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Updating the theory of industrial marketing: Industrial marketing as a Bayesian process of belief-updating

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ABSTRACT

While industrial marketing often comprises a process that, at least in principle, mirrors Bayesian reasoning, the notion of Bayesian inference has predominantly been utilized in the marketing field as a methodological tool. This article suggests that the practice of industrial marketing itself should be (re)conceptualized as a Bayesian process of belief-updating that entails a continuous cognitive cycle of formulation of hypotheses (i.e., beliefs about the market) and the subsequent updating of those hypotheses through exposure to market evidence (e.g., data from the market). A Bayesian perspective on industrial marketing enables a synthesis of a broad body of extant research as well as a focus on the interconnection between executives' market beliefs (theories-in-use) and belief-updating (assessing the validity of those beliefs in view of market evidence). A view of industrial marketing as a Bayesian process not only enhances our understanding in general but also fosters insights into market learning in uncertain and volatile situations. A Bayesian conceptualization suggests a new understanding of industrial marketing that also informs a typology of marketing approaches. We outline opportunities for developing a better understanding of the Bayesian foundation of industrial marketing.

> *"You have to challenge your assumptions."*
>
> *Jim Hagemann Snabe, Chairperson of Siemens and Maersk*

1. Introduction

The practice of industrial marketing is often predicated upon the mental models and internalized theories of industrial marketers entailing expectations concerning how markets function and how buyers will respond to different corporate actions (e.g., Nevett, 1991; Zeithaml et al., 2020).[1] As Zaltman, LeMasters, and Heffring (1982) posit, individuals' mental theories (i.e., theories-in-use, TIU) may be conceptualized as a set of "if-then" relationships between actions and outcomes. For example, an industrial marketer may have a theory that "a firm's customer centricity improves its profitability, but an increase in customer centricity beyond a certain level adversely affects firm profitability because it is too costly. That is, there is an inverted U-shaped relationship" (Zeithaml et al., 2020, p. 34).

While it has long been acknowledged that such internalized theories serve as the foundation for market-based behavior (e.g., Prahalad & Bettis, 1986; Vargo & Lusch, 2004), these theories-in-use must be tested for validity and subsequently updated according to market feedback in order to ensure long-term market performance and corporate longevity (e.g., Burgelman & Grove, 2007; Jaworski, Kohli, & Sahay, 2000; Miller, 1992). The need for executives to update their theories-in-use according to evidence is reflected in the idea that "firms can hold competitive advantages simply because their rivals entertain erroneous beliefs about them" (Foss, 2007, p. 249). As suggested by Zeithaml et al. (2020, p. 34): "the theory construction process involves developing novel if-then propositions. In contrast, the theory-testing process involves empirically assessing the validity of previously developed propositions. While the two processes and their aims are distinct, they potentially can be

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[1] The "practice of industrial marketing" refers to the way in which marketing is effectuated by marketing practitioners. As posited by Nevett (1991, p. 13-14) "the marketing practitioner frequently must make decisions that cannot be justified scientifically … Lack of reliable information, particularly on competitors' likely strategies, sometimes leaves no alternative but to make judgments based on experience, a 'feel' of the situation, and a measure of imagination."

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interrelated."

It follows that the successful practice of industrial marketing comprises a dual and interrelated cognitive sequence of first conceptualizing market-based theories (or beliefs) and subsequently updating those theories in view of market evidence. This reflects the process of Bayesian belief-updating—that is, the cognitive capacity to rationally update prior beliefs based on observed evidence, suggesting continuous market learning, in line with the principles stipulated in Bayes' Theorem (Bayes, 1763; for short introductions, see Andraszewicz et al., 2015; McCann & Schwab, 2020). Despite this conceptual match, the academic fields of industrial marketing, and marketing in general, have largely viewed Bayesian statistics as a methodological tool for data analysis (see, e.g., Rouziou & Dugan, 2020; Van der Borgh & Schepers, 2018). However, a complementary, but widely overlooked, topic in industrial marketing research relates to Bayesian reasoning—the cognitive learning process of updating subjective probabilities of initial beliefs in view of new information. This paper fills this gap by (i) structuring existing debates on TIU in marketing, market sensing, and market learning into a formal framework and logic that draws from Bayesian inference, and (ii) by suggesting that the practice of industrial marketing is essentially a learning-process based on the formulation and updating of subjective market beliefs.

Our main contention is that industrial marketing practice should be seen as Bayesian reasoning (Fig. 1, see also literature on situational awareness, e.g. Marcus et al., 2020). While much work in industrial marketing has covered the methodological aspects of Bayesian statistics (see Appendices A & B), little is known on how the practice of industrial marketing can be (re)conceptualized as Bayesian reasoning. Against this backdrop, we contribute by (i) providing a frame of Bayesian reasoning to integrate existing literature streams, heeding the calls from MacInnis (2011) and Jaakkola (2020) for conceptual integration, (ii) using this frame as a basis to introduce four different marketing (mal)practices, where the Bayesian approach is framed as 'update-driven marketing', and (iii) establishing both theoretical and managerial implications to drive forward the field and practice of industrial marketing.

Our paper proceeds as follows. In the next section, we explain and review Bayesian inference. We then discuss how Bayesian reasoning relates to and advances industrial marketing. We also illustrate the managerial implications of this approach in the context of industrial marketing during the COVID-19 crisis. Thereafter, we relate the Bayesian approach to other (mal)practices of industrial marketing. Finally, we propose a research agenda.

2. Bayesian inference

Bayesian inference is based on hypotheses, probabilities, and evidence (Bayes, 1763; for short introductions, see Andraszewicz et al., 2015; McCann & Schwab, 2020). Hypotheses are beliefs held by a person or a group of people, such as an organization, that point to a causal relationship or an expectation, essentially comprising a prediction of what will happen. In business-to-business marketing, such hypotheses may, for example, propose that investing in customer relationships leads

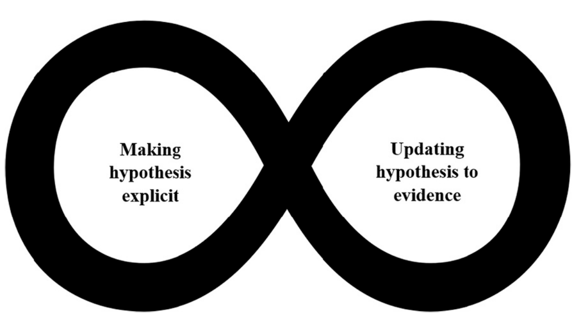

Fig. 1. Bayesian process of an eternal Möbius loop.

to superior performance, that the use of social media is important for winning new customers, or that all customers will pay their invoices.

Probabilities are expressions of the likelihood that something is true or can happen. A "probability is a quantitative notion that assigns a value ranging between 0 and 1 to a hypothesis on the basis of a body of information" (Galavotti, 2015, p. 745). The likely true state of the world is expressed as Bayesian probabilities (Griffiths & Tenenbaum, 2006), which in Bayesian inference reflect "personalistic interpretations of probability" (Roberts, 1963, p. 1). Referring to the sample hypotheses above, one might believe that superior performance results from investing in customer relationships in 8 out of 10 cases (i.e., allocate a Bayesian probability of 0.80 to this hypothesis) or that 50% of potential customers will react to a social-media campaign. Likewise, customers' payment of invoices may be regarded as nearly certain with a Bayesian probability of 0.99. Finally, evidence—such as customers increasing their purchases, new customers referring to a social-media advertisement as their reason for contacting a supplier, or customers not paying invoices—serves as a reason for revising the hypotheses.

Conceptually, Bayesian inference updates the probability that a hypothesis is true in light of evidence and the probability of that empirical evidence. Therefore, Bayesian inference involves the continual processing of empirical evidence. In other words, the probability of a hypothesis is updated as evidence is collected and analyzed. Bayesian inference calculates the posterior probability of a hypothesis—the new probability of the hypothesis after the empirical evidence has been considered—according to Bayes' theorem:

$$P(H|E) = \frac{P(E|H) \times P(H)}{P(E)},$$

where

- | means conditional probability;
- H is the hypothesis, the probability of which may be affected by the evidence;
- E is the new evidence;
- P(H|E) is the posterior probability that a hypothesis is true given the evidence (i.e., the probability of H after E is observed);
- P(E|H) is the probability of the evidence given the hypothesis is true (i.e., the probability of E under the assumption that H is true);
- P(H) is the prior probability (i.e., the probability that the hypothesis is true before the evidence is observed); and
- P(E) is the probability of the evidence (i.e., the general probability of the evidence occurring without considering the hypothesis).

Bayesian inference presumes that there is both a hypothesis and a prior probability that a hypothesis is true before the evidence is observed, and that one can assign probabilities to the evidence as well as the evidence given the hypothesis (Silver, 2012). Hence, Bayesian richness "results from the natural and principled way of combining prior information with data within a solid and coherent decision theoretical framework" (Rouziou & Dugan, 2020, p.118). Put differently, Bayesian inference is an analytical and processual mode of reasoning that entails the formulation of a hypothesis and probabilities as well as evidence collection and analysis. In essence, it is therefore a cognitive process (Griffiths & Tenenbaum, 2006; McCann, 2020).

Notably, Bayesian statistics differ from the frequentist approach, as "the two approaches view probability differently. Frequentists view probability in terms of relative frequency of an event in the long run. In contrast, Bayesians associate probability with degrees of belief or knowledge. These fundamentally different views imply deep and meaningful differences in how empirical data is interpreted and the corresponding statistical models to be used" (McCann & Schwab, 2020, p. 11–12). Hence, as a methodological approach, it represents a different philosophical stance. The increasing popularity of Bayesian methods is emphasized in Kruschke's sentiment (2011, p. 272) that while the twentieth century was dominated by frequentist statistics, the twenty-first century should "become a Bayesian century."

We can use Bayes' theorem to link existing literature streams in marketing (Fig. 2). Here, P(H) arguably relates to the TIU literature stream (e.g., Zeithaml et al., 2020), as it addresses the probability of managers' internalized theories or market beliefs. That is, P(H) entails that (i) managers make their assumptions, or rather internalized theories, about the market explicit, (ii) they formulate it as a falsifiable hypothesis, and (iii) they ascribe a probability measure to it. Zeithaml et al. (2020, p. 34) support this interpretation of TIU, as they state that their focus is on "the theory construction process for developing new theory about a phenomenon." As P(H) refers to the prior probability that a hypothesis is true (i.e., the probability of a hypothesis before new evidence is observed), it relies solely on the a priori mental models of managers.

P(E) resonates with the literature on market sensing (e.g., Day, 1994). In other words, as P(E) refers to the probability of the evidence in general, i.e. without considering the hypothesis, it is in line with market sensing due to its emphasis on market data and its validity. As such, market sensing, or here the active observation of evidence and assignment of probabilities for such observations of evidence P(E), is related to information processing rather than market learning in itself. According to Day (1994, p. 43): "The process of market sensing follows the usual sequence of information processing activities that organizations use to learn". For market learning to take place, the Bayesian theorem would, however, suggest a more intricate mechanism.

P(E|H) can be said to refer to the interaction of the market sensing and TIU literature streams, as it emphasizes the probability of the evidence given the hypothesis. That is, it suggests that the probability of evidence should be assessed in view of an existing market belief (theory). Put differently, the statement suggests that the perceived probability of the evidence is not only viewed in general through market sensing but is also interpreted through the lenses of a particular (internalized) theory. Interestingly, this interpretation resonates with a philosophical anchor in critical realism and is arguably a close representation of market sensing in practice, yet it is a point that is largely missing from the marketing literature.

Finally, the outcome of the theorem is P(H|E), which relates to the literature on market learning (e.g., Jaworski et al., 2000). Put differently, the objective is to learn about the market – and in this case, the learning takes place through a Bayesian mechanism by updating the assigned probabilities. In other words, as the theorem explains updating the probability that a hypothesis is true given new evidence, it explicates the learning process in which market beliefs are updated on the basis of market feedback. Hence, it is the a posteriori probability of a given hypothesis that manifests the learning which have taken place through the Bayesian process. The strength of the Bayesian theorem is not only that it offers structure to the literature streams, but also that it positions these important literature streams in relation to one another and

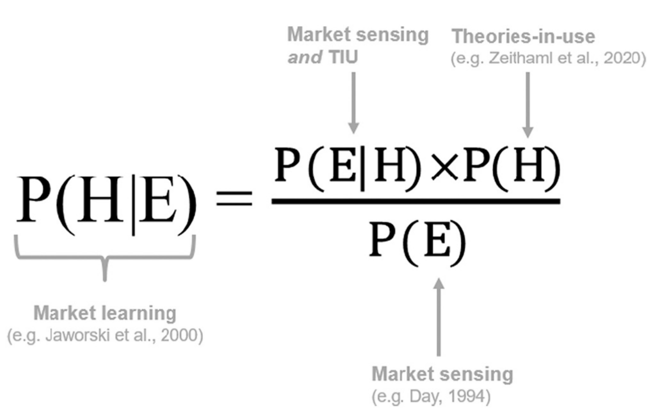

Fig. 2. Synthesizing literature streams in Bayes' theorem.

demonstrates their mutual interrelationship in a market-learning process.

Our (re)conceptualization of industrial marketing as a Bayesian learning process can also be further situated and positioned with the various literatures. While we do not aim to provide an exhaustive review of the literature, a few literature streams are particularly relevant in relation to belief-updating in marketing. First, we highlight the growing body of research on TIU in marketing (e.g., Zaltman et al., 1982; Zeithaml et al., 2020). While this emerging stream of literature has already provided substantial insights into how practitioners rely on mental models in their decision making, we still lack evidence on how they update those models in evolving markets.

Second, our work builds on the extensive research on market orientation, which involves "learning about market developments, sharing this information with appropriate personnel, and adapting offerings to a changing market" (Jaworski et al., 2000, p. 45). Similar notions are expressed regarding "market sensing" ("continuously sense and act upon events and trends;" Day, 1994, p. 34) and "customer knowledge competence" ("processes that generate and integrate market knowledge;" Li & Calantone, 1998, p. 13). While the TIU stream emphasizes the first part of the Bayesian process (belief formation), the market-orientation stream accentuates the latter part (collecting market data). As such, although the extant research provides extensive insights into the collection and application of market evidence, it has abstracted away from the crucial role that predefined beliefs play in understanding and assessing market observations.

A third body of research concerns Bayesian statistics in marketing (e.g., Lee, Boatwright, & Kamakura, 2003; Rossi, Allenby, & McCulloch, 2005; McCann & Schwab, 2020; see also Appendix B for selected papers on Bayesian statistics in notable marketing journals). While this body of research acknowledges the importance of Bayesian statistics, it also suggests that its predominant role is as a methodological and analytical tool rather than a form of cognitive reasoning that describes the market learning practice of industrial marketing itself.

Here, we suggest that Bayesian reasoning is predominantly a market learning mechanism, i.e. it explains how individuals learn through updating their TIUs based on market evidence. Yet, obtaining new knowledge often only realizes its full value if it is put to practice, i.e. when one acts upon the new knowledge. As such, new knowledge should ideally inform decisions. However, we acknowledge that there is some debate in the decision-making literature concerning the extent to which Bayesian inference accurately depicts how individuals make decisions (e.g., Aven, 2020; Pitz, 2018). While not all individuals are Bayesian in their decision making, evidence suggests that at least some are proficient Bayesians (e.g., McCann, 2020; Silver, 2012; Tetlock, 2005; Tetlock & Gardner, 2016). One way to combine these conflicting stands can be to note that being a Bayesian decision maker is *possible* but not necessarily *probable* unless effort is expended to become one, i.e. one needs to develop a Bayesian capability over time through incremental learning.[2] In the words of Aven (2020, p. 5) "there is a leap between formal analysis and actual decision making, reflecting the fact that the analysis has limitations in capturing all aspects of interest for decision makers," while at the same time acknowledging that "applying a formal decision analysis process can provide structure and knowledge important for decision-making." This paper aims is to make the Bayesian nature of decision making in industrial marketing explicit, and thus support the development of a better understanding of decision making and (mal-) practices in industrial marketing, and how Bayesian reasoning is a

[2] To be sure, we are not arguing that one needs to be a Bayesian decision maker in order to become a Bayesian decision maker (circular reasoning). We are arguing that being Bayesian enables a learning process where decision makers need to be cognizant of the process and dedicate effort to learn this skill (i.e., learn to learn). As such, being a Bayesian decision maker is based on a capability, i.e. repetitive, routinized behavior trained over time.

learning process which in itself can be learned.

3. Bayesian inference as a method in marketing

The notion of Bayesian inference is not new to the marketing field. In the first issue of *Industrial Marketing Management*, Pearce (1971, p. 23) mentioned Bayesian statistics as a potential method for creating market intelligence. Likewise, Groeneveld (1976, p. 313) proposed considering "potential applications of Bayesian analysis to the marketing operations of industrial firms." However, less than 50 papers published in *Industrial Marketing Management* to date mention Bayesian inference (see Appendix A), and the majority of those papers use Bayesian statistics as a methodological technique in their empirical studies. The other papers only mention "Bayesian" in passing or in summaries (e.g., review papers). Interestingly, Bayesian inference increased in popularity in 2020, making 2020 the year with most mentions of Bayesian inference in *Industrial Marketing Management*.

Green (1963) discussed Bayesian decision theory and Roberts (1963) raised the issue of Bayesian statistics in the *Journal of Marketing*. Despite these early references to the concept, only 17 (including the two mentioned above) of the papers published in the *Journal of Marketing* in the past 50 years mention "Bayesian." All of these papers use Bayesian inference as a method in their statistical analyses. A similar picture emerges for the *Journal of the Academy of Marketing Science*, where the first two papers with Bayesian reasoning date back to 1973 (i.e., the first issue). However, only 12 papers published since then use Bayesian inference as a method (Appendix B).

In conclusion, Bayesian inference received some attention in early marketing research. However, it has not attracted a great deal of interest over the years, especially when compared to the use of other statistical methods, such as regression analysis and structural equation modelling. Moreover, we know of no studies that seek to (re)conceptualize marketing as a cognitive process that mirrors Bayesian inference. This gap is interesting, as we argue that the logic of Bayesian inference is closely related to marketing thinking. As such, it constitutes the intellectual foundation of marketing theory and practice.

4. Marketing as Bayesian inference

The marketing field has longstanding traditions of collecting information about markets and using that information to learn how to better serve those markets and, ultimately, achieve superior performance. This is in line with the literature on market sensing, where "market-driven firms are distinguished by an ability to sense events and trends in their markets ahead of their competitors" (Day, 1994, p. 44). This notion has been conceptualized as market orientation (e.g., Kohli & Jaworski, 1990; Narver & Slater, 1990), which comprises the collection of market intelligence and the distribution of that information throughout the organization to enable better decision making.

In other words, the foundation of marketing lies in the ability to recognize relevant events (e.g., customers' buying behaviors, competitors' actions), the ability to reconsider one's own beliefs in light of the new evidence, and the ability to make better decisions based on updated beliefs. This understanding resembles Bayesian inference. Therefore, we argue that Bayesian inference can serve as the bedrock of marketing.

4.1. An example of Bayesian inference in industrial marketing

The coronavirus crisis illustrates why Bayesian reasoning may be a timely phenomenon for industrial marketing practitioners and scholars. Consumer behavior is rapidly changing owing to either governmental decrees (e.g., travel restrictions) or new demands for safety (e.g., the increase in online shopping to avoid crowds). Consequently, future demand is uncertain, as the length and depth of the crisis are unknown (e.g., Pedersen, Ritter, Benedetto, & Lindgreen, 2020). Relatedly, as a result of the crisis, some offerings have been transformed with little warning (e.g., from onsite restaurant meals to take-away), some have temporarily become irrelevant (e.g., conferences/events), and some have experienced unexpected growth that is difficult to manage (e.g., Zoom, Netflix, and Amazon). In this setting, established mental models and internalized theories no longer seem to hold, at least one cannot be sure about them. Therefore, marketers need to update their beliefs, assumptions, and theories according to observed data.

While all of these issues give rise to important research questions for the industrial marketing field (e.g., Bond III et al., 2020), the coronavirus crisis highlights a much deeper and more fundamental challenge. With only one pandemic (i.e., COVID-19) occurring at the moment, little can be inferred from frequentist statistics,[3] as one would need a large number of similar pandemic crises (which have historically happened approximately once every 100 years) from similar contexts (present day) to accurately infer market behavior.[4] Bayesian reasoning is arguably better able than frequentism to deal with small sample sizes (Lee & Song, 2004), allow for the use of prior information, and handle non-normal distributions (Rouziou & Dugan, 2020; Van de Schoot et al., 2014). The latter point is especially important, as frequentist statistics presume the existence of Gaussian distributions, which, in turn, assume independent data points, even though much of the real world is comprised of interdependent data points that create Paretian power law distributions (Andriani & McKelvey, 2009).[5] Cirillo and Taleb (2020) posit that pandemics follow a Pareto distribution. Flyvberg (2020, p. 615) not only concurs but also goes on to suggest: "We live in the age of regression to the tail. Tail risks are becoming increasingly important and common because of a more interconnected and fragile global system of human interaction for travel, commerce, finance, etc." In such an environment, beliefs need to be updated in light of incoming evidence. Moreover, a single case may also be enough to inform a preexisting hypothesis as suggested by Bayesian reasoning (e.g., Siggelkow, 2007).

Consider, for instance, an industrial marketing example from the COVID-19 crisis. By early February 2020, most Western marketing managers had heard about the spread of the coronavirus in China as well as a few cases in Italy. Based on their knowledge of the SARS crisis in China in 2003 as well as the MERS crisis in Saudi Arabia and South Korea in 2015, each of which had only regional consequences, these managers would not have expected the new coronavirus to be much of a threat. Thus, we can assume that the hypothesis "the coronavirus will significantly damage my business" might have been assigned a probability of 1%. Now consider new evidence: a customer cancels an order, which is a typical event for approximately 10% of the customers of a given firm. In addition, the probability of a customer cancelling an order when the hypothesis is true is 100%. In other words, if the coronavirus damages the business, customers will cancel their orders. This is how the coronavirus crisis has an impact. While such assumptions are common among managers, they are rarely explicitly noted like they are in Table 1.

If we use these numbers in Bayesian statistics, the first cancelling customer raises the probability of the hypothesis that the coronavirus will significantly damage the business from 1% to 9%, the second cancelling customer increases the probability from 9% to 50%, and the

[3] Frequentists view probability as the relative frequency of an event, while Bayesians perceive probability as reflecting degrees of belief.

[4] However, we acknowledge that B2B firms have been exposed to a variety of crises (e.g., political boycotts, the 2008–2009 financial crisis, Brexit), which may provide them with crisis-relevant experience. We also acknowledge that the COVID-19 crisis affects firms in different ways—some are struggling for survival, others are enjoying business as usual, and still others are experiencing significant growth.

[5] While these differences are important, we acknowledge that frequentist methods would collect data to refute or not refute a theory, which would eventually result in improvements in line with Bayesian reasoning and the empirical cycle (see, e.g., DeGroot, 1961). We are thankful to an anonymous reviewer for raising this point.

Table 1
Bayesian inference.

Prior probability		
Initial estimate of the likelihood that the coronavirus will have a significant negative impact on business	x	1%
New event: *a customer cancels an order*		
Probability of cancellation if the coronavirus has negative impact	y	100%
Probability of cancellation if business is normal	z	10%
Posterior probability		
Posterior probability after *first* customer cancelled	$\frac{xy}{xy + z(1-x)}$	9%
Posterior probability after *second* customer cancelled	$\frac{xy}{xy + z(1-x)}$	50%
Posterior probability after *third* customer cancelled	$\frac{xy}{xy + z(1-x)}$	90%

third cancelling customer raises the probability to a staggering 90%. Thus, with only three customer cancellations, managers could have had the evolving business impact of the coronavirus on their radar and they could have taken action. Similar related examples can be envisioned with the emergence of new epidemic waves and COVID variants such as Omicron, e.g. *how likely will it be that we will undergo new restrictions due to a new wave/variants of the pandemic?*

This thought experiment above is not merely theoretical—it is supported by research and practice. While some cognitive research finds that the human brain is Bayesian in how it learns from pieces of evidence and subsequently makes predictions (e.g., Griffiths & Tenenbaum, 2006), other work finds that the best forecasters follow Bayesian principles of belief-updating (Silver, 2012; Tetlock, 2005; Tetlock & Gardner, 2016) and that practicing managers make judgments that can be interpreted as Bayesian (McCann, 2020). Moreover, the skill of Bayesian updating can, to a certain extent, be learned (Silver, 2012; Tetlock, 2005; Tetlock & Gardner, 2016). Nevertheless, individuals differ in whether they are good Bayesian updaters. In other words, such skills are not natural to everyone. For instance, Tetlock and Gardner (2016) find that few people fully follow Bayesian principles in forecasts. However, research on how industrial marketers are dealing with the COVID-19 pandemic provides a stylized fact suggesting that practitioners gradually update their beliefs as more evidence becomes available (e.g., Cortez & Johnston, 2020; Oehmen, Locatelli, Wied, & Willumsen, 2020; Rapaccini, Saccani, Kowalkowski, Paiola, & Adrodegari, 2020; Ritter & Pedersen, 2020). For instance, Ritter and Pedersen (2020) find that across industries, industrial marketers have beliefs about the different impacts of COVID-19, and they revise and update those beliefs as new information is obtained. Moreover, Bayesian reasoning has been equated with how epidemiologists have generally thought during the crisis, as evidenced by airborne transmission of COVID-19 being considered less likely in the beginning of the pandemic and the W.H.O. later considering it being a factor after experiencing mounting evidence.[6] As a result, one commenter has argued that "understanding Bayes's theorem is a matter of life and death right now", accentuating the necessity to update one's priors.[6] Furthermore, companies have varied in terms of their urge of amassing face masks and protective shields early on in the crisis, which could suggest that they were equally diverse in their capacities for Bayesian reasoning. Beyond a crisis context, Bayesian reasoning was arguably illustrated during the strategic inflection point of Intel's evolution from memory chips to microprocessors, as the probability of the market belief "there is a growing market for memory chips" decreased severely over time – losing out to the probability of the competing hypothesis that "there is a growing market for microprocessors" (Burgelman & Grove, 1996).

However, we do not view the Bayesian process as merely an analytical tool (although it has merit in this respect). We contend that it describes a (idealized) mode of thinking among industrial marketers operating in dynamic and uncertain environments, like the one created by the coronavirus crisis. As the above example illustrates, it is of paramount importance that the industrial marketer accurately assesses the probability of the hypothesis given the evidence and continuously refines that probability given newly collected evidence. Hence, marketers must be able to make realistic assessments of data and do so continually. While this is easy to understand as an intellectual phenomenon, such practices are often difficult to carry out in the real world. Nevertheless, adhering to such ideals would arguably significantly improve industrial marketing management and shed light on numerous overlooked barriers to successful market-management processes.

4.2. Four improvements in market learning from Bayesian inference

Market learning is here understood as a process of updating the probabilities of hypotheses through the consideration of evidence and its implications in light of a given hypothesis. Based on this conceptualization, we propose four ways of improving market practices based on the Bayesian theorem:

1 Managers need to make their assumptions explicit. Cognitive and TIU theories propose that all marketing behavior is based on cognitive assumptions (i.e., on hypotheses and beliefs held by decision-making managers). While this may appear to be a theoretical, abstract, and challenging demand, the opposite is true—managers arguably do have beliefs (see also Foss, 2007).
2 Managers need to make their probabilities explicit. Managers implicitly acknowledge that their beliefs may be wrong to some extent, but that extent needs to be made clear. In particular, humans tend to be biased when assessing their predictive accuracy if that accuracy is not made explicit (i.e., hindsight bias; Tetlock, 2005). Again, this does not suggest a new or alien practice—"probability statements are an incredibly common part of managerial conversations and decisions. They are easy to recognize when stated with exact numbers, but words like 'usually,' 'likely,' 'probably,' 'possibly,' and the like all reflect probability statements too" (McCann, 2020, p. 28).
3 Managers need to perceive events that have a general probability. As such, it is less important to recognize any one event and more important to perceive events with a probability. In other words, managers need to evaluate how likely the experienced evidence is in general.
4 These events need to be assigned a probability under the assumption that the hypothesis is correct. As such, managers need to be explicit about two probabilities: the likelihood of the evidence in general (as mentioned in point 3) and the likelihood of the event if the hypothesis is valid.

While these four ways of improving market learning practices based on the Bayesian theorem may seem rather technical, they can be achieved in practice. In fact, they are often practiced, but not necessarily intentionally.[7] In this regard, it is worthwhile to consider the alternative situation. First, if managers have no hypotheses when making decisions, their decision making will be random because the consequences are unknown. Second, a probability of zero would imply a lack of a hypothesis and, as such, be identical to the first situation. At the same time, assigning a probability of 1 to a hypothesis would indicate that the belief

[6] https://www.nytimes.com/2020/08/04/science/coronavirus-bayes-statistics-math.html

[7] While many individuals and companies enact processes that are similar to Bayesian reasoning, they (i) differ in how capable they are in this, and (ii) only very few companies are intentional about Bayesian reasoning. These stylized facts point towards the paradox that being Bayesian should at the same time feel familiar and challenging for B2B practitioners.

never fails, which is unrealistic. Thus, all managers have implicitly assigned probabilities. Third, the inclusion of new market information is only meaningful when that information provides evidence related to a hypothesis or, in other words, when the evidence means something. Such meaning can only be derived if the event has a probability in relation to the focal hypothesis. If an event is unrelated, it is irrelevant. Finally, if one does not consider the general probability of an event, one cannot say something meaningful about the impact of that event on decision making. Thus, all elements can be assumed to exist, at least latently and implicitly. In other words, it is fair to assume that people have a working hypothesis when, for instance, they act in a market and that they have an assumption about how likely some evidence is given their impression of the market (e.g., an event is "strange" or "surprising" (low probability) or an event is as expected (high probability)). These hypotheses and probabilities may not be explicitly formulated and communicated, but every actor needs some theory to guide their actions. If they do not, then all actions are random.

The use of Bayesian inference in industrial marketing offers key opportunities to improve marketing practice not only by meeting the four requirements above but also by creating evidence that is well-suited for updating hypotheses. The quality and impact of marketing research can be greatly improved when evidence is more carefully designed in relation to hypotheses and associated probabilities.

The conceptual integration of Bayesian reasoning and industrial marketing is arguably appropriate, as Bayesian reasoning focuses on the impact of evidence on the belief in a hypothesis. That is, marketers incrementally revise their hypotheses in view of updated evidence. However, strong beliefs in an initial hypothesis may complicate these revisions, as those beliefs influence how much weight the evidence carries. Therefore, Bayesian reasoning emphasizes the importance of both initial beliefs and updated evidence for posterior beliefs. We argue that the Bayesian theorem captures many of the intricate elements in market learning under uncertainty and, in particular, provides an ideal model for market responsiveness. It posits that decision makers should continuously and incrementally update their hypotheses based on new evidence. These steps in incremental learning form an accurate managerial model for effective strategic responses in contexts of uncertainty (Fig. 3). They also promote a self-critical, curious, and open managerial mindset.

The industrial marketing profession shares this built-in Bayesianism with many other professions in the management field. As McCann (2020, p. 28) suggests, "probability statements are an incredibly common part of managerial conversations and decisions." More generally, Tetlock (2005) studied expert political judgment by evaluating predictions from experts in different disciplines. He analyzed the cognitive styles most strongly associated with successful predictions and found that many of the cognitive traits of Bayesian forecasters can explain the variance in prediction success. As Tetlock (2005, p. 121) noted, "good judges should be good hypothesis testers: they should update their beliefs in response to new evidence and do so in proportion to the extremity of the odds they placed on possible outcomes before they learned which one occurred. And good judges should not be revisionist historians: they should remember what they once thought and resist the temptation of the hindsight or 'I knew it all along' bias." As all decisions entail a prediction (*"If I do X, then Y will happen"*), it is possible to create a link between forecasting accuracy and the decision-making success of industrial marketers.

4.3. Marketing (mal-)practices

While we argue for an understanding of industrial marketing as a Bayesian cognitive process, we acknowledge that not all managers and organizations can master its implementation (Fig. 2). However, this does not imply that market learning as a Bayesian process is wrong. It only suggests that there will be heterogeneity among firms because they vary in their implementation of the Bayesian process, just like there are different levels of market orientation, customer relationship management, and commercial excellence among firms. According to Bayes' theorem, the drivers of an updated belief, a new probability or, in Bayesian terms, the a posteriori *probability* is the a priori *belief* (the probability of a hypothesis) as well as an event's perceived probability in general and under the assumption that the a priori belief is true. Thus, we can distinguish marketing practices that adopt a Bayesian perspective based on the application of these two elements for updating beliefs.

In Fig. 4 and Table 2, we illustrate the four marketing practices in a typology, thereby synthesizing and juxtaposing the wide body of literature relevant for the academic field and the practice of industrial marketing. The four industrial marketing approaches differ in their abilities related to the two Bayesian activities of formulating market beliefs and perceiving evidence in view of those beliefs. In this regard, firms may possess abilities that are either (i) in line with or below the industry average, or (ii) above the industry average. Hence, the Bayesian process comprises a firm-level capacity or capability entailing maturity levels in these two Bayesian activities. When combined, we see four very different approaches to industrial marketing decision making, which we explore in the following.

4.3.1. Luck-driven marketing

When organizational members do not have an updated belief, they rely solely on luck in their decision making, as they have not made any assumptions about the market. In other words, any market success (or failure) is caused by randomness and luck. These firms are not skilled in formulating initial beliefs about the market or assessing novel market events for evidence. Such approaches can be observed in technology-oriented organizations where customer demand is more of an afterthought. For instance, Brown (2005, p. 1233) points to the oil industry's success in the seminal article 'Marketing Myopia' by Ted Levitt, suggesting that the article "is best remembered for its customer centric contentions but it also contained detailed analyses of the oil industry, which showed that chance, happenstance and happy accident shaped every stage of the iconic industry's development". The notion of "luck" in markets has been explained in strategy (Barney, 1986), entrepreneurship (Dew, 2009), and marketing (Brown, 2005) research. According to Barney (1986), luck may be a source of advantage in strategy implementation, while Dew (2009) posits that serendipity plays an important role in entrepreneurship. Similarly, Brown (2005) acknowledges that luck is key in the development of marketing and the commercial equation. While luck is often not a source of sustainable competitive advantage, it is part of everyday life, and firms often enjoy good fortunes in their operations. Consequently, this approach deserves some attention. Moreover, it must be acknowledged that the foundations for luck can also be created, as evidenced by several success stories of entrepreneurs following an effectual logic (Wiltbank, Dew, Read, & Sarasvathy, 2006). In instances where the environment may be unpredictable but the situation can be controlled, the probability of being lucky can arguably be enhanced. This is also evident in effectuation theory's treatment of unexpected events, as it looks for and leverages positive surprises (Wiltbank et al., 2006; see also Read, Dew, Sarasvathy, Song, & Wiltbank, 2009).

4.3.2. History-driven marketing

When organizational members have strong a priori market beliefs but perceive little, if any, evidence, they stick with their a priori probability. These firms rely on historical ideas, which often become outdated over time. In other words, their market success is determined by the quality of the initial hypothesis. Examples of such practices can be found in "fallen giants" like Nokia, Blackberry, and Blockbuster—all firms exhibiting a lack of updated beliefs about their markets and, thus, ultimately failing in their businesses. An example of this is documented in the competitive trajectory of ITT, where "ITT's success – or more specifically, its manager's reactions to success – caused it to amplify its winning strategy and to forget about everything else. It moved from

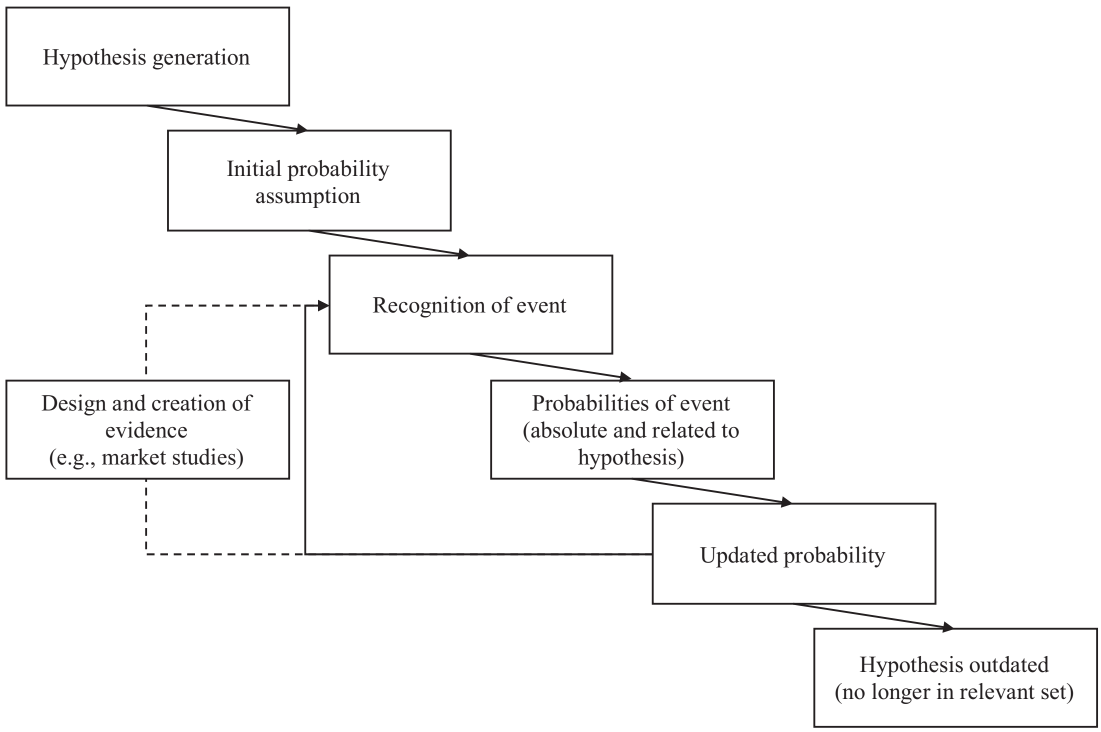

Fig. 3. Bayesian process of marketing.

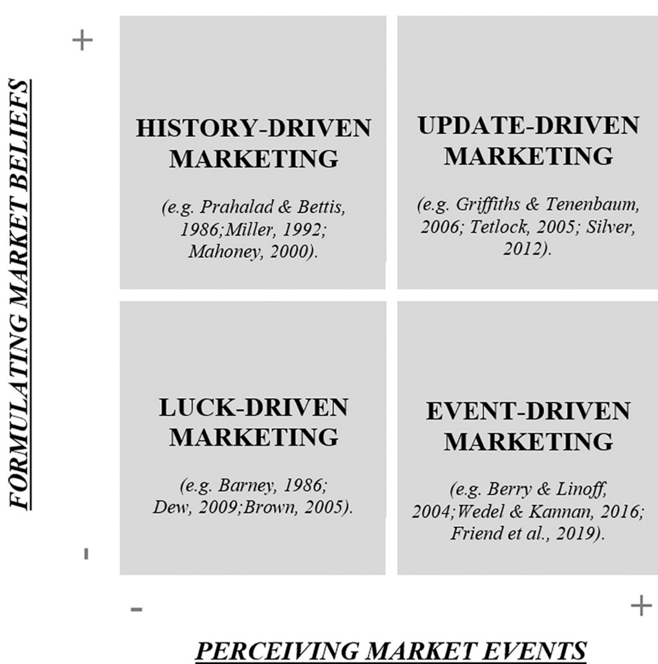

Fig. 4. Different industrial marketing approaches.

sensible and measured expansion to prolific and groundless diversification" (Miller, 1992, p. 26).

Relevant literature in this area includes work on dominant logics (e.g., Prahalad & Bettis, 1986), path dependence (e.g., Mahoney, 2000), the Icarus paradox (Miller, 1992), and industry standards (Shapiro & Varian, 1999). For instance, Prahalad and Bettis (1986) state that managers often adopt a collective mindset or worldview (i.e., a dominant logic) about what will and will not work for the business based on prior experience. Yet, as noted by Miller (1992), what helped establish prior success will not necessarily be relevant in an evolving market. Therefore, relying on an obsolete dominant logic may result in the competitive demise of an organization. Part of the explanation revolves around the path dependence created by previous decisions, which locks organizations into certain trajectories. Competitive standards create such path dependencies (Shapiro & Varian, 1999), although standards wars may create a situation in which a new standard emerges and the pre-existing dominant logic becomes obsolete. In sum, forecasts of future trajectories are based more on prior market beliefs supported by historical success rather than on updated information.

4.3.3. *Event-driven marketing*

When members of an organization predominantly rely on new evidence because their a posteriori beliefs are driven by experiences of new events instead of initial hypotheses, their decision making is driven by short-term oriented data. These organizations will change their strategies quickly and in very different ways in response to the evidence presented to them. Their market success is determined by their ability to

Table 2
Overview of marketing approaches.

	Luck-driven marketing	History-driven marketing	Event-driven marketing	Update-driven marketing
Key trigger(s):	Haphazardness	Mental models	External evidence	Updated beliefs
Illustrative source:	Brown (2005)	Miller (1992)	Berry and Linoff (2004)	Tetlock (2005)
Example:	Oil industry	ITT	Facebook	Intel
Internal orientation:				
External orientation:				

collect and analyze market data, and by their ability to quickly react to it. To succeed, they must use relevant data that is representative of their markets and they must be agile. An example of this approach can be seen in Facebook, which collects and analyzes massive amounts of "big data" to derive market insights. One challenge lies in the fact that market positioning might suffer, as the organization moves quickly and customers can become confused. Moreover, it could be argued that they miss out on the counterintuitive insights that typically create grand visions of future market directions – simply because it is not evident in the data. For instance, Felin and Zenger suggest that "No doubt bias and error are important concerns in strategic decision-making. Yet it seems quite a stretch to suggest that the original strategies developed by people like Apple's Steve Jobs, Starbucks' Howard Schultz, or even Walmart's Sam Walton had much to do with error-free calculations based on big data".[8] Hence, what they gain from their capacities of perceiving and analyzing external events and information, is the bases for updating their original market beliefs and thus create a great understanding of markets.

Examples of topics covered in this body of research include data mining (Berry & Linoff, 2004), marketing analytics (Wedel & Kannan, 2016), and fast failing in selling (Friend, Ranjan, & Johnson, 2019). For instance, Berry and Linoff (2004) suggest that firms form relationships with their customers, which result in the production of data on nearly every customer interaction. This data should be turned into customer knowledge through analytical techniques. Wedel and Kannan (2016) provide a critical examination of marketing-analytics methods and identify trends that shape marketing analytics. Friend et al. (2019) posit that fast sales failures can entail potential benefits, as they provide insight into what works and what does not. In sum, event-driven marketing is preoccupied with market sensing (Day, 1994) and spontaneous reactions in an ad-hoc fashion, but less with the formulation of market beliefs and market learning.

4.3.4. Update-driven marketing

When members of an organization rely on both a priori market beliefs and events to update their a posteriori market beliefs, they are engaged in Bayesian belief-updating. In other words, they formulate explicit initial market beliefs, which they subsequently test, and the results of those tests lead to appropriate revisions of the initial beliefs. As such, the approach draws upon and synthesizes work on theories-in-use (e.g., Zeithaml et al., 2020) and market orientation (Day, 1994; Jaworski et al., 2000; Li & Calantone, 1998). Moreover, the approach is exemplified by studies in cognitive science (e.g., Griffiths & Tenenbaum, 2006), expert political judgment (e.g., Tetlock, 2005), and forecasting (e.g., Silver, 2012). For instance, Griffiths and Tenenbaum (2006) suggest that the human mind is surprisingly good at guessing and that it applies Bayesian reasoning to do so. Tetlock (2005) and Silver (2012) are more pessimistic about the inherent Bayesian traits of individuals, but acknowledge that training can help individuals become better forecasters in a variety of domains.

Notably, the Bayesian process of updating-driven marketing is the only truly dynamic process, and it encompasses the advantages of both the history-driven and event-driven approaches to marketing. Consequently, we contend that it represents a superior type of industrial marketing. In a dynamic and uncertain situation, like the COVID-19 crisis, the relevance of the update-driven approach for the practice of industrial marketing seems particularly evident. This is because it is the only approach that synthesizes the marketing vision needed to envision novel opportunities (Jaworski et al., 2000) as well as a realistic assessment of emerging evidence and its influence on the mental models of marketers (Day, 1994). The approach suggests that industrial marketing practice should be a cognitive phenomenon (i.e., *learning*) that is distributed across the organization (i.e., *social*), and that it is a continuous process (i.e., *perpetual*). It follows that Bayesian update-driven marketing is a perpetual and social process of cognitive learning about the market. As such, it echoes a logic in marketing that has always been present but not necessarily explicitly pursued. Examples of update-driven marketing can be seen in Intel's move from memory chips to microprocessors (Burgelman & Grove, 1996), IBM's early recognition of the commercial potential of the internet (Hamel, 2000) and how *USA Today* reinvented itself for the internet age (O'Reilly & Tushman, 2004). What they all have in common is that they had preexisting market beliefs which were subsequently revised according to market events and eventually replaced by competing market beliefs with higher probabilities. Such is the mechanism of update-driven marketing.

5. Implications, limitations, and opportunities for further research

Bayesian statistics have a long tradition as a niche analytical tool in the field of marketing. Yet, Bayesian inference has not experienced the same interest as a mode that enables marketers to reason and learn cognitively, even though they likely learn in this manner (e.g., Griffiths & Tenenbaum, 2006). A more explicit focus on the potential of Bayesian thinking could arguably encourage marketing practitioners to learn this important skill (e.g., Silver, 2012; Tetlock, 2005) and increase the marketing field's interest in Bayes as a cognitive phenomenon relevant for many marketing constructs. We believe this paper could be an important catalyst for spurring debate on this important topic.

However, several limitations must be noted. While we have conceptualized a model for applying Bayesian reasoning in practice, both Bayesians and frequentists would ask for empirical evidence to determine the verisimilitude of the hypothesis. Hence, we need additional work to clarify the mechanisms at work in the model. Moreover, we would welcome additional empirical evidence on whether and how frequentist and Bayesian reasoning may coexist and complement each other in organizations. Finally, this paper has only provided a general view on the philosophical traditions of Bayesian statistics and its long-standing rivalry with frequentist statistics. Therefore, additional research could provide a more exhaustive overview of these differences and how they materialize in a marketing context.

The Bayesian thought process has important implications as a way to conceptualize market learning in industrial marketing and, as a result, it can inform industrial marketing practice. However, what does a Bayesian conceptualization of industrial marketing imply for research? We suggest three avenues for future research.

First, a Bayesian conceptualization of industrial marketing implies that it is more a mode of cognitive reasoning than a set of discrete activities, although such activities are often the artefacts of the underlying reasoning and even though the cognitive reasoning is often distributed across organizational members. Consequently, future research should examine the practice as a cognitive phenomenon among key decision makers. At the same time, these cognitive processes materialize in decision-making behavior. Therefore, Bayesian marketers should be a phenomenon of study, where the focus should be on the links between how these marketers think (cognition) and how they act (decision making). Such studies can also focus on biases that create a disconnect between what Bayesian reasoning tells these marketers to think and how they subsequently act. Such a focus on cognition and decision making would lead to a much closer linkage between the academic fields of industrial marketing, cognitive science, and decision making than has hitherto been evident in prior studies. Therefore, there is ample room for future work across these disciplines.

Moreover, additional insights are needed into whether Bayesian marketers are a result of nature or nurture. In other words, do they have biological predispositions to think and act as they do, or are they trained to think and act as Bayesians? Relevant research questions along these lines include:

[8] What Sets Breakthrough Strategies Apart (mit.edu)

1) How do Bayesian industrial marketers think and act? How can Bayesian reasoning be observed and analyzed?
2) How do biases create a disconnect between Bayesian industrial marketers' thoughts and actions?
3) Is Bayesian thinking a result of nature or nurture? How can Bayesian thinking be trained and cultivated in organizations?

Second, Bayesian reasoning is a processual and ongoing phenomenon. Consequently, future research must study these cognitive processes and subsequent market strategies through a longitudinal lens. This implies that research designs must take time into account. Moreover, we have explained how different marketing modes may coexist (e.g., luck-driven marketing, event-driven marketing, history-driven marketing, and update-driven marketing) as well as different analytical and philosophical approaches (i.e., frequentist and Bayesian). Yet, we still lack answers regarding: (i) the extent to which these modes and approaches coexist simultaneously in organizations, (ii) how the modes and approaches relate to one another in terms of competition or complementarity, and (iii) how coexisting modes and approaches evolve over time in the same organizations. Relevant research questions in this regard include:

4) How can we best reinforce update-driven marketing over time?
5) Do different modes of marketing decision making co-exist simultaneously?
6) If so, do they complement or compete with each other?
7) How do different modes and approaches evolve over time in the same organization?

Third, a Bayesian conceptualization of marketing decision making implies that marketing is both an evidence-based, analytical process and a process driven by (creative) a priori theories about the market. This suggests tensions and interesting interactions between the two approaches to marketing. Researchers have long debated the extent to which marketing is an art or a science (Brown, 2001; Pedersen, 2021). A Bayesian approach could, perhaps, shed light on this debate and bridge viewpoints, as the prior hypothesis *may* entail a creative vision that is artful in nature, while the subsequent updating of that hypothesis typically follows an analytical pattern found in science. Additional research is needed to shed light on the underlying mechanisms that bridge the two modes. Relevant research questions along these lines include:

8) How can "whole-brained" thinking be stimulated in update-driven marketing?
9) What is the impact of coordinating marketing creativity and marketing analytics in Bayesian reasoning?
10) What are the antecedents of marketing creativity, marketing analytics, and update-driven (Bayesian) marketing decision making?

In sum, decision making in industrial marketing can be understood as a process of Bayesian belief-updating in which managers need to formulate market theories and assess the probability of those theories based on evidence from the market. This paper offers a "hypothesis" about how industrial marketing decision making can best be conceptualized, but additional research is needed to collect the "evidence" needed to assess the verisimilitude of the Bayesian approach in relation to the academic field of industrial marketing.

In conclusion, Bayesian thinking increases the power of a single case, as a single case provides enough evidence to update a belief (Andriani & McKelvey, 2009). In a similar vein, Siggelkow (2007) argues that encountering one anomaly might have a strong impact on updating a belief. However, this effect also depends on the strength of that belief. For example, the coronavirus crisis will lead to many changes in beliefs and, consequently, it may change decision making. Executives are unlikely to discard the experience of the crisis and wait until they have seen a large enough number of crises, which illustrates the power of a single case.

The coronavirus crisis also illustrates how Bayesian thinking better fits managerial action under uncertainty. As little is known about the further development of the crisis, executives need to move towards the unknown in small steps and constantly update their beliefs while they are on the move. In other words, they have to "build the plane while flying." In contrast, a frequentist approach, or "using p-value null hypothesis significance testing (pNHST)" (Andraszewicz et al., 2015, p. 521; for a comparison of frequentist and Bayesian methods, see also, e.g., Zyphur & Oswald, 2015) would require large-scale testing. Not only would this take too long but the results would also be outdated before they became available. The power of evidence for updating beliefs highlights the importance of experiments for creating events and information relevant for updating. As such, one does not need a large-scale study to start an updating process—initial, small-scale tests can serve as the perfect starting point. However, we acknowledge that frequentist statistics have their merits, and that certain situation are particularly well-suited for this branch of reasoning. Hence, we believe that these two approaches can and should co-exist, and that industrial marketers need to pursue a contingency approach in their applications. Finally, as with other marketing constructs, we assume that cross-departmental interactions will improve Bayesian inference, as a wide range of evidence is produced that can allow for sound updating. Likewise, top management's support is needed as is the autonomy to launch experiments. In sum, the evidence is clear—industrial marketing beliefs must and should be updated.

Declaration of Competing Interest

None.

Appendix A. Papers in Industrial Marketing Management that refer to Bayesian inference (in chronological order)

Pearce, F. T. (1971), Intelligence: A technology for the 1980's?, Industrial Marketing Management, Volume 1 (1), 11-26.

Mazze, Edward M. (1972), An information based approach for measuring the relationships between public policy and industrial purchasing decisions, Industrial Marketing Management, Volume 2, Issue 1, 77-83.

Hill, R.W.; A. Meidan (1975), The use of quantitative techniques in industrial marketing, Industrial Marketing Management, Volume 4 (2–3), 59-68.

Evans, R.H. (1975), The industrial salesman in an economy of scarcity: An application of Bayesian statistics, Industrial Marketing Management, Volume 4 (5), 249-255.

Pearce, F.T. (1976), Business intelligence systems: The need, development, and integration, Industrial Marketing Management, Volume 5 (2–3), 115-138.

Groeneveld, Leonard (1976), New approaches in industrial marketing involving subjective probability, Industrial Marketing Management, Volume 5 (4), 213-219.

Gentry, Dwight L.; William A. Hailey (1981), Industrial survey sampling, Industrial Marketing Management, Volume 10 (3), 183-189.

Cardozo, Richard N. (1983), Modelling organizational buying as a sequence of decisions, Industrial Marketing Management, Volume 12 (2), 75-81.

Schill, Ronald L. (1985), Managing risk in contract pricing with multiple incentives, Industrial Marketing Management, Volume 14 (1), 1-16.

Kohoutek, Henry J. (1988), Coupling quality assurance programs to marketing, Industrial Marketing Management, Volume 17 (3), 177-188.

Samli, A. Coskun (1996), Developing futuristic product portfolios: A major panacea for the sluggish American industry, Industrial Marketing Management, Volume 25 (6), 589-600.

Weber, John A.; Utpal Dholakia (1998), Planning Market Share Growth in Mature Business Markets, Industrial Marketing Management, Volume 27 (5), 401-428.

Weber, John A. (2002), Managing the marketing budget in a cost-constrained environment, Industrial Marketing Management, Volume 31 (8), 705-717.

Katsikea, Evangelia; Robert E. Morgan (2003), Exploring export sales management practices in small- and medium-sized firms, Industrial Marketing Management, Volume 32 (6), 467-480.

Seshadri, Sudhi; Randhir Mishra (2004), Relationship marketing and contract theory, Industrial Marketing Management, Volume 33 (6), 513-526.

Brown, Brian P.; Alex R. Zablah, Danny N. Bellenger, Naveen Donthu (2012), What factors influence buying center brand sensitivity?, Industrial Marketing Management, Volume 41 (3), 508-520.

Yan, Ruiliang; Kai-Yu Wang (2012), Franchisor–franchisee supply chain cooperation: Sharing of demand forecast information in high-tech industries, Industrial Marketing Management, Volume 41 (7), 1164-1173.

Huang, Yimin; Ian F. Wilkinson (2013), The dynamics and evolution of trust in business relationships, Industrial Marketing Management, Volume 42 (3), 455-465.

Lee, Kun Chang; Habin Lee, Namho Lee, Jaehoon Lim (2013), An agent-based fuzzy cognitive map approach to the strategic marketing planning for industrial firms, Industrial Marketing Management, Volume 42 (4), 552-563.

Wu, Jie (2014), Cooperation with competitors and product innovation: Moderating effects of technological capability and alliances with universities, Industrial Marketing Management, Volume 43 (2), 199-209.

Jain, Megha; Shadab Khalil, Wesley J. Johnston, Julian Ming-Sung Cheng (2014), The performance implications of power–trust relationship: The moderating role of commitment in the supplier–retailer relationship, Industrial Marketing Management, Volume 43 (2), 312-321.

Jahromi, Ali Tamaddoni; Stanislav Stakhovych, Michael Ewing (2014), Managing B2B customer churn, retention and profitability, Industrial Marketing Management, Volume 43 (7), 1258-1268.

Wu, Jie; Zefu Wu (2015), Key supplier relationships and product introduction success: The moderating roles of self-enforcement and interdependence between buyer and supplier, Industrial Marketing Management, Volume 46, 183-192.

Vesalainen, Jukka; Marko Kohtamäki (2015), Toward a typological view of buyer–supplier relationships: Challenging the unidimensional relationship continuum, Industrial Marketing Management, Volume 49, 105-115.

Hunter, Gary K.; Nikolaos G. Panagopoulos (2015), Commitment to technological change, sales force intelligence norms, and salesperson key outcomes, Industrial Marketing Management, Volume 50, 162-179.

Forkmann, Sebastian; Stephan C. Henneberg, Peter Naudé, Maciej Mitrega (2016), Supplier relationship management capability: a qualification and extension, Industrial Marketing Management, Volume 57, 185-200.

Swani, Kunal; George R. Milne, Brian P. Brown, A. George Assaf, Naveen Donthu (2017), What messages to post? Evaluating the popularity of social media communications in business versus consumer markets, Industrial Marketing Management, Volume 62, 77-87.

LaPlaca, Peter; Adam Lindgreen, Joëlle Vanhamme (2018), How to write really good articles for premier academic journals, Industrial Marketing Management, Volume 68, 202-209.

Ford, Jerad A.; Martie-Louise Verreynne, John Steen (2018), Limits to networking capabilities: Relationship trade-offs and innovation, Industrial Marketing Management, Volume 74, 50-64.

Pei, Zhi; Ruiliang Yan (2019), Cooperative behavior and information sharing in the e-commerce age, Industrial Marketing Management, Volume 76, 12-22.

Kumar, Prashant; Arun Sharma, Jari Salo (2019), A bibliometric analysis of extended key account management literature, Industrial Marketing Management, Volume 82, 276-292.

Agnihotri, Raj; Wei Zhang (2021), Developing benchmarks to capture relative performance for sales force incentives decisions: Lessons from B2B insurance industry, Industrial Marketing Management, Volume 92, 55-71.

Vesalainen, Jukka; Anni Rajala, Joakim Wincent (2020), Purchasers as boundary spanners: Mapping purchasing agents' persuasive orientations, Industrial Marketing Management, Volume 84, 224-236.

Kumar, Bipul; Arun Sharma, Sanket Vatavwala, Prashant Kumar (2020), Digital mediation in business-to-business marketing: A bibliometric analysis, Industrial Marketing Management, Volume 85, 126-140.

Feng, Xiangnan; Yiwei Li, Xiaolin Lin, Yijian Ning (2020), Mobile targeting in industrial marketing: Connecting with the right businesses, Industrial Marketing Management, Volume 86, 65-76.

Zhang, Jonathan Z., George F. Watson IV (2020), Marketing ecosystem: An outside-in view for sustainable advantage, Industrial Marketing Management, Volume 88, 287-304.

Oehmen, Giorgio Locatelli, Morten Wied, Pelle Willumsen (2020), Risk, uncertainty, ignorance and myopia: Their managerial implications for B2B firms, Industrial Marketing Management, Volume 88, 330-338.

Kottika, Efthymia; Ayşegül Özsomer, Pernille Rydén, Ioannis G. Theodorakis, Kostas Kaminakis, Konstantinos G. Kottikas, Vlasis Stathakopoulos (2020), We survived this! What managers could learn from SMEs who successfully navigated the Greek economic crisis, Industrial Marketing Management, Volume 88, 352-365.

Paschou, T.; M. Rapaccini, F. Adrodegari, N. Saccani (2020), Digital servitization in manufacturing: A systematic literature review and research agenda, Industrial Marketing Management, Volume 89, 278-292.

Inigo, Edurne A., Paavo Ritala, Laura Albareda (2020), Networking for sustainability: Alliance capabilities and sustainability-oriented innovation, Industrial Marketing Management, Volume 89, 550-565.

Swani, Kunal; Brian P. Brown, Susan M. Mudambi (2020), The untapped potential of B2B advertising: A literature review and future agenda, Industrial Marketing Management, Volume 89, 581-593.

Liu, Yuwen; Chin Chia Liang, Fred Phillips (2020), Precursors of intellectual property rights enforcement in East and Southeast Asia, Industrial Marketing Management, Volume 90, 133-142.

Kauffmann, Erick; Jesús Peral, David Gil, Antonio Ferrández, Ricardo Sellers, Higinio Mora (2020), A framework for big data analytics in commercial social networks: A case study on sentiment analysis and fake review detection for marketing decision-making, Industrial Marketing Management, Volume 90, 523-537.

Bouncken, Ricarda B.; Viktor Fredrich, Paavo Ritala, Sascha Kraus (2020), Value-creation-capture-equilibrium in new product development alliances: A matter of coopetition, expert power, and alliance importance, Industrial Marketing Management, Volume 90, 648-662.

Maghssudipour, Amir; Luciana Lazzeretti, Francesco Capone (2020), The role of multiple ties in knowledge networks: Complementarity in the Montefalco wine cluster, Industrial Marketing Management, Volume 90, 667-678.

Jia, Yu; Tao Wang, Kefeng Xiao, Chiquan Guo (2020), How to reduce opportunism through contractual governance in the cross-cultural supply chain context: Evidence from Chinese exporters, Industrial Marketing Management, Volume 91, 323-337.

Mullick, Shantanu; Néomie Raassens, Hans Haans, Edwin J. Nijssen (2020), Reducing food waste through digital platforms: A quantification of cross-side network effects, Industrial Marketing Management,

Xu, Bing; Shenghong Zhang, Xiaohui Chen (2020), Uncertainty in financing interest rates for startups, Industrial Marketing Management, 2020.

Appendix B. Papers in marketing journals that refer to Bayesian inference (in alphabetical order)

Author(s)	Year & Journal	Form	Key results
Agarwal, Hosanager, & Smith	2011, Journal of Marketing Research	Hierarchical Bayesian estimation model	By using this method, the authors find “that an advertisement's conversion rate increases with position, and revenue increases with position for more specific keywords. Because the ranking mechanism the search engines use does not account for conversion rate, advertisements placed in the top position do not always maximize revenues.”
Allenby	2011, Journal of the Academy of Marketing Science	Bayesian reasoning as a theoretical foundation	Continuous models of heterogeneity, models of direct utility maximization, models of strategically determined covariates, and models of heterogeneous variable selection are discussed as solutions to these modeling challenges. For each, a Bayesian implementation is discussed.
Anderson & Salisbury	2003, Journal of Consumer research	Bayesian decision theory	”[…] find that market-level expectations adjust faster when perceived quality declines, suggesting that negativity biases manifest at a macrolevel—a phenomenon that has not been previously observed.”
Ansari, Essegaier, & Kohli	2000, Journal of Marketing Research	Hierarchical Bayesian approach	“Typically, the recommendations are based on content and/or collaborative filtering methods. The authors examine the merits of these methods, suggest that preference models used in marketing offer good alternatives, and describe a *Bayesian preference model* that allows statistical integration of five types of information useful for making recommendations: a person's expressed preferences, preferences of other consumers, expert evaluations, item characteristics, and individual characteristics.”
Arora & Hubler	2001, Journal of Consumer Research	Hierarchical Bayesian choice model	The paper proposes aggregate customization as an approach to improving individual estimates using a hierarchical Bayes choice model. “In this article we show that efficient choice designs can be generated through reasonable prior estimates of consumer preferences. We use preference estimates from available data, such as an earlier study, to build an efficient design for the average respondent. Because a common design optimized for the average respondent is used, we call our approach aggregate customization. A hierarchical Bayes choice model then obtains preference estimates at the individual level.”
Arunachalam, Ramaswami, Herrmann, & Walker	2018, Journal of the Academy of Marketing Science	Bayesian reasoning as an analysis tool	“Wang and Preacher (2015) demonstrated the accuracy of these priors and the superiority of Bayesian methods over ML and distribution-free bootstrapping methods for complex models that involve multiple moderators.”
Assaf, Josiassen, Ratchford, & Barros	2012, Journal of Retailing	Bayesian methodology as a way to measure cost efficiency and Bayesian estimation and Bayesian MCMC procedures for model estimation	“We found that the impact on performance of internationalization is stronger for firms which internationalize through more extensive M&A. Retailers that expand internationally through merging with or acquiring a going concern appear to achieve a higher level of cost efficiency that retailers that expand using their own resources. Evidently the acquiring or merging firm benefits from the local market experience of the acquired firm.”
Batra, Lenk, & Wedel	2010, Journal of Marketing	Bayesian factor-analysis model	“[…] we developed and estimated a random effects, hierarchical factor model using consumer perception data on brand personality ratings that (1) separates ‘category personality’ from the brand's own ‘unique personality’; (2) computes the contribution of the latter to its total brand personality imagery, and thus the degree to which it is atypical of its original product category; and (3) quantifies the extent to which its unique brand personality imagery fits the personality imagery of several ‘candidate’ product categories.”
Biswas, Zhao, & Lehmann	2011, Journal of Consumer Research	Normative Bayesian model	“Interestingly, greater processing motivation for sequential frequency data leads to updated confidence judgments that are

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Author(s)	Year & Journal	Form	Key results
			lower than normative Bayesian predictions but consistent with the averaging model."
Bradlow, Gangwar, Kopalle, & Voleti	2017, Journal of Retailing	Theoretical article on how Bayesian reasoning should be used in retailing	The paper builds a case for why theory-driven retailing should leverage, reconcile, and complement the use of big data and predictive analytics. The authors discuss statistical issues, including a focus on the relevance and uses of Bayesian analysis techniques (data borrowing, updating, augmentation, and hierarchical modeling) and others.
Briesch, Krishnamurthi, Mazumdar, & Raj	1997, Journal of Consumer Research	Bayesian information criterion as a tool	"[…] certain specifications of reference price (e.g., PASTCHBR in all four data sets) do not produce any improvement in the fit over a model that contains no reference price term (i.e., the NOREF model). This finding is significant because it demonstrates that a mis specified reference price model can obscure the reference price effect, even when it may actually exist." "[…] some instances (e.g., in liquid detergent category), reference price models perform better than the NOREF model regardless of how the reference price is operationalized."
Briesch & Rajagopal	2010, Journal of Consumer Psychology	BIC as a measurement tool and Bayesian estimation	The paper describes ANNs (artificial neural networks) as an extremely powerful technique. Part of that power results from the versatility of the network structures and the fact that the functional forms are part of the analytical discovery. In this regard, and given their minimalist assumptions (e.g., little concern for the distributional form), ANNs are related to nonparametric estimations.
Brinberg, Lynch Jr, & Sawyer	1992, Journal of Consumer Research	Bayesian analysis	"By applying this Bayesian analysis, we find that a hypothesis can receive support from a study with known flaws. Our analysis also implies that the status of an explanation is independent of whether it was proposed a priori or post hoc."
Chakravarti, Grenville, Morwitz, Tang, & Ülkümen	2013, Journal of Consumer Psychology	Hierarchical Bayes as an estimation tool	The paper's experimental study suggests that "price sensitivity measures recovered from a conjoint study can be malleable, influenced by simple factors such as prior screening questions."
Chintagunta & Lee	2011, Journal of the Academy of Marketing Science	Bayesian reasoning as a model and as a framework for model estimation	"The models are simultaneously estimated within a Bayesian framework. Consistent with the previous literature, we find that including information on intentions improves our ability to predict behavior, with the recent intentions being the most informative."
Choi, Hui, & Bell	2010, Journal of Marketing Research	Bayesian spatiotemporal model	Using this Bayesian spatiotemporal model, the authors "focus on the dynamic role of imitation based on geographic proximity and demographic similarity in generating new buyers over space and time. We find that in the initial phases of demand growth, proximity effects are more prominent."
Cooper	2000, Journal of Marketing	Bayesian networks	The Bayesian network approach works well at more "levels." "When the future unfolds in a way that does not correspond to the exact scenario assumptions, the scenario planners are left to either start over or guess at the underlying network. The Bayesian approach, however, combined with policy simulations still can provide valuable quantitative insights to the strategic questions."
Danaher, Sajtos, & Danaher	2020, International Journal of Research in Marketing	Bayesian reasoning as an estimation tool	"Because Bayesian estimation pools information across the entire sample, we have estimates for reward and marketing effects for reward categories and marketing effort that a Loyalty Program member may never have experienced."
De Jong, Steenkamp, & Fox	2007, Journal of Consumer Research	Bayesian inference and Bayesian tests	"[…] hierarchical IRT model allows consumer researchers to compare countries substantively despite lack of invariance for any of the items. Moreover, because the ordinal nature of the data is recognized, cross-national differences in scale usage are also accommodated. We found strong noninvariance of scale metrics and of scale usage across countries for SNI. Current CFA-based methodologies are not well suited to account for differences in scale usage because they ignore the ordinal nature of the data (Lubke and Muthén 2004)."
DeSarbo & Edwards	1996, Journal of Consumer Psychology	Bayesian rules as an estimation tool	The study identifies and characterizes two manifestations of spending that, on the surface, look like compulsive buying behavior, but that are distinguishable based on level and motivational differences.
Donthu	1991, Journal of the Academy of Marketing Science	Estimation technique	"[…] combined the Bayesian, likelihood, and cross-validation approaches to produce a simple comparison method called the Bayesian Cross Validation Likelihood (BCVL) method for comparing non-nested quantitative models. The BCVL method is Bayesian and provides specification of prior probabilities."
Feinberg	2012, Journal of Consumer Psychology	Theoretical study (comparing Bayesian estimation to classical methods)	"A conceptually appealing, readily implemented measure to assess mediation for a far wider range of data type combinations than traditional OLS-based analyses permit." "Simulation-based methods—in particular, those relying on Bayesian estimation via data augmentation (Tanner and Wong 1987; Edwards and Allenby 2003), which "fills in" many data types to allow an underlying OLS-based representation—may soon allow researchers to assess mediation for essentially any sort of variable,

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Author(s)	Year & Journal	Form	Key results
			including censored, complex categorical forms, interactions, and even to allow coefficient heterogeneity (e.g., random effects or hierarchical models)."
Gershoff, Broniarczyk, & West	2001, Journal of Consumer Research	Bayes' theorem as a measurement	The study's results show that consumers frequently select inferior agents for providing recommendations and choose product alternatives that should be avoided because they fail to recognize when a task calls for a conditional rather than an overall assessment of an agent's prior performance. A final study attempts to isolate the reasons for these shortcomings by examining the process underlying consumers' diagnostic assessments' of information sources.
Granbois & Summers	1975, Journal of Consumer Research	Bayesian reasoning as a measurement tool	"These findings indicate a better estimate of the level of total planned expenditure might be obtained by interviewing couples jointly than either husbands or wives individually." "Although the study's findings suggest implications for the use of purchase probability data for forecasting major household expenditures, a major limitation is that it deals with a single time period."
Herr, Kardes, & Kim	1991, Journal of Consumer Research	Bayesian theorem	"[…] information accessibility mediates the effects of WOM information on product judgments (experiment 1). However, information-accessibility effects on judgment are reduced when more diagnostic information, such as prior impressions or extremely negative attribute information, is available (experiment 2)."
Hoch & Ha	1986, Journal of Consumer Research	Bayesian reasoning as a tool for data interpretation	When consumers have access to unambiguous evidence, judgments of product quality depend only on the objective physical evidence and are unaffected by advertising. Advertising influences quality judgments by affecting the encoding of the physical evidence. Retrieval of ad-consistent evidence also appeared to occur, although to a lesser degree.
Howell, Lee, & Allenby	2015, Marketing Science	Estimation technique	"Price promotions complicate the estimation and analysis of direct utility models because they induce kinks and points of discontinuity in the budget set. We propose a Bayesian approach to addressing these irregularities … Finds that the majority of the effect of a price promotion is through the budget set, not through changes in the utility function."
Hui, Bradlow, & Fader	2009, Journal of Consumer Research	Bayesian reasoning as a framework	"[…] link behavioral theories to statistical models for field data in the spirit of studies […]" "[…] provide consistent directional support for the aforementioned behavioral hypotheses, although the strength of these effects varies. First, as consumers spend more time in the store, they become more purposeful in their trip—they are less like to spend time on exploration and are more likely to shop and buy. Second, we also find (weak) support for licensing behavior (Khan and Dhar 2006). After purchasing virtue categories, consumers are more likely to shop at locations that carry vice categories. Licensing, however, does not significantly affect visit decisions. Third, the social presence of other shoppers attracts consumers toward a zone in the store, but it reduces consumers' tendency to shop at that zone. Finally, we also provide some evidence that consumers exhibit planning-ahead behavior during their in-store shopping trip."
Hui, Krishnamurthy, Kumar, Siddegowda, & Patel	2019, Marketing Science	Bayesian reasoning as a model	"We develop an integrated Bayesian model to disentangle the role of prevention versus detection in PEO programs. Our results show that PEO programs appear to be not effective in preventing STI, but they do facilitate earlier detection by enhancing sex workers' knowledge and ability to recognize STI symptoms."
Kamakura & Mazzon	1991, Journal of Consumer Research	Bayesian reasoning as a measurement tool	"By directly identifying these value systems from the observed value rankings, this approach departs from the traditional focus on after-the-fact comparisons of groups formed a priori on the basis of demographic, attitudinal, or behavioral data. In this sense, this approach is similar to the value-segmentation method proposed by Kahle (1983) that is based on the top-ranked item from a list of nine values. However, the present model makes full use of the priority ran kings obtained from each individual and, consequently, is directly related to the theoretical concept of value hierarchy or value system."
Kim, Kannan, Trusov, & Ordanini	2020, Marketing Science	Analysis tool	"Applied the Bayesian IJC method to separately identify the social interactions from other confounding correlations (e.g., homophily, correlated unobservables, and simultaneity) by taking advantage of the rich specification for heterogeneity." The paper finds that fundraisers can increase the chance of success by adjusting goals and platforms can grow by allocating resources to projects with a high likelihood of success.
Kopalle, Kannan, Boldt, & Arora	2012, Journal of Retailing	Empirical study	"We use a nested logit framework to model brand choice and purchase incidence under two alternative model specifications—a latent class model and a hierarchical Bayes model" "In the empirical analysis, we find that households are quite heterogeneous in terms of their gain and loss effects. For some

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Author(s)	Year & Journal	Form	Key results
			households a gain has higher impact than a corresponding loss, while the opposite is true for others."
Kosyakova, Otter, Misra, & Neuerburg	2020, Marketing Science	Baseline for a framework	"[…] develop Bayesian inference for a hierarchical version of the MCM leveraging the recently proposed exchange algorithm in combination with perfect sampling of data from the MCM to overcome the problem of a computationally intractable normalizing constant in the likelihood."
Kotschedoff & Pachali	2020, Marketing Science	Bayesian reasoning as an estimation tool	"[…] estimate a hierarchical Bayesian multinomial logit model with a flexible mixture of normals first-stage prior to account for consumer heterogeneity. The results show substantial heterogeneity in preferences across households for animal welfare– differentiated eggs. Our structural model makes it possible to isolate the price effect of mandating higher minimum quality standards."
Kumar, Petersen, & Leone	2010, Journal of Marketing Research	Bayesian tobit model	"[…] model each customer's Customer referral value (CRV) as a function of predictor variables using a Bayesian Tobit model." "They find that to maximize profitability, it is critical to manage customers in terms of both their customer lifetime value (CLV) and CRV scores and that understanding the behavioral drivers of CRV can help managers better target the most profitable customers with their referral marketing campaigns."
Landsman & Stremersch	2020, Journal of Marketing	Estimation technique	A Bayesian approach can be used in line with Difference in Differences (DID) and "enables us to estimate brand-specific elasticities over time and across countries while controlling for car model and time effects on sales, as well as production capacity constraints."
Liu, Duan, & Mahajan	2020, International Journal of Research in Marketing	Bayesian model as a baseline for new models	"[…] brands are often interdependent and that the company a brand keeps matters. Brands may be competing, but also rely on one another to increase the value of the portfolio in a category or in a strategic group, which has important implications for category management and strategic group management." "[…] we also build a new Bayesian dynamic linear model that can both accommodate the dynamic evolution of brand revenue and identify conference-specific peer effects."
Luo & Jong	2010, Journal of the Academy of Marketing Science	Hierarchical Bayesian approach (HBA)	"Apply hierarchical Bayesian approach (HBA) to enhance the rigor of modeling analyses and enrich implications of findings. HBA is advantageous in several aspects. For example, HBA allows for parameter variations across firms."
Lynch Jr, Alba, Krishna, Morwitz, & Gürhan-Canli	2012, Journal of Consumer Psychology	Bayesian perspective on belief change and rigor used for argumentation on a paper's level of contribution	"[…] one could examine which participants noticed the signs, assess how they rated them on normative and other aspects, and then determine how the normative ratings affected behavior." "[…] important for phenomenon-driven research since judging whether a phenomenon is interesting or important to study inherently involves subjective evaluations and is likely to have lower inter-judge reliability. Editors should strive to be guided not by the average of what reviewers recommend but by those who seem able to see the largest possible legitimate contribution of the work."
Lynch Jr & Srull	1982, Journal of Consumer Research	Bayes' theorem	"[…] present discussion of how various cognitive processes may affect decision making and of what methodologies would allow one to address these processes has been highly speculative. Very little empirical work, either in consumer choice or in behavioral decision making, has used such methodologies."
Martin & Hill	2012, Journal of Consumer Research	Bayesian reasoning as an estimation tool	"[…] without consumption adequacy, psychological need fulfillment has little effect on the poverty–well-being relationship, emphasizing the hopelessness of individuals living in extreme poverty. Findings also suggest to researchers that impoverished consumers not only face different circumstances but actually respond to those circumstances in unique ways."
McClelland, Lynch Jr, Irwin, Spiller, & Fitzsimons	2015, Journal of Consumer Psychology	Bayes' theorem as part of the argumentation	"Contrary to the arguments of IPKSP, there is no compelling reason to split continuous data at the median. Splitting a continuous independent variable at its median introduces random error by creating a sample-dependent step function relating Y to latent X."
McDonnell Feit & Berman	2019, Marketing Science	Using the Bayesian rule	"The proposed test design achieves nearly the same expected regret as the flexible yet harder-to-implement multi-armed bandit under a wide range of conditions"
Meyer, Shankar, & Berry	2017, Journal of the Academy of Marketing Science	Bayesian reasoning as an analysis tool	"Moreover, managers need to know the effect of interaction between service quality variability and bundle quality on the *variance* in WTP for a hybrid bundle because of its implications for consumer segmentation. […] Our research makes substantive and empirical contributions and fills the gaps by investigating these effects using choice-based incentive-aligned conjoint experimental studies estimated by hierarchical Bayesian analysis."
Moiseeva & Timmermans	2010, Journal of Retailing and Consumer Services	Empirical and theoretical (uses results from a pilot study)	"This paper provides an insight into the advantages of advanced tracking technologies such as GPS for collecting travel behaviour of individuals in retail research. The evaluation of the results of the pilot study shows that applying Bayesian belief networks (BNN) has

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Author(s)	Year & Journal	Form	Key results
			a big potential for the correct imputation of activity episodes and trip types from GPS tracers."
Morrin, Lee, & Allenby	2006, Journal of Consumer Research	Hierarchical Bayes model	"We compared the proposed model to a standard logit model and to a model that restricts the association strengths to sum to one. The results in table 3 indicate that the proposed model best fits the data. Table 4 shows that the contextual factors generally have the effects predicted."
Mrkva, Johnson, Gächter, & Herrmann	2019, Journal of Consumer Psychology	BIC as a measurement tool	Respondents who are older and less educated are more loss averse, suggesting that research using students may underestimate the size and importance of loss aversion
Mullins, Meguc, & Panagopoulos	2019, Journal of the Academy of Marketing Science	Bayesian estimation (with MCMC)	"Uncover a framework of salesperson, leader, customer, and team factors that help explain salesperson motivation for VBS (value based selling). Importantly, we link VBS to customers' adoption of new products to support VBS's role for selling new products."
Niemand & Mai	2018, Journal of the Academy of Marketing Science	Bayesian reasoning mentioned in the discussion	"Relative performance compared to the traditional 'ML-SEM' approach applied here has not been investigated systematically. We therefore advocate simulations that address the Bayesian 'PP' alternative to χ2 and suggest comparing its performance to ML-based fit indices."
Noseworthy, Wang, & Islam	2012, Journal of Consumer Psychology	BIC as a measurement tool	The paper shows that consumers tend to classify new hybrid products by contrasting them with the competitive context. Attributes from the supplementary category become more salient and, thus, contribute greater utility in choice. "From a methodological perspective, we offer the unique approach of embedding conjoint techniques, like DCE, within a broader experimental paradigm. This mixed approach could be used in the future to generate insight into moderators for alignable and non-alignable preference. One of the strengths of DCE is that it allows for superior alignable and non-alignable differences to co-occur."
Pieters & Wedel	2007, Journal of Consumer Research	Bayesian framework used for formulation and estimation purposes	"We find it of interest that the attention patterns for free viewing and the ad-appreciation goal were brief and remarkably similar. This not only reveals the predicted, fast implementation of the ad-appreciation goal but also hints at the possibility that consumers may have adopted an ad-appreciation goal during free viewing—as the default goal." "[…] findings support Yarbus's thesis that the informativeness of objects in scenes is goal contingent and that "eye movements reflect the human thought processes; so the observer's thought may be followed to some extent from records of eye movements" (1967, 190), even during the brief moments that consumers choose to attend to ads."
Plassmann, Ramsøy, & Milosavljevic	2012, Journal of Consumer Psychology	Bayesian statistics to identify factors	The paper shows how "[…] scholars in consumer psychology can integrate findings and concepts from neuroscience without actually applying neuroscientific methods. This approach is of great potential for developing an interdisciplinary under-standing of how consumers make decisions and may provide significant improvements in our understanding of preference formation and decision making."
Raman	1994, Journal of Consumer Research	Bayesian analysis of inductive inference	"I provide an adaptive control model to develop the optimal stopping policy for replications, based on the accumulated evidence for the theory, the precision deemed necessary, and the cost of replicating. This model provides a rigorous framework for the valuation of replications and makes explicit the conditions that should encourage or discourage an additional replication in a particular field."
Ramanathan & McGill	2007, Journal of Consumer Research	BIC used for assessment	Findings for experiment 2 provide direct evidence that participants looking at each other influenced their subsequent emotional expressions. "[…] show that sharing the experience with another person may cause the consumer's moment-to-moment evaluation to become more like that of the other person, through processes of emotional contagion. Further, this shared pattern of judgment emerges in a subtle fashion over a fluid, broad time frame and not over short periods, reflecting local agreement in moment-to-moment evaluations. Further, our results suggest that when later asked if an experience was good or not, the evaluation may depend on the extent to which the consumer was indeed moving in quiet tandem with the other person."
Ravul, Bhatnagar, & Ghose	2019, International Journal of Research in Marketing	Bayesian reasoning as a framework	"[…] show that the impact of such cross-effects on purchase outcomes depends on whether the omni-coupon was sourced digitally or from a catalog."
Rouzio & Dugan	2020, Journal of Personal Selling & Sales Management	Bayesian inference in sales research	"We review the extant literature that employs Bayesian methods, with an emphasis on how these studies provide insight that may elude to frequentist methods. Then, using a sample of 146 B2B salespeople, we empirically demonstrate that the use of Bayesian methods is both within the methodological reach of the vast

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Author(s)	Year & Journal	Form	Key results
			majority of sales researchers, and can also provide different empirical insights using the same dataset, than would frequentist methods."
Rutz & Bucklin	2011, Journal of Marketing Research	Bayesian dynamic linear model	"[…] combine [their] awareness model with a dynamic branded search activity model and estimate the two components together in a Bayesian framework."
Sándor & Wedel	2001, Journal of Marketing Research	Bayesian design procedure	"Bayesian theory enables us to construct designs that have higher efficiency at parameter values that are judged likely by managers. In our empirical illustration, not only did a Bayesian design-generating procedure produce choice designs that resulted in lower estimated standard error than procedures proposed heretofore, but it also provided higher predictive validity."
Sawyer, Lynch Jr, & Brinberg	1995, Journal of Consumer Research	Bayesian analysis in Brinberg et al. (1992)	The analysis can be used to conduct a "sensitivity analysis" of how differing estimates of trait validity of manipulation checks that are either included or omitted may influence the interpretation of different empirical outcomes. "The analysis reveals situations in which manipulation and confounding checks have large information value and cases in which their information value is near zero."
Scott & Yalch	1980, Journal of Consumer Research	Bayesian model	"Consumers who purchase a product on a deal, and who attribute their purchase to the deal, are likely to be receptive to negative information about the product and unreceptive to positive information. This might not only affect their satisfaction when using the product, but might also cause them to agree with negative verbal information about it that may be forthcoming from competitors."
Smith, Rossi, & Allenby	2019, Marketing Science	Bayesian reasoning used as an approach to inference	"[…] propose a Bayesian method of joint inference for the partition and other demand parameters. An immediate benefit is that we are able to use the data to find potentially less obvious grouping structures."
Solgaard & Hansen	2003, Journal of Retailing	Hierarchical Bayes model and Bayesian as a tool for estimation	The paper shows "[…] how some of the major problems in operationalizing store choice models using the framework of the logit model potentially could be overcome by an alternative model specification, the random parameters or coefficients logit model, and we have demonstrated how hierarchical Bayes estimation appear to be an effective way of estimating random utility models."
Steiner, Brezger, & Belitz	2007, Journal of Retailing and Consumer Services	Empirical study	"We proposed a new semiparametric model embedded in a Bayesian framework to predict retail sales. Our results from an empirical application based on retail scanner data for brands of orange juice showed that flexible estimation of price response functions can improve the predictive validity of a sales response model substantially."
Swait & Adamowicz	2001, Journal of Consumer Research	Bayes information criterion (BIC) as the basis for selection of measures	The paper uses the "[…] measures of complexity in a model that allows for changes in decision-making strategies over ranges of task complexity. This latent classification scheme provides the link between the choice environment and the potential for the selection of different processing strategies by the respondent." "[…] empirical analysis suggests that a distinct, simpler processing strategy arises in cases with high levels of task complexity (or after significant expenditure of processing effort, through cumulative entropy) later in the task sequence."
Trusov, Bodapati, & Bucklin	2010, Journal of Marketing Research	Propose using a different type of Bayesian shrinkage	"[…] the proposed Bayesian approach offers significant potential benefits to managers concerned with targeting users for advertising and retention."
Van der Borgh & Schepers	2018, Journal of the Academy of Marketing Science	Bayesian reasoning as an analysis tool	"[…] we conducted a confirmatory factor analysis (CFA) that accounted for the non-identification problem that may occur with small sample sizes (i.e., the CFA is the Bayesian) and that considered the nested nature of our data."
Van Osselaer, Alba, & Manchanda	2004, Journal of Consumer Psychology	Bayesian information criterion (BIC) as a tool for analyzing data	In four experiments, the paper shows that irrelevant information can influence choice when other easily justifiable bases for decisions are available. Therefore, irrelevant information can function as more than a tie-breaker.
Van Osselaer & Janiszewski	2001, Journal of Consumer Research	Bayesian models as a reference	"Four studies show that consumers have not one but two distinct learning processes that allow them to use brand names and other product features to predict consumption benefits." "We find adaptive learning of feature-benefit associations when consumers are motivated to learn to predict a benefit (e.g., because it is perceived to have hedonic relevance) but find HAM learning when consumers attend to an associate of lesser motivational significance."
Venkatesan, Kumar, & Bohling	2007, Journal of Marketing Research	Bayesian decision framework	"The proposed Bayesian decision theory–based selection strategy identifies profitable customers better than current practices at the collaborating firm … the proposed Bayesian decision theory–based strategy is better at identifying profitable customers, the level of profits provided by the customers could be higher if the firm had used the recommended optimal marketing decision variables."
Wachtel & Otter	2013, Marketing Science	Theoretical foundation	

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Author(s)	Year & Journal	Form	Key results
			"The fact that we can estimate the saturated at all is entirely owed to the Bayesian approach and the use of proper subjective priors."
Wedel & Dong	2020, Journal of Consumer Psychology	Theoretical study (with empirical examples)	"This article introduces a Bayesian extension of ANOVA for the analysis of experimental data in consumer psychology. The approach, called BANOVA (Bayesian ANOVA), addresses some common challenges that consumer psychologists encounter in their experimental work, and is specifically suited for the analysis of repeated measures designs." The article explains how to use: "a Bayesian framework for ANOVA of repeated measures, mixed within–between-subjects experiments, as well as for standard between-subjects experiments, and illustrated it with several applications to previously published data. The applications illustrated the additional insights afforded by the BANOVA analyses. BANOVA is implemented in an easy-to-use (free) R-package that interfaces with the STAN software."
Wlömert & Papies	2019, International Journal of Research in Marketing	Bayesian reasoning as a model	"[…] use a Bayesian multilevel model to explore between-country heterogeneity in the associations between these variables and broadband Internet adoption and business model innovations. […] the negative association between broadband Internet penetration and music revenue is weaker in high-income countries, where income restrictions are less likely to drive demand towards illegitimate piracy services."
Wood & Swait	2002, Journal of Consumer Psychology	Bayes information criterion (BIC) as a measurement tool	"[…] results of this research suggest that choice behavior can be influenced by the consumer's basic regard for thought and change. Not only are these individual difference variables important covariates to consider in studies concerning change or innovation, but also, choice behavior may be differentially influenced by the manipulation of consumers' ability to process information and consumers' perception of choice novelty."
Yang & Allenby	2003, Journal of Marketing Research	Introduce "Bayesian spatial autoregressive discrete-choice model"	"[…] introduce an autoregressive multivariate binomial probit model to study interdependent choices among consumers. We specify the model in a hierarchical Bayes framework, and we derive estimation algorithms using data augmentation to simplify the computations. We investigate the effects of two possible sources of interdependent influence: geographic neighbors and demographic neighbors."
Zhang	2019, Journal of the Academy of Marketing Science	Bayesian reasoning as a modelling framework	"This research proposes a Bayesian spatio-temporal model that simultaneously captures the effects of the interactions between customers and the firm, the static interdependence due to customers' inherent similarities, and the dynamic interdependence arising from observed interactions among customers."
Zhang	2019, Marketing Science	Bayesian reasoning as a model	"The model is applied to a rich dataset of university alumni donation and event attendance spanning 27 years. The results yield significant static and dynamic interdependence among the group as well as synergistic effects between static and dynamic structures. This research demonstrates that not accounting for such interdependence, when such interdependence exists, would provide a biased view of firms' marketing effectiveness, yield inferior prediction of customer behaviors in group settings, and miss opportunities to develop group marketing strategies."
Zhang, Wedel, & Pieters	2009, Journal of Marketing Research	Bayesian statistical model	"We developed a Bayesian statistical model of mediation to investigate how attention influences the effects of feature ad design characteristics on sales of the featured product and to obtain accurate estimates of the sales effects of these characteristics."

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