Decision-making with artificial intelligence: Towards a novel conceptualization of patterns

Completed Research Paper

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Abstract

The rapidly increasing amount of data available in society and business drives the development of Artificial Intelligence (AI). As the number of AI-based services is increasing, customers delegate intimate and relevant decisions to AI. However, current literature lacks understanding of what patterns of decision-making processes with AI involved exist, and it remains unclear how to structure and classify AI-based services accordingly. Therefore, we present and evaluate a set of seven patterns of decision-making processes with AI involved. Building on decision-making theory as justificatory knowledge, we focus on the business-to-customer context to provide a novel perspective on the interactions of customers with AI. We apply the patterns to real-world examples of companies offering AI-based services. Our work contributes to the descriptive knowledge of AI and decision-making theory providing a foundation for future research and supporting practitioners in designing AI-based services.

Keywords: Artificial Intelligence, AI, Decision-making, Patterns

Introduction

Digital devices produce more and more digital data, and computing capacity is growing at an unprecedented pace. For example, the number of connected devices is predicted to reach 75 billion in 2025 (Columbus 2016; Statista 2019). The ‘datafying’ of human environments is generating new levels of customer intimacy with these devices (Newell and Marabelli 2015). The resulting (big) data is more and more effectively and efficiently processed by artificial intelligence (AI) to support everyday activities (Newell and Marabelli 2015). As a result, humans can delegate tasks to AI, as the well-established example of AI financial trading shows (Kissell and Malamut 2006). With the ongoing progress of AI-based services, today, increasingly intimate and relevant decisions are delegated to AI, as GM’s car emergency and Amazon’s replenishment services demonstrate. Whereas the first example delegates emergency calls in case of an accident to the car’s AI, the latter promises that customers‘ will never have to order groceries again (Heathmann 2018) because the AI takes care of it.

AI refers to computational technologies that sense, learn, reason, and take action following the way humans do (Stone et al. 2016). Academic and practical literature has examined AI decision-making from various functional and industrial perspectives. On the one hand, a significant stream of research focuses on mathematical and statistical methods for realizing AI decision-making, as the work of Venkatasubramanian et al. (2003), Jahanshahloo et al. (2006), and Mellouk et al. (2018) demonstrate. On the other hand, Jarrahi (2018), Günther et al. (2017), and Gomez-Uribe and Hunt (2016) investigate the potential of AI from a value-oriented business perspective. Further, Danaher et al. (2017), Corbett-Davies et al. (2017) and Newell and Marabelli (2015) discuss ethical and long-term societal effects of 'datafication' and AI. From an industry point of view, AI-focused research ranges from the financial (Kissell and Malamut 2006) over machinery (Baptista et al., 2018; Li et al., 2014; Venkatasubramanian et al., 2003) to the marketing and consumer context (Erevelles et al. 2016; Inanc-Demir and Kozak 2019). Traditionally, research in the marketing field has been centered around product presentations and targeted communication to the consumer (Grönroos 2007). Marketing today, however, pays increasing attention to decision-making by AI instead of humans. In this regard, Gal and Elkin-Koren (2017) were the first to describe AI that takes over the role of the customer 'that will not only make purchase recommendations but will also predict what we want, make purchase decisions, negotiate and execute the transaction […] thereby replacing human decision-making' (Gal and Elkin-Koren 2017). However, beyond these valuable insights, further studies examining decision-making of AI on behalf of human customers are still missing, which is particularly relevant in the business-to-customer (B2C) context (Traumer et al. 2017). Specifically, the body of knowledge lacks design options for AI decision-making on behalf of customers, i.e., how and to what extent customers can delegate decision-making to AI. This is a prerequisite for sense-making research and necessary to support practitioners in designing AI-based services in the B2C context (also highlighted from a practitioners perspective; McKinsey Analytics 2018).

Existing classifications of AI mainly focuses on its ability to take over tasks and associated complexity (Kaplan and Haenlein 2019; Traumer et al. 2017). These abilities focus on dimensions of cognitive intelligence, emotional intelligence, social intelligence and artistic creativity. Furthermore, the complexity of executing tasks (low, medium, complex) (Traumer et al. 2017) is targeted from a general perspective, but not from the perspective of human decision-making. Building on such work, the next step is to characterize how AI aligns with humans in decision-making processes, i.e., which tasks AI takes over with regards to business-to-customer (B2C) interactions (Jarrahi 2018). While this perspective has been highlighted to be relevant in an organizational context (Jarrahi (2018), no categorization has been offered. As such, we address the following research question: *Which patterns of decision-making processes with AI exist in the B2C context?*

In response to this question, we develop and evaluate seven patterns of decision-making with AI involved in the B2C context. For this, we follow the taxonomy development method of Nickerson et al. (2013) employing the conceptual-to-empirical path with one iteration for this conceptual paper. We draw on decision-making theory (Dörner and Schaub 1994; Gonzalez et al. 2003) as a foundation for conceptualizing patterns of decision-making processes with AI involved. The choice on the perspective of this stream of research targeting cognitive/analytic decision-making is rooted in our focus of analyzing the functional options AI. Further, we identified 371 real-world examples to demonstrate the applicability of our proposed patterns. Our work contributes to the descriptive knowledge of AI and decision-making theory, providing a foundation for future research and supporting practitioners in designing AI-based services (McKinsey Analytics 2018).

The remainder of this paper is structured as follows: First, we outline our research methodology before we set the stage by discussing the theoretical background of AI and decision-making. Second, we present our results in terms of patterns of decision-making processes with AI involved. Third, we then provide empirical evidence regarding the existence of our patterns in the real world by highlighting real-world examples and conclude by discussing implications, limitations, and stimuli for future research.

Theoretical background

Dynamic decision-making

Human decision-making is typically dynamic, i.e., informed by experiences with decisions over time (Dörner and Schaub 1994; Gonzalez et al. 2003). Figure 1 illustrates this process. Phase 1, the assessment of options, covers the preparation of a decision in which the goal for making a decision is chosen, options are searched by collecting data, evaluated and ranked. Phase 2, execution of the decision, involves a specific option being chosen, and the decision is executed. Phase 3, assessment of the results, captures the perceived feedback connected to the outcome of a decision. Outcomes of phase 3 then inform future decision-making. We chose to group all activities related to a dynamic decision in three phases as we do not want to elaborate each functionality in detail but rather provide the elementary phases which refer to *before, execution of* and *after* a decision. Compared to static decision-making, the assessment of results influences the assessment of options for the next similar decision, i.e., each decision is directly influenced by prior decisions. In contrast, static decision-making does not occur again and is generally informed by experiences from other (potentially unrelated) decisions.

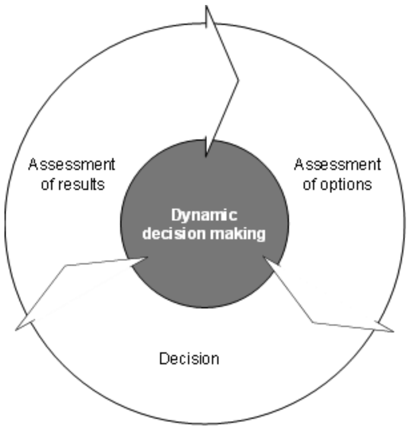

Figure 1. Dynamic decision-making process.

These phases are typically subject to human errors as humans have difficulties in remembering details properly, or do not have enough time and mental capacities to think decisions through, or have difficulties in linking executing a decision and the related feedback (Dörner 1996; Kahnemann 2012; Sterman 1989). Due to these time and cognitive limitations, humans are often applying an intuitive reasoning style, which is spontaneous, emotional, and sometimes biased. Contrary, an analytic reasoning style requires deliberate and effortful thinking, but humans still have limited memory of the past, and such thinking often requires time that is not available in a decision-making situation. AI follows an analytic reasoning style and will make the same decision in similar conditions not being influenced by a situation or emotions (unless programmed otherwise, e.g., by self-learning modes or unintentionally biased programmers).

Delegating decision-making to AI

Given the challenges of dynamic decision-making, humans see advantages in delegating decision-making or parts of the process to an AI. Despite its relevance in research and practice, Stone et al. (2016) found that there is no precise and universally accepted definition of AI. In their “One Hundred Year Study on AI” they broadly define AI as both “a science and a set of computational technologies that are inspired by—but typically operate quite differently from—the ways people […] sense, learn, reason, and take action” (Stone et al. 2016, p. 4). More specifically, Russel and Norvig (2016) derive four broad categories of AI definitions: ‘Thinking humanly’, ‘acting humanly’, ‘thinking rationally’, and ‘acting rationally’. Further, current research distinguishes ‘strong AI’, that relates to the creation of artificial (i.e. human-like) intelligence, from ‘weak AI’, that focuses on AI-enabled systems that take over specific tasks (Kurzweil 2006; Stone et al. 2016). In this study, we relate to Stone et al.’s (2016) broad definition and ‘weak’ form of AI, where we focus on specific decision-making tasks, irrespective of whether they are performed in a 'human-like' manner. Thus, we include a wide range of digital technologies and application scenarios, that span across varying levels of 'intelligence'.

The fundamental difference between AI and traditional software (e.g., decision support systems) lies in its ability to learn from big data with different formats and various time spans and to draw conclusions from such data (Zuboff 2019). The processing of this data does not have to be programmed in advance but can emerge over time from a machine learning process as the AI processes the data received as input (Kellogg et al. 2020). Based on this learning mechanism, AI-enabled software can develop its representation of a decision problem, and deliver its conclusions on the best results for a defined goal (Dietvorst et al. 2015).

The affordances of AI are not completely new ideas, but are often not available on the market because it is too much effort for human beings or impossible to develop efficiently or cost-effectively (Ng 2016). AI typically works on behalf of someone (company or human) who is delegating a certain task to an AI (Schneider and Leyer 2019). Hence, AI competes with offers by human beings and allows either for a better execution or for new offers to be made. The following major characteristics distinguish them from human execution (Hoffman 2016; Moore 2016): (1) Infinite memory, (2) Capable of processing huge amounts of information, (3) Low cost for acting 24/7, (4) Fast execution.

Given these distinct characteristics of AI, AI changes the types of service offerings available and the relationship between customers and service providers (Reeves and Ueda 2016). For this, there is a variety of AI types ranging from simple deterministic to self-learning (Abraham 2005), from decision support to full delegation (Schneider and Leyer 2019) as well as from static to dynamic. Dynamic AI refers to rules being changed after executing them, based on feedback or integrating updated information from the environment the AI is operating in. In doing so, AI can support decision-making or replace phases in the decision-making of humans.

As we are interested in AI supporting the decision-making process, dynamic decision-making theory is guiding us in developing patterns of AI decision-support. Hence, AI can execute decision-making by taking over the assessment of options (e.g., judgement in case of platforms providing a ranking of different offers), the choice to be executed (e.g., navigation unit providing the best route without the user interfering), and assessing feedback for future decision-making. In the first phase, assessment of options, AI can observe an humans' data or behavior to assume the goal of a potential decision, search for options (also based on keywords provided), evaluate options according to criteria set or determination by data, and provide a ranking of decision options based on these criteria. In the second phase, decision, AI can select an option from the ranking according to the criteria set and automatically execute the decision without an human being involved. In the third phase, assessment of results, AI can gather data on the consequences of a decision from a device, track how the parameters identified for decision-making are affected and use analytical models to provide results on the impact of the decision.

Delegation to AI according to the phases of decision-making can occur in two ways: an augmented decision phase with AI or an automated decision phase (Martin 2019; Raisch and Krakowski forthcoming). The augmentation decision phase involves a partial delegation within the phase is the case which is resulting in a combined execution of the phase by human and AI. This can either be an ongoing interaction in the phase or a prior definition of criteria by an human. The automated decision phase involves the complete phase of decision-making being executed by AI.

AI needs some minimum amount of input to be able to decide or perform a task effectively on behalf of humans. Be it data about the level of coffee remaining in the coffee machine or information on a car's condition and repair requirements. AI with more and more accurate information might outperform AI with fewer insights. Hence, corporates need to reflect on how to get seamless access to their customer's behaviors, decisions, and lives in general. For example, Google's nest thermostat not only provides remote control to the customer but generates great insights from the connected home ecosystem that Google leverages and sells across customers. Another famous example is Amazon, closely tracking a customer's buying decisions through an humanized online account to provide targeted recommendations.

Patterns of decision-making processes with AI involved

We follow the theory of dynamic decision-making of assessment of options, execution of the decision, and assessment of the results. Assessment of options captures the processes before deciding, in which information is collected about the decision, options are weighed/considered, and intentions are formed. Execution of the decision is the point in the decision-making process when a decision is acted on. For example, when the purchase of a product or service is made. The feedback stage of the decision-making process involves post-decision assessment of the results, such as, was the product or service good an human decided on, did it meet the customer need, did it perform well. All the information generated in the feedback phase can inform future delegation stages in decision-making before a repeated or adjusted purchase decision.

In the age of AI, humans no longer must play the primary role across each and all these three phases of decision-making (assessment, execution, feedback). In this paper, we propose seven patterns of decision-making processes with AI involved, capturing the varying roles of the human or AI in offering an assessment of options, execution of the decision, and feedback on the decision. These patterns include: evaluator, evaluator with hindsight, fully automated, informed outsourcing, executioner, learner, and deferrer (Figure 2). Automation can occur in each pattern when the AI is fully responsible for decision-making, while augmentation occurs when an human decides to hand over the automated execution to AI within the different phases. Each pattern is described below with accompanying examples of existing products or services to allow for a better understanding of its abstract nature.

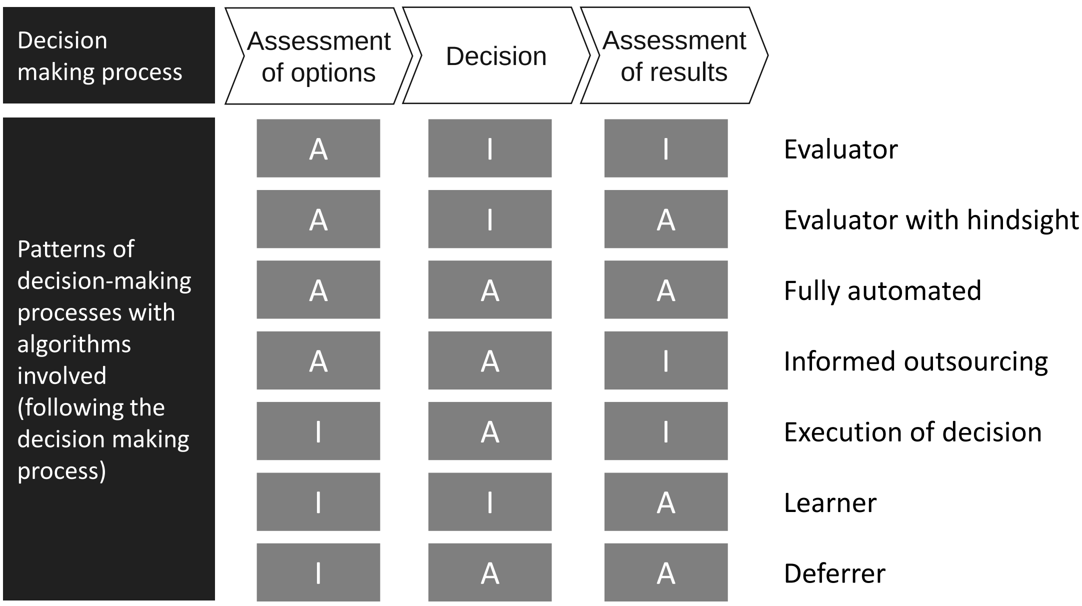

Figure 2. Overview of patterns of decision-making processes with AI involved (I: Human; A: AI).

Evaluator

AI in this pattern provides a set of options to humans that are ranked according to one or several criteria initially provided by the user (the decision-maker). To do so, the AI has searched for available options, assessed these according to these criteria and conducted the ranking. In the case of automation, the decision-maker simply must choose the favorable option. The assessment of results is not included. An example of the evaluator pattern is a booking platform for flights, which provides best options according to flight duration, price, and the number of stops regarding selected dates and locations. Using an AI to augment one’s own decision, an human either provides a set of options to an AI or uses the results of an AI to conduct further assessments. In the example, an human would take the results and perform their search for flight options that might not have been provided by the AI. This can then continue in an repetitively when an human is then using the AI with updated information again to receive better options.

Evaluator with hindsight

AI in this pattern provides a set of options to humans that are already ranked according to one or several criteria, the human then makes the decision, and the AI then evaluates the outcome of the decision. In the first part, the AI has searched for available options, assessed these according to criteria and conducted the ranking of which the decision-maker simply must choose the favorable option. After the human makes the decision, the AI tracks experiences of the human decision-maker with the selected option where data is available to adjust the evaluation criteria for the next decision.

An example of the evaluator with hindsight pattern are shoes that have been recommended to a runner for which a digital watch tracks sensors in the shoe assessing whether the shoes are aligned to the runner's feet. The results can be used to exchange the shoes in the first two weeks, recommend a different shoe next time, or suggest when the shoes should be changed.

In the augmented version, an human either provides the first set of options to an AI, uses the results of an AI to conduct further assessments or conducts observations on the results himself/herself. In an extension of the assessment phase, as described, an human could do their observations based on the feeling of the shoe, which might either add to or differ from, the AI result. There can even be an option for feedback to the AI from the human regarding its assessment results reported.

Fully automated

AI in this pattern takes care of each phase in the decision-making process, without human input. The AI searches for available options, assesses them, decides and gathers feedback to for further decisions. An example of a fully automated pattern is a dishwasher that uses sensors to detect when the box for detergent is expected to be empty. It then calculates when new detergent needs to be made available based on the anticipated degree of dirt, the available length and intensity of the cleaning program as well as the amount of detergent used. These insights are then used to search for detergent offers on trading platforms, in which AI selects and orders based on the experienced usage efficiency. The usage efficiency is then calculated (after the human has manually added the detergent to the dishwasher) based on how much detergent is required for the cleaning operations to inform future decision-making of the order process.

As noted, the augmented version requires that a human setting the decision criteria upfront and the AI is executing automatically according to the criteria defined. The same holds for the assessment of options as well as an assessment of results, as the human can provide guiding criteria for these activities. Hence, there is not an ongoing interaction with the AI and the human but rather an initial definition and periodical review of decision criteria. However, the human is not involved in the ongoing decision-making process so that the AI can execute the decision-making process in a fully automated fashion. In the dishwasher example a human can define relevant marketplaces or product criteria (e.g., ecological products), limit the maximum price to be ordered, or provide feedback for usage behavior (e.g., indicating upcoming holiday in the parameters suggesting increased demand).

Informed outsourcing

AI in this pattern searches for available options, assesses them, and makes the decision. It is up to the human to provide feedback on the choices made to inform the AI of good or bad decision-making. The feedback is then considered for future decision-making by the AI. An example of the informed outsourcing pattern is a music streaming service in which the user can discard music choices made by AI for future playlists. The AI will then avoid similar music.

The augmented version of this pattern involves a human providing decision-making parameters to the AI. Moreover, if a human wants to discard a decision made by AI, it is also covered by the assessment of the result and making a different decision in the future. In the example of music streaming, an human can exclude certain genres before having to listen to them.

Execution of decision

AI in this pattern executes the decision. Once a human has searched for available options, assessed them against specific decision criteria, the AI makes the decision. The feedback assessment is done by the human to change the decision criteria for future decision-making. An example of the execution of the decision pattern is automated stock buying in an online banking environment. The human has decided on a specific product and defined the price for which the product should be bought. An AI takes care of purchasing when it is available in the defined quantity with the defined price. AI can do this by continuously monitoring the stock market without the human needing to.

As noted before, the augmented version of this pattern refers to a human providing decision criteria to be considered by the AI when deciding. In the stock buying example, this could be the exclusion of certain trading platforms or stock types.

Learner

AI in this pattern gathers experiences on decisions made automatically and assesses them to provide recommendations to the human on the results of their decisions for future decisions. An example of the learner pattern is a fitness tracker, which observes the health parameters of a user as a result of decisions to exercise. Recommendations can be provided according to intensity, scheduled time, or type of exercise.

In the augmented version of this pattern, a human can also provide feedback to an AI himself/herself. This feedback is then incorporated into the learning process. In the example, health parameters could be weighted by the user, or bandwidths could be adapted by the user manually.

Deferrer

AI in this pattern takes over the decision execution and the assessment of feedback on those decisions. A human has first searched for available options, assessed them and defined criteria according to which decisions should be executed in a particular moment. The assessment of the feedback is done by the AI to provide the human with feedback on the outcomes of decisions for future evaluation. An example of the deferrer pattern is an online shopping AI, which is supplied with the objects to be ordered by a human and then searches for shopping platforms to execute the order. Feedback on the proper delivery by the marketplace and quality of the product is then considered for future selection of marketplaces.

As noted before, a human provides certain decision criteria to be considered by the AI in the augmented version. Similar to the stock market example, certain payment options on platforms could be excluded that influence decision-making but are not part of the decision-making criteria.

Empirical evidence on the distribution of the patterns in practice

We gather empirical evidence from CrunchBase regarding existing business models, including AI offers for human decision-making processes. CrunchBase is the most relevant source for getting a profound overview of technology-based business models (Oberländer et al. 2018) in our case, targeting AI offers for humans. We searched the database using the search term “algorithm”, “AI” and “artificial intelligence” which are the typical terms to be used to describe related business models. This led us to identify 371 AI-driven business models addressing organizations and humans as customers. Each business model contains a short description of the functionality of the AI-service offered. Of these, we randomly (using the random function of Excel) selected 100 AI-based offers relating to a business to human (B2C) context. The business models target a variety of industries and the needs of humans. For these, we extracted information from the descriptions provided in CrunchBase and the respective websites of the companies according to the three categories of assessment of options, decision and assessment of results. The result was a text for each AI-based offer stating what is offered to support humans in their decision-making.

We assigned each of them to our seven patterns of AI (for an overview of the distribution see Figure 3). The assignment was done by two researchers and triangulated by gathering feedback from humans using clickworker (a platform similar to Amazon Mturk). Each text was analyzed, and it was indicated for each of the underlying three categories of decision-making processes, whether AI or humans executed the task. For clickworker, we randomly selected ten AI descriptions (4 AIA, 3 AAI, 3 AII), out of the 100 and presented them to 30 participants with random ordering. Applying attention tests resulted in 21 participants remaining in the sample. The test regarding interrater reliability (Intraclass Correlation Coefficient; Shrout and Fleiss 1979) Intraclass Correlation Coefficient shows that our ratings are confirmed to be consistent (.732 [p <.001] > threshold of .7) with a mean confirmation of 68%. These results indicate that sufficient reliability is ensured.

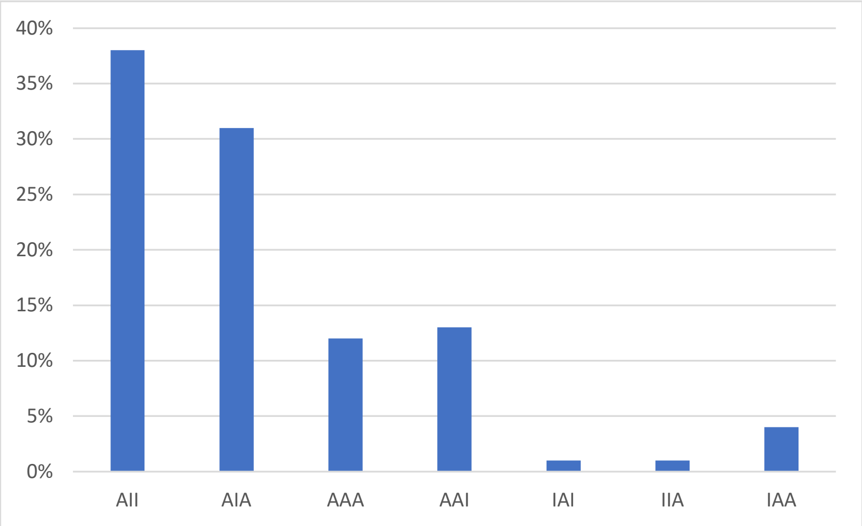

Figure 3. Distribution of patterns in the sample (N=100).

The distribution shows that the majority of AI is within the assessment of options and feedback; some provide complete automation, while few are assessing feedback of decision from humans. The augmented forms were not included as no description of offers could be found that were specifically describing augmented forms. It is, however, possible to use the AI offers for augmentation and automation purposes.

Discussion and Implications

Although in the digital economy increasingly intimate and relevant decisions are delegated to AI, current literature lacks a comprehensive overview of design options for decision-making with AI on behalf of humans. Against this background, this study addressed the research question: *Which patterns of decision-making processes with AI exist in the B2C context?* Our primary response to this question builds on seven patterns of decision-making processes with AI involved in the B2C context distinguishing them from a decision-making perspective. Some patterns can be used as automated or augmented versions while patterns involving the handover of decision-making to AI do not allow for augmentation. Our patterns deliberately distinguish patterns not based on technology-related, but on interaction-based and decision-related characteristics among AI and humans, which are persistent in a rapidly changing technology-driven environment.

The results regarding the distribution of patterns also highlight the chances for empirical and conceptual research. While there are quite a lot of concepts available for patterns AII (Evaluator) and A-I-A (Evaluator with hindsight), empirical work is more relevant to analyze the concepts and draw conclusions on how AI is characterized with variations (e.g., concerning technological options, products and services targeted) in these patterns. Contrary, there should be more conceptual work on patterns such as IAI (Execution of decision), IIA (Learner) and IAA (Deferrer) to provide blueprints how domains with regard to products/services and technology should be targeted. While the general pattern describes the integration on a higher level, quite some details can be different, which also influence whether a specific solution within a pattern is successful or not.

Theoretically, this paper offers a novel catalytic idea that helps academics and practitioners structure the service design for AI in the B2C context. We conceptualize our patterns based on dynamic decision-making theory and highlight how exactly collaborations between AI and humans can be shaped. Hence, this conceptualization extends on existing classifications that, for example, focus on the complexity of AI and the resulting ability to take over tasks (Kaplan and Haenlein 2019; Traumer et al. 2017) or the fundamental difference of augmentation and automation (Martin 2019; Raisch and Krakowski forthcoming). Taking the perspective of human decision-making, the provided patterns allow us to understand possible interactions between AI and humans in the B2C context. The patterns could also be used to inform service redesign decisions related to AI-based services and business models. Thus, our work provides a foundation for the theory-led design and supports practitioners in designing AI-based services (Shirley and Hevner 2013).

This work has several practical implications. Although we do not claim to provide an exhaustive overview of all available AI in the B2C context, the identified examples yield useful insights. Our classifications, for example, show that hitherto most investigated AI aimed at informing humans rather than taking over the actual decisions. Companies can analyze how customers perceive and accept different patterns of AI using the classification. Currently, AI is operating in closed ecosystems such that devices will order replenishments from one source (e.g., Alexa only buys Amazon-sold products or products listed by Amazon). Take, for example, the Amazon DASH replenishment service whereby customers hit a button when they perceive the need to order more of a specific product (e.g., washing powder). This product would then be ordered from Amazon. There is no opportunity at this stage for the customer to press the DASH button and have other retailers compete with Amazon to replenish that product. Amazon created the DASH button for this competitive reason. It is fair to expect that at some point competition regulators will intervene to ensure equitable access for other providers (Kowalkiewicz et al. 2017). This will open the ecosystem to enable cars, fridges, and more, to buy products or services from any organization competing in a Business to Things (B2T) marketplace without humans involved. The future may see an evolution of more dynamic, tailored AI that can change based on a customer's current financial position (e.g., I'm cash poor, therefore only order home-brand food this week), mood (e.g., 'treat 'yourself' purchases enabled for luxury goods), or goals such that purchases are only made in accordance with the customer's desire to save for a house or eat healthily.

Conclusion and future work

The emergence of AI that acts on behalf of customers will create a lot of opportunities if those involved in the new ecosystems are prepared. Manufacturers will need to learn how to build devices that order products and services on behalf of humans. Marketers will need to learn to sell to AI. Customers will need to learn to work with AI. While some jobs as we know them today may disappear, there are the opportunities of new jobs: fridge campaign managers (fridges as a target group), proactive delivery couriers (I need one to deliver my coffee before I run out of beans), and others. Preparing workers for the transition into these new jobs is critical. It is then essential, however, to determine, which type of AI fits which situation and the respective acceptance of these patterns by humans. Hence, our catalogue provides the foundation for practitioners to design AI-based services effectively.

Future research should address the following limitations. First, we focus on the B2C context leaving business-to-business (B2B) interactions out of the analysis. In the latter, decision-making is not limited to humans but also to group decision-making (e.g., management board). There are also guidelines throughout an organization that must be followed in decisions. Hence, the theoretical foundation in a next step should also incorporate the group level, which will potentially lead to different but related patterns of decision-making processes with AI involved. Second, our empirical set of AI stems from a selected sub-sample from CrunchBase, covered a certain period and the Asian market is hardly covered. While it is challenging due to language barriers of the authors to analyze the Asian market, the idea of presenting the empirical evidence in this conceptual paper was to show the relevance of the patters for current real-world examples. Third, since we have chosen a cognitive/analytic perspective, we did not include aspects of cost for using AI as well as deployment issues. There should be further analyzed to consider such aspects for the patterns derived, which will rather result in an adoption model and the description of related decision-making for adopting AI. Fourth, the identified patterns assume that the decision-making steps are either performed by a human or AI. In the future, it would be interesting to study the collaboration of humans and AI in the respective steps and which synergy effects might arise. Fifth, our analysis is limited to the patterns. In the next steps, we will also engage in theories for design and action to provide academics and practitioners with guidance on the construction of AI-led services and business models based on the patterns.

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