more transparent about the criteria used to rank the algorithm's choice offers. Proposals must be based on rational arguments such as the average rating that consumers give to products (Rozenkrants et al., 2017), consumers' past purchases, or product geolocalization.

On the other hand, voice assistant players must be transparent regarding exclusive contracts they may have with some suppliers and clearly acknowledge that the algorithm's choice proposition is a private label of the voice assistant's brand owner. The results show that some consumers may blindly trust the algorithm choice. They think voice assistants are dedicated to increasing consumer welfare by choosing the products that best suit their needs. If consumers inadvertently learn that the algorithm choices are made to increase the giant tech profits without considering the consumers' interests, it may lead to a feeling of betrayal from the consumers' point of view. Brand betrayal should be avoided as it is likely to ruin the brand relationship, and then it becomes difficult for marketers to deflect, which has lasting consequences (Reimann et al., 2018). It is also clear that if conversational AI platforms abuse their power by proposing these kinds of experiences, they are likely to fail in the long run. Full transparency is needed to develop the perception of honesty toward voice assistant players and build trust in them (Brunner & Ostermaier, 2019; Chopra, 2019).



#### *5.4. Limitations and future research directions*

Although this research makes important contributions to both theory and practice, it is not without limitations. These limitations provide researchers with many opportunities for future work.

First, although the qualitative methodology based on face-to-face interviews has helped obtain a comprehensive understanding of the appropriation factors of conversational commerce technology, there are still some important limitations that should be addressed. The conclusions of the research conducted are based on perceptions. As the interviews were arranged around themes and questions about voice assistant usage for conversational commerce, priming can occur. Priming is defined as a subconscious form of human memory that is activated by context cues, which then exert a passive influence on individuals' cognition, affect and behavior (Bargh, 2006; Chartrand & Bargh, 1996). When responding to a questionnaire or open-ended questions, it has been demonstrated that participants are inclined to retrieve different pieces of information from memory search that become more salient (Moss & Lawrence, 1997; Wyer & Hartwick, 1980). As a result, as participants' attitude may be influenced by a preceding question or questions (Moss & Lawrence, 1997), the priming effect may contaminate the measurements and analyses within surveys and interviews (Gibson & Bahrey, 2005; Vitale et al., 2008). To overcome this important limitation, future research must adopt observations (Boote & Mathews, 1999; Wells & Lo Sciuto, 1966) that limit the questioning of informants.

Second, also related to our qualitative method, while a small sample size is adopted by research engaging in interpretative phenomenological analysis with an idiographic aim (O. C. Robinson, 2014; Willig & Rogers, 2008), future research may opt for a nomothetic aim based

on a more important sample size of informants to be able to generalize the results established (O. Robinson, 2012).

Third, the study did not explore privacy concerns and did not focus on conversational commerce's quantitative effect on purchase behavior or other behavioral reactions such as word-of-mouth intentions. A natural extension would be to empirically test the impact of conversational commerce on buying behavior and the relative weight of the dark and bright side effects on the decision to continue buying through an algorithm-based voice assistant.

Finally, another major issue for forthcoming research may be to identify the factors that undermine the dark side effects of conversational commerce from the supplier's point of view. Brand equity and the embedded ties that measure the close and reciprocal relationship between the supplier and the IA platform provider (Noordhoff et al., 2011; Vassinen, 2018) might be two important factors to consider.

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