When Algorithms Go Shopping: Analyzing Business Models for Highly Autonomous Consumer Buying Agents

Michael Weber[1], Marek Kowalkiewicz[2], Jörg Weking[1], Markus Böhm[1], and Helmut Krcmar[1]

[1] Technical University of Munich, Chair for Information Systems, Garching, Germany
{mic.weber, joerg.weking, markus.boehm, helmut.krcmar}@tum.de
[2] Queensland University of Technology, Chair in Digital Economy, Brisbane, Australia
marek.kowalkiewicz@qut.edu.au

Abstract. Consumer buying agents (CBAs) are software programs that automate tasks in the consumer buying process (e.g., product search and evaluation). Recently, CBAs have the ability to nearly automate the whole buying process, executing transactions with only minimal human involvement. With the rise of such highly autonomous CBAs, updates to business models (BM) of involved parties are expected (e.g., adding a sales channel and increasing customer value). However, our understanding of BMs for highly autonomous CBAs remains limited. In this work we aim to close this gap. We investigate 23 cases and develop a BM taxonomy for highly autonomous CBAs. We further encode these cases into the taxonomy and derive BM patterns. Our work contributes to research by setting a foundation for the conceptual understanding of BMs for highly autonomous CBAs. Practitioners can use our taxonomy and patterns for strategic guidance and to support BM innovation.

Keywords: Consumer Buying Agent, Autonomous Agent, Autonomous Shopping, Business Model, Taxonomy.

1 Introduction

With the rise of E-commerce, scholars have begun discussing potential use cases for software agents, which are continuously running, personalized software programs capable of carrying out actions on their own [1]. Software agents assist and automate tasks for both businesspeople and consumers. For example, businesses can use agent technology to automate procurement activities [2, 3] or to deliver a personalized marketing experience [3, 4]. On the consumer side, agents can support buying decisions by comparing offerings or making recommendations [1, 5]. Whereas the traditional role of agents is decision support, a shift toward more autonomous and decisive agents is occurring, putting humans in the supervising role [2, 3].

A recent trend features connected things able to purchase goods and services on behalf of consumers [6, 7]. As an example, air filters monitor their lifecycle and printers detect shortages of ink. When needed, they can place new supply orders without human intervention. Voice assistants (e.g., Amazon's Alexa) can process

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simple shopping commands to select and purchase products (on human consent). Thereby these things take on typical tasks of a consumer: analyzing needs, choosing among different offerings and executing transactions. Because only minimal human interaction and decision making is required, these things become *highly autonomous consumer buying agents* (CBA).

With the advent of highly autonomous CBAs, updates to business models[1] (BM) of involved parties (e.g., retailers and appliance manufacturers) are expected. First, CBAs create new sales channels [8]. Second, automatic replenishment and voice shopping reduce customer efforts and enable less-frictional purchases [6]. The increased convenience will likely become the standard customer expectation. Therefore, it becomes a key part of the value proposition. Lastly, key partnerships will probably play an essential role to ensure that the offerings are actually considered by CBAs [9]. For involved businesses, it is important to understand the dynamics of such trends to adapt and innovate their BMs. The process of business model innovation (BMI) is a necessary activity to sustain competitive advantage in an ever-changing environment [10, 11]. However, past cases have shown that BMI can be difficult to implement [12].

Existing BM research has not yet analyzed highly autonomous CBAs. Therefore, there is a lack of conceptual understanding on the topic. In this work, we build a BM taxonomy for highly autonomous CBAs and derive business model patterns (BMP). We aim to bridge the research gap and provide valuable insights for practitioners striving for BMI.

The rest of the paper is structured as follows. We first summarize related work on BMs and CBAs, to provide both context and background. We then continue by describing our research method. As the result of our study, we present a BM taxonomy and BM patterns for highly autonomous CBAs. We then discuss our outcomes regarding both research and practice before we conclude the paper.

2 Related Work

2.1 Business Models

Many definitions for the BM have been proposed [13], however they seem to agree on a common set of components. According to Gassmann, Frankenberger and Csik [14], a BM describes the *customer segment (who)*, *value proposition (what), value chain (how),* and *profit mechanism (why)* of a firm. Similar components are used in other definitions, such as those by Teece [11] and Osterwalder and Pigneur [15].

BMPs can be generalizations of reoccurring BMs with similar characteristics [16, 17]. BMPs can both describe whole BMs or only specific parts [16] (e.g., the profit mechanism). Practitioners can use BMPs for BMI and collaborative ideation [14]. Various generic BMPs have been presented or collected in different works [14-17].

[1] We interpret business models as formal concepts [13]

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Apart from general research on BMs, scholars have analyzed BMs in specific information system (IS) domains (e.g., carsharing [18], fintech [19], industry 4.0 [20], internet of things (IoT) [21], or product service systems [22]). Such works contribute to a better understanding of the business side of these technology-driven trends, such as by creating taxonomies, analyzing important dimensions, or deriving common patterns. Thus far, studies have not yet targeted CBAs as actors in BMs.

In summary, extant research provides us with generic dimensions and patterns, which can be used to analyze BMs for CBAs. However, BM literature does not yet provide an in-depth investigation on CBAs. Therefore, no specialized tools exist.

2.2 Consumer Buying Agents

CBAs[2] can be defined as software programs that automate parts of the consumer buying process [1]. The consumer buying behavior model (Figure 1) can be used to analyze agent-automated tasks [1, 23]. The consumer buying behavior model describes all steps a consumer typically goes through when making a purchase. Agents can thus identify needs [1, 3], collect and evaluate information on products and merchants [1, 3, 23], negotiate conditions [1, 3, 23], and potentially execute the purchase [1]. Depending on the novelty and risk of the purchase, consumers prefer different tasks to be automated by CBAs [24]. Highly autonomous CBAs have thus far not been addressed by extant literature. There is a lack of understanding on what tasks they automate and how they relate to “traditional” CBAs.

Furthermore, scholars have studied the impact of CBAs. Consumers can save time and improve decision quality by using recommender [5, 25] or product comparison agents [25, 26]. On business side, CBAs impact firm performance. It has been shown that retailers’ use of recommender agents can drive sales [27]. However, the success also depends on the suppliers and their pricing strategies [28].

To the best of our knowledge, there is only indirect evidence for the use of CBAs in BMs. CBAs have been discussed in the context of direct selling and third-party marketplace BMs [25], mediating transactions between buyers and sellers [1, 23]. In addition, CBAs are recognized as value-added services of firms [27]. Nevertheless, BMs for CBAs remain an understudied topic, lacking a direct investigation.

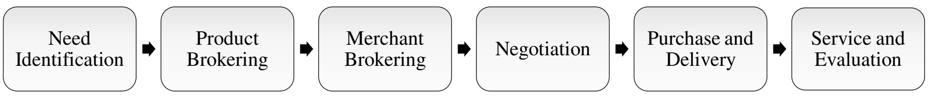

Figure 1. Consumer buying behavior process model (Maes, Guttman and Moukas [1])

[2] We refer to consumer buying agents as all kinds of agents automating tasks in the consumer buying process. Highly autonomous consumer buying agents represent a subset within this definition with a certain level of autonomy (see section 3.1 for a detailed definition).

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3 Research Method

Our research follows a four-step approach. First, we define the scope of our research and determine the criteria for highly autonomous CBAs. Second, we collect cases based on these criteria. Third, we use these cases to develop a BM taxonomy, which allows to describe the underlying BMs. Finally, we apply the taxonomy to the cases, and we encode the respective BMs. We derive BMPs via qualitative cluster analysis.

3.1 Definition of Scope

For the scope of our research, we further refine the term *highly autonomous consumer buying agent* and set criteria to guide case selection. According to Jennings, Sycara and Wooldridge [29], an autonomous software agent should be able to act without human intervention and to exercise control over its own actions. If we apply this definition to CBAs, a *fully autonomous* CBA must be able to identify needs, select appropriate goods or services, and execute the purchase without human intervention. However, consumers do not necessarily want to give all control to software agents, especially not in novel, high-risk purchase situations [24]. To ensure practical relevancy, we therefore focus on a slightly weaker notion of autonomy, referred to as highly autonomous in this paper. We use the consumer buying behavior process model to define highly autonomous.

We first include all fully autonomous CBAs that automate the whole buying process (type 1). In addition, we include CBAs that, based on a human command, can select a matching good or service (out of multiple options) and subsequently execute the purchase (type 2). Thereby type 2 CBAs automate the whole buying process up to the purchase, except for the need identification step.

We exclude CBAs that execute the purchase of a *fixed* good or service based on a human command (e.g., reorder buttons). In that case, the good or service selection is skipped. We argue that the CBA does not make any decisions, and therefore has no control over its own actions. Moreover, we also exclude all CBAs that cannot execute the purchase step (e.g., recommender, comparison agents), as they are merely supporting decisions instead of autonomously executing purchases.

3.2 Case Collection

We build our case collection on the method suggested by Larsson [30]. Thus, we first identified the cases we were already familiar with. Second, we conducted a case search to identify new cases. The case search consisted of different search strategies and sources, which helps to reduce case collection bias [30]. Owing the novelty of our perspective on CBAs, we could not rely on extant literature for case collection. Instead, we looked at business reports, databases for enterprise information, news articles, and websites. To find these potential sources, we used web search, app stores, and queried the database CrunchBase[3], both by combining different search terms

[3] https://www.crunchbase.com/ (queried 24.06.2019)

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(e.g., bot, assistant, shopping, purchase, automation, reorder, replenish). Some sources for one case additionally refer to other cases that we had not identified at that time. For example, we looked at Amazon Alexa's[4] and Google Assistant's[5] app stores to discover other cases with a voice interface. Hence, similar to backward and forward search in literature reviews, we could identify cases based on the already known ones.

We considered all active cases where highly autonomous CBAs (type 1 or type 2) were involved and where enough information was available to understand the underlying BMs. In the case of start-ups, the respective company must have still existed during our study. For Amazon Dash Replenishment, we only considered one case for a certain type of appliance to avoid redundancy. For example, we only considered Kyocera printers, whereas other firms offered a similar service.

We identified 23 cases in total. We stored all data in a central case base [31]. For each case, we tried to find additional sources by searching the web for the firm's name and the "title" of the CBA. We triangulated the data by synthesizing the findings from all sources for a case, helping us to build a more profound understanding of the underlying BM. Such data triangulation helps to increase the construct validity of a case study [31]. Appendix A lists all cases, references the main sources used, and shows to what type of highly autonomous CBA the cases adhere (type 1 or type 2).

3.3 Taxonomy Development

We applied the iterative method of Nickerson, Varshney and Muntermann [32] for taxonomy development. This method has successfully proven itself in several related IS studies, where BMs in a certain domain were investigated with the development of a taxonomy [18-20]. Furthermore, it follows a holistic approach, in which well-funded theoretical knowledge and empirical insights can be combined.

As a first step, we defined meta-characteristics for the taxonomy. Meta-characteristics are the most comprehensive characteristics of the taxonomy and serve as the basis for further selection [32]. We used the four dimensions of the widely accepted BM definition of Gassmann, Frankenberger and Csik [14] as our initial set of meta-characteristics: *customer segment (who)*, *value proposition (what)*, *value chain (how)*, and *profit mechanism (why)*. These dimensions are both comprehensive and abstract enough to serve as suitable meta-characteristics for our BM taxonomy.

Second, we set ending conditions for the taxonomy development. We used the objective and subjective ending conditions suggested by Nickerson, Varshney and Muntermann [32].

Third, we iteratively created the taxonomy. During the first iteration, we used the conceptual-to-empirical approach, building upon related work. In particular, we considered how CBAs create value for consumers in the buying process as well as how "traditional" CBAs are used in BMs. We evaluated the identified characteristics using concrete cases and grouped them into the dimensions *target customer*, *purchase*

4 https://www.amazon.com/alexa-skills/b/?node=13727921011 (last accessed 01.11.2019)
5 https://assistant.google.com/explore (last accessed 01.11.2019)

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automation, *purchase brokering*, *market role*, and *revenue model.* During the second iteration, we applied the empirical-to-conceptual approach, analyzing a subset of cases with a focus on the value chain and key partners. We identified new characteristics, added the dimension *purchase scope*, and split up the dimension *market role* into *endpoint type*, *endpoint belonging*, and *provisioning*. At this moment, the taxonomy now considered fine-grained differences in the value chain. During the third iteration, using the empirical-to-conceptual approach again, we analyzed a larger subset of cases from a technical viewpoint. We identified new characteristics, added the dimensions *agent stage*, *agent deployment*, and *agent interface*, and split up *revenue model* into *ongoing revenue* and *upfront revenue*. During the fourth iteration, we chose the empirical-to-conceptual approach once more, this time analyzing all cases using our taxonomy. The analysis and comparison of the cases did not require to add or modify any of the characteristics or dimensions. All other ending conditions were met. We stopped the process and the resulting taxonomy can be applied to all cases.

3.4 Derivation of Business Model Patterns

The BMPs were derived following a qualitative analysis approach. First, we encoded the cases in a matrix (see Appendix A). Each row of the matrix represents a case. Each column of the matrix represents a dimension in the BM taxonomy. With the help of the matrix, we performed a qualitative cluster analysis [31] to derive BMPs. At the highest level, we identified three overarching BMPs. Within these three overarching BMPs, we further distinguished eight sub-patterns.

4 Results

4.1 Business Model Taxonomy

The BM taxonomy builds upon the four meta-characteristics: *customer segment*, *value proposition*, *value chain*, and *profit mechanism*. Table 1 shows 34 characteristics along 12 dimensions. The taxonomy describes BMs for highly autonomous CBAs. It covers concrete CBA instances and their supporting ecosystem. As an example, BMs for agent platform providers can also be described. In this case, some dimensions of the taxonomy might be intentionally left blank, because they depend on the concrete instantiation of an agent. For instance, an agent platform might not prescribe whether the agent sells its own products or third-party products. Each dimension is briefly explained below.

Businesses can both directly target consumer (i.e., business-to-consumer (B2C)) with agent instances, or they can target other businesses (i.e., business-to-business (B2B)) with agent-enabling services (*target customer*). Businesses can offer a ready-to-use agent for consumers, agent blueprints, or extendible agent platforms for other businesses (*agent stage*). Agents can either fully automate purchases by identifying needs or be triggered by human commands (*purchase automation*). Agents might

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consider different types of products and different merchants for their decision. However, some agents might do no brokering at all and just purchase a fixed offering (*purchase brokering*). Agents can purchase a single offering, offerings in a certain domain, or even across multiple domains (e.g. booking hotels and public transport) (*purchase scope*). Agents can be deployed in mobile or web applications, on an agent platform, or via connected devices such as printers and dishwashers (*agent deployment*). Agents can be controlled through a graphical user interface, through a conversational interface (e.g., voice or chat), or with no interface at all (e.g., for fully automatic purchases). In this case, the human might monitor the agent in some way (*agent interface*). Agents can either purchase from their own business or from external business partners (*endpoint belonging*). For the choice of offering, agents can consider a single vendor that provides the offering, a set of vendors, or a marketplace (*endpoint type*). Businesses can provide purchased goods or services on their own, rely on third parties, or follow a mixed approach (*provisioning*). Businesses can generate ongoing revenue through direct sales, transaction-based commission fees, subscriptions, or generate no revenue at all. In this case, they might profit in other ways (e.g., through platform network effects) (*ongoing revenue*) [33]. Businesses might require consumers to purchase a physical device before an agent can be used (e.g., in the case of appliances) (*up-front revenue*).

Table 1. Business model taxonomy for highly autonomous consumer buying agents

Meta-charact.	*Dimension*	*Characteristics (No. of cases)*			
Customer Seg.	Target Customer	B2C (18)	B2B (5)		
Value Proposition	Agent Stage	Agent Application (18)	Agent Blueprint (1)	Agent Platform (4)	
	Purchase Automation	Automated (13)	Human-triggered (10)		
	Purchase Brokering	Product (2)	Merchant (3)	Both (4)	None (11)
	Purchase Scope	Single G/S (14)	Domain (2)	Cross-Domain (4)	
Value Chain	Agent Deployment	Web/Mobile (4)	Agent Platform (7)	IoT Device (12)	
	Agent Interface	GUI (1)	Conversational (10)	None/Monitoring (12)	
	Endpoint Belonging	Own Endpoint (6)	External Endpoint (13)		
	Endpoint Type	Single Vendor (4)	Set of Vendors (5)	Marketplace (10)	
	Provisioning	Own G/S (7)	3rd Party G/S (8)	Both (3)	
Profit Mechanism	Ongoing Revenue	Sales (7)	Commission (12)	Subscription (2)	None (1)
	Up-front Revenue	Sales of Device (10)	None (13)		

4.2 Business Model Patterns

We identify three overarching BMPs for highly autonomous CBAs and eight sub-patterns. At the highest level, we differentiate between *agents for direct sales* (pattern 1), *agents as mediators* (pattern 2), and *agent enablement* (pattern 3). For *agents for*

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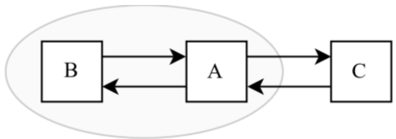
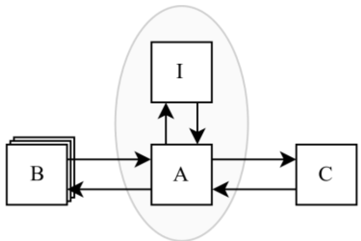
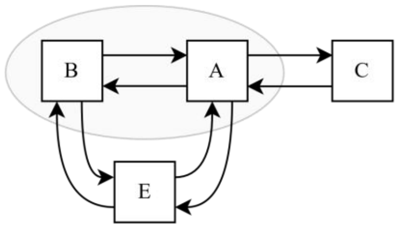
direct sales, a business uses an agent to sell their own goods or services to a consumer. For *agents as mediators*, an intermediary uses an agent to mediate transactions between a consumer and one or many businesses. In contrast to that, *agent enablement* is not concerned with the actual usage of an agent. Rather, it enables third parties to use agents. Table 2 illustrates and summarizes the three overarching BMPs with their respective sub-patterns. Below the table, we describe the eight sub-patterns within the three overarching BMPs in more detail.

Table 2. Business model patterns for highly autonomous consumer buying agents

Pattern & Sub-patterns (No. of cases)	*Illustration*
Pattern 1: Agents for Direct Sales • IoT-enabled Auto-Selling (6) • Conversational Selling (2)	
Pattern 2: Agents as Mediators • IoT-enabled Auto-Mediation (3) • Agent-enabled Mediation (5) • Agent-supported Mediation (2)	
Pattern 3: Agent Enablement • Agent Platform (2) • IoT-Integration Platform (2) • Solution Provision (1)	
Legend Actor Set of actors Interaction Agent belonging B: Business A: Agent C: Customer I: Intermediary E: Enabler	

Pattern 1: Agents for Direct Sales. Businesses deploy agents to directly sell goods and services to their customer. The agent becomes an additional sales channel that automates the purchasing process for the customer. We identify two sub-patterns for direct sales:

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IoT-enabled Auto-Selling. Connected appliances or products can track their status and detect the need for a replacement. In case of an upcoming need, an order can be placed automatically without human intervention. For example, HP, Inc. offers instant ink replenishment for their printers. Filtrete uses Amazon Dash Replenishment to let their smart filters replace themselves.

Conversational Selling. Businesses provide a conversational interface to order goods or services via chat or voice. The agent enables simple purchases and can assist the customer in the decision process. For example, Virgin Train built a voice app on Amazon Alexa for ticket bookings and information. Walmart allows its users shop via voice using the Google Assistant, learning their preferences from past orders.

Pattern 2: Agents as Mediators. Intermediaries deploy agents to mediate between buyers (consumers) and sellers (businesses). The agent assists consumers in their purchasing decisions. We identify three sub-patterns for mediators:

IoT-enabled Auto-Mediation. As for IoT-enabled Auto-Selling, connected appliances and products automatically detect needs and can reorder replenishables. However, the agent owner does not sell its own goods. Instead, the agent mediates between the consumer and a third party. For example, GE Appliances uses Amazon Dash Replenishment on their connected dishwashers to automatically reorder dishwasher pods. WePlenish developed a smart container for a set of compatible coffee pods that can automatically restock via Amazon Dash Replenishment.

Agent-enabled Mediation. The agent integrates multiple goods or service providers and connects them with potential consumers. The agent provides an individualized service for customers (e.g., shopping inspiration, best price comparison, or process automation). Through this mediation, a marketplace is created that is enabled by the agent. For example, Myia is a bot that automates switching to the cheapest energy provider in the U.K. In India, Niki.ai is a chatbot that assists with various transactions, such as mobile recharges, public transport tickets, hotel bookings, or electricity bills.

Agent-supported Mediation. Here the intermediary is already running a BM that connects buyers and sellers. The agent is used to support mediation by providing a convenient interface with automation to the customer. In contrast to *Agent-enabled Mediation*, the agent is not essential for the mediation model. Amazon uses Alexa to enable its users to shop at their online marketplace by using simple voice commands. Google follows a similar approach with the Google Assistant and Google Express marketplace.

Pattern 3: Agent Enablement. Enablers provide services for other businesses to enable their agents. In contrast to the previous patterns, this BMP does not involve a concrete agent instance. We identify three sub-patterns for enablers:

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Agent Platform. Agent enabler provide a platform for other businesses to develop and deploy agents. The agent enabler can monetize their services and potentially benefit from network effects on the platform. Third-party businesses can benefit from technical expertise and the reach of the platform. For example, Amazon and Google offer an app store for their personal voice assistants, where third parties can publish agents with a voice interface.

IoT-Integration Platform. Agent enabler provide a platform for IoT-enabled auto-replenishments. Third parties connect their appliances and products to the platform and thereby instantiate an agent. The agent enabler can monetize from the ongoing transactions. For example, Amazon offers Amazon Dash Replenishment, a service for automated replenishments on the Amazon marketplace. U.K. start-up Pantri builds a holistic subscription platform that integrates appliances for automated replenishments.

Solution Provision. Agent enabler provide third parties with services to create and manage their agents. Third parties can be provided with a non-technical interface, configurable agent blueprints, and the management of multi-platform deployments. As an example, Blutag enables retail voice applications for Amazon Alexa and Google Assistant.

5 Discussion

Highly autonomous CBAs have the potential to change the ways consumers buy and the ways businesses sell products and services. However, BMs for highly autonomous CBAs remain understudied. Therefore, we developed a BM taxonomy and derived BMPs for highly autonomous CBAs.

The three overarching BMPs are *agents for direct sales*, *agents as mediators,* and *agent enablement*. Because of their high level of generalization, we can find similar concepts in existing BMPs (e.g., *direct selling*, *online brokerage,* or *value chain service provider* [16]). Other patterns cover the idea of agency, where a business represents the interests of a buyer and profits from successful transactions (e.g., *agent models* or *search agent* [16]). The differentiating aspect of our proposed BMPs is the algorithmic agent, which nearly autonomously executes transactions on behalf of the consumer. These highly autonomous CBAs provide superior added value and become an essential part of the overall value chain.

The agent creates value by either completely automating purchases or by brokering the best-fitting offer. Complete automation seems to be especially suited for low-risk, frequent purchases for which the purchase need can be physically measured (e.g., *IoT-enabled auto-selling* and *IoT-enabled auto-mediation*). This then becomes quite similar to a typical *subscription model* [16]. However, in case of full automation, we can expect regulators stepping in to protect consumers (e.g., forcing the inclusion of multiple offerings [7], or forbidding "blind" purchases [34]). The brokering of offerings can be used to select the best-fitting offer for the consumer. The agent can broker the offerings of established sellers (*conversational selling*, *agent-supported-*

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mediation). However, the agent can also create a novel marketplace via the brokering activity (*agent-enabled mediation*). This seems to be particularly suited for start-ups. In cases where CBAs broker from multiple offerings, we do not see full automation. Whether consumers will ever completely distribute complex purchasing decisions to agents remains open.

Moreover, the agent becomes an essential part of value chain, placing itself as a mediator between businesses and consumers. On business side, CBAs represent an additional sales channel. On consumer side, CBAs can offer novel ways of interacting, such as conversational interfaces. Because conversational interfaces provide limited interaction possibilities, they seem to align well with highly autonomous agents.

Furthermore, we find that agent enablers play an important role in the ecosystem. Out of 23 cases, 11 cases built on enablers and five were enablers themselves. Agent enablers serve with technological expertise in a rather complex field. In the case of platforms, enablers provide a user base and reach across multiple channels. We identified Amazon and Google as tech giants leading the field. However, start-ups like Pantri and Blutag reveal niche opportunities in the market.

We thus contribute to the research with, to the best of our knowledge, the first investigation of BMs for CBAs. Therefore, our taxonomy and proposed patterns set a foundation for the conceptual understanding of BMs for CBAs. Furthermore, by specifically setting the scope on highly autonomous CBAs, we raise the research community's awareness for the increasing autonomy of CBAs.

Our work also contributes to practice. We built a taxonomy and a structured set of patterns that can be systematically applied. The results provide practitioners strategic guidance by giving insights to the BMs of a previously understudied trend. Practitioners can use the taxonomy and the patterns to analyze and innovate their BMs.

Our study comes with limitations. First, because highly autonomous CBAs represent a recent trend, we could only analyze 23 cases in our study. Nonetheless, our results provide valuable insights for both research and practice. Additionally, the BM taxonomy and the respective BMPs are extendable, such that future research can build upon our results when more cases emerge. Second, as Nickerson, Varshney and Muntermann [32] argued, taxonomies are never perfect, but should rather be useful with regards to their purpose. We argue for the usefulness of our taxonomy, because it allows us to describe and compare BM cases that lead to the derivation of BMPs.

Looking at future research, the emergence of novel types of highly autonomous CBAs provides a fruitful avenue for research. Building upon our study, additional cases can lead to a more extensive BM taxonomy and potentially to the discovery of additional BMPs. Quantitative methods could be used to further validate the results. Furthermore, researchers could analyze BMs of less autonomous subsets of CBAs and compare their results with ours to get a more holistic view of the field. Moreover, as with "traditional" CBAs, future research could investigate the impact of highly autonomous CBAs on consumers, firms, and supply chains (e.g., through simulation), as well as evaluate certain design features (e.g., explaining automated actions).

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6 Conclusion

Software agents are now capable of near autonomous behavior, purchasing goods and services on behalf of consumers. These highly autonomous CBAs are expected to influence BMs by providing added value, additional sales channels, and new key partnerships. It is important for businesses to understand such trends to adapt and innovate their BMs in an ever-changing competitive environment. However, until now, the literature has not investigated BMs for highly autonomous CBAs. Our goal was to close this research gap with this paper. We first refined the term *highly autonomous consumer buying agent*. Based on this understanding, we collected 23 cases. We used the method by Nickerson, Varshney and Muntermann [32] to develop a BM taxonomy for highly autonomous CBAs. We encoded the cases using the BM taxonomy and derived three overarching BMPs and eight sub-patterns. We found out that businesses could use agents to either directly sell products or to mediate between buyers and sellers. Agents provide added value to the consumer buying process and become important actors in the value chain. Furthermore, we identified agent enablers as important players in the business ecosystem, enabling highly autonomous CBAs.

We contribute to the literature by setting the foundation for the conceptual understanding of BMs for highly autonomous CBAs. Practitioners can use our BM taxonomy and BMPs as strategic guidance to support BMI. Future research can build upon our work, especially after more cases of highly autonomous CBAs have emerged.

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Appendix A Case List and Taxonomy Encodings

ID	Case Title	Ref.	Type	Target Customer	Agent Stage	Purchase Automation	Purchase Brokering	Purchase Scope	Agent Deployment	Agent Interface	Endpoint Belonging	Endpoint Type	Provisioning	Ongoing Revenue	Upfront Revenue
1	Google Assistant Voice Shopping	[35]	2	B2C	App	Human-triggered	Both	Cross Domain	Platform	Conver-sational	Own	Marketplace	Both	Commission	None
2	Amazon Alexa Voice Shopping	[36]	2	B2C	App	Human-triggered	Both	Cross Domain	Platform	Conver-sational	Own	Marketplace	Both	Commission	None
3	Kyocera Printer	[37]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	External	Marketplace	Own G/S	Sales	Sales of Device
4	GE Appliances Dishwasher	[38]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	External	Marketplace	3rd Party G/S	Commission	Sales of Device
5	Filtrete Smart Filter	[39]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	External	Marketplace	Own G/S	Sales	Sales of Device
	Petcube Bites Treat Dispenser	[40]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	External	Marketplace	3rd Party G/S	Commission	Sales of Device
	Illy Coffee Machine	[41]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	External	Marketplace	Own G/S	Sales	Sales of Device
	WePlenish Smart Container	[42]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	External	Marketplace	3rd Party G/S	Commission	Sales of Device
	Oral-B Electronic Toothbrush	[43]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	External	Marketplace	Own G/S	Sales	Sales of Device
	HP Instant Ink	[44]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	Own	Single Vendor	Own G/S	Subscription	Sales of Device
	Xerox Metered Supplies	[45]	1	B2C	App	Automated	None	Single G/S	IoT Device	None	Own	Single Vendor	Own G/S	Sales	Sales of Device
	Pantri Platform	[46]	1	B2B	Platform	Automated	None	Single G/S	IoT Device	None	-	-	-	-	None
	Garbican Smart Trash Bin	[47]	2	B2C	App	Human-triggered	Merchant	Domain	IoT Device	None	External	Set of Vendors	3rd Party G/S	Commissions	Sales of Device
	MealIQ Meal Planer	[48]	2	B2C	App	Human-triggered	Both	Domain	Web/Mobile	GUI	External	Set of Vendors	3rd Party G/S	Commission	None
	Blutag Retail Voice Apps	[49]	2	B2B	Blueprint	Human-triggered	-	-	Platform	Conver-sational	-	-	-	Subscription	None
	Virgin Train on Amazon Alexa	[50]	2	B2C	App	Human-triggered	Product	Single G/S	Platform	Conver-sational	Own	Single Vendor	Own G/S	Direct Sales	None
	Myia Energy Bot	[51]	1	B2C	App	Automated	Merchant	Single G/S	Web/Mobile	Conver-sational	External	Set of Vendors	3rd Party G/S	Commission	None
	Niki Chatbot	[52]	2	B2C	App	Human-triggered	Both	Cross Domain	Web/Mobile	Conver-sational	External	Set of Vendors	3rd Party G/S	Commission	None
	Walmart on Google Assistant	[53]	2	B2C	App	Human-triggered	Product	Cross Domain	Platform	Conver-sational	Own	Single Vendor	Both	Direct Sales	None
	LookAfterMyBills	[54]	1	B2C	App	Automated	Merchant	Single G/S	Web/Mobile	Conver-sational	External	Set of Vendors	3rd Party G/S	Commission	None
	Amazon Alexa Platform	[55]	2	B2B	Platform	Human-triggered	-	-	Platform	Conver-sational	-	-	-	Commission	None
	Google Assistant Platform	[56]	2	B2B	Platform	Human-triggered	-	-	Platform	Conver-sational	-	-	-	None	None
	Amazon Dash Replenishment Platform	[57]	1	B2B	Platform	Automated	None	Single G/S	IoT Device	None	External	Marketplace	-	Commission	None

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