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Advertising's sequence of effects on consumer mindset and sales: A comparison across brands and product categories

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A B S T R A C T

Advertising has the power to influence how consumers experience, think, and feel about brands, but the sequence of these mindset effects may differ by brand and category. This paper analyzes how the mindset factors of cognition, affect, and experience mediate advertising effects on sales, using data from 178 fast-moving consumer good brands in 18 categories over seven years. The authors compare the models proposed in the literature and conclude that the concept of sequentiality in advertising effects holds up well. Importantly, the sequence varies across brands, with the affect → cognition → experience (ACE) sequence being the most common. Brand differentiation and the hedonic versus utilitarian nature of the product category moderate the incidence of the ACE sequence: this sequence is even more likely for utilitarian products and less differentiated brands. For managers, the results show that the last mindset factor in the sequence is the most important in driving sales, with cognition being most responsive to advertising among the mindset factors. Moreover, in utilitarian categories, highly differentiated brands can expect about seven times higher advertising responsiveness of affect than less differentiated brands.

1. Introduction

Imagine three recently graduated MBAs, each working as a brand manager in competing detergent companies. All three have access to data on past marketing activities for their brand and resulting sales, but also to survey-based data on consumer mindset metrics (e.g., brand awareness, liking, purchase intention). In order to decide on next year's advertising activities, each of them thinks through the relationships between advertising, mindset metrics, and sales but they remember different elements from the marketing courses they took.

Ariane has excellent memories of her marketing communications course and understood the usefulness of the AIDA (i.e., Awareness, Interest, Desire, and Action) model. In her analysis of the available metrics, awareness (a cognition measure) comes first, interest and desire (affect) follow in sequence, and lead to action at some point. Therefore, Ariane conceives a

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communication campaign with a primary goal of appealing to consumers' cognition by raising awareness of her brand. Victor took the same course but he remembers instead an article by Vakratsas and Ambler (1999), who conclude that there is little support for any temporal sequentiality in the consumer mindset, as the three mindset factors— cognition, affect, and experience—occur at the same time (instead of sequentially as in the AIDA model). Because he believes purchase decisions are mostly driven by emotions, Victor designs a campaign with the objective of strengthening consumers' affective bond with the brand. Finally, Bridget took a course on marketing analytics and modeling. She digs up Bruce, Peters, and Naik (2012) and rediscovers that the authors find evidence of a temporal sequentiality in consumers' mindset, in which experience precedes cognition, which in turn precedes affect. Inspired by this result, Bridget decides to combine ads with free sampling to get consumers to experience her product with advertising focusing on the usage experience.

Our three imaginary MBAs adequately applied the advertising's sequence of effects frameworks learned in their courses. And their professors diligently anchored their teaching in solid academic research. Unfortunately, that research is apparently contradictory and does not provide clear guidance for managerial decision-making. Marketing textbooks also do not provide specific advice as they typically discuss response sequences based on a summary of historical references and conclude that different sequences have been proposed over the years (e.g., Belch & Belch, 2018; Kotler & Armstrong, 2018; Kotler & Keller, 2012). Moreover, the focus of these comparisons has been on category differences and thus imply the same sequence for the different detergent brands of our three managers. But, what if the characteristics of the brand they manage also make a difference? Furthermore, to draw actionable insights from the advertising's sequence of effects, the three MBAs made different assumptions on which mindset factor is most responsive to advertising and which has higher influence on sales. To what extent are these assumptions empirically valid?

With the regular tracking of consumer mindset metrics (e.g., Keller, 2003), knowing which framework to apply for their brand is important for managers. This knowledge allows them to track sequential effects (e.g., from advertising to cognition, from cognition to affect, from affect to experience) and to identify which steps of the customer decision process they should focus on with their marketing actions (Batra & Keller, 2016). Only brand-level aggregate data points over time and econometric analysis are needed for this purpose.

Therefore, we address the following research questions: 1) Is there a hierarchical sequence of effects of advertising? 2) If yes, what is the operating sequence of advertising effects for each brand and category? 3) What are the moderators of the sequence of advertising effects across product categories and brands? 4) Which mindset factor is most responsive to advertising?, and 5) Which mindset factor is most important in driving sales?

Past literature does not yet answer these research questions. Vakratsas and Ambler (1999) present a review of more than 250 journal articles and books, none of which examine empirically the complete sequence from advertising through mindset metrics to sales to determine which sequence applies. Srinivasan, Vanhuele, and Pauwels (2010) were the first to effectively include mindset metrics in a brand-level sales response model with the different marketing mix instruments. Their main objective was to analyze the added explanatory value of including customer mind-set metrics in a sales response model that already accounts for short- and long-term effects of advertising, price, distribution, and promotion, but they did not examine the possible sequential nature of these metrics. In contrast, Bruce et al. (2012) developed a brand-level dynamic sales response model of advertising to infer the sequence of mindset factors that best explains sales. Unfortunately, they only had data for one brand, and their model faces convergence issues. It is therefore not possible to draw general substantive conclusions on advertising's sequential effects on the consumer mindset from their work.

For all the attention that advertising's sequence of effects on the consumer mindset has received in the marketing discipline in the past decades by both academics and practitioners (Talbot, 2019; Weilbacher, 2002), the lack of empirical evidence is surprising. Current research does not suffice for our three managers to understand the sequence of the effects of their brand's advertising (the input) through the mindset metrics (the throughput) on brand sales (the output). We therefore undertake a large-scale econometric analysis in which we compare, for each brand, six sequences of effects of advertising proposed in the literature, using 13 models. These advertising effect sequences include the classical sequence of effects (based on the AIDA model), simultaneous advertising effects on sales (i.e., no sequential effects, based on Vakratsas & Ambler, 1999), and an integrated sequence of effects (Bruce et al., 2012). We estimate the corresponding models for 178 brands in 18 different fast-moving consumer goods (FMCG) categories on brand-level tracking data, collected by a market research firm for usage by brand managers. The product categories differ in the extent to which they are utilitarian or hedonic, and brands vary in level of differentiation and market share, allowing us to investigate these variables as potential moderators of the sequence.

Our study contributes to the empirical marketing literature on advertising effects on sales in three ways. First, we reconcile prior mixed findings on the presence and sequential patterns of advertising's effects on consumer mindset metrics. We show that the sequence of advertising effects differs by brand, with the affect → cognition → experience (ACE) sequence being the most common in our sample. Second, building on the framework of advertising information processing by MacInnis and Jaworski (1989), we propose and show that the hedonic versus utilitarian nature of the category and brand differentiation moderate the sequential ordering of cognition, affect, and experience. Specifically, the incidence of the ACE sequence is higher for utilitarian products and for less differentiated brands. Market share does not significantly moderate the sequence of advertising effects. In this way, we contribute empirical generalizations on the moderating role of category and brand characteristics on advertising's sequence of effects on consumer mindset and sales. These findings are important for marketing academics who conduct research on advertising response and teach advertising and market research in their marketing curricula.

For managers, we show how advertising's sequence of effects can be assessed by leveraging the brand-level data that many companies collect to monitor their brand's health and performance. Specifically, identifying the right sequence helps determine which mindset factor is most important in driving sales and how responsive the mindset factors are to advertising for the type of brand and product the firm sells. Finally, we show that cognition is the mindset factor most responsive to advertising, and that the last mindset in the sequence is the most important in driving sales. Our findings therefore help inform the design of advertising and communication campaigns and allocation of budgets to differentially influence the sequence of effects for the brand.

2. Relevant literature

The central idea of advertising's sequence of effects is that advertising moves consumers through a sequence of mental phases. These mental phases have been conceptualized with three mindset factors: consumers' cognition (C), to describe the "thinking" dimension of consumer response; affect (A), for the "feeling" dimension; and experience (E), for the memories of prior interactions with the brand (Vakratsas & Ambler, 1999), which originally was labelled as the conative component with a desire to buy (Lavidge & Steiner, 1961). Literature has offered multiple sequence of effects models that propose different relationships and sequentiality (or lack thereof) among the three mindset factors. Bruce et al. (2012) classify these models into three groups: the classical sequence of effects, the simultaneous effects, and the integrated sequence of effects.

The classical sequence of effects framework is based on the AIDA model, which has influenced advertising theory and practice for decades (Colley, 1961). The central idea is that the consumer's awareness of a solution for their needs, often by advertising exposure, is the first step of the purchase process. This 'Awareness stage' precedes the construction of a 'consideration set' of plausible solutions ('Interest stage'). Next follows an evaluation of the consideration set with a formation of preferences ('Desire stage'). Finally, the purchase occurs ('Action stage'). AIDA was envisioned as a linear process, progressing from one stage to the next, with marketing exerting influence at each stage.

The simultaneous effects framework proposes that advertising simultaneously triggers the three mindset factors, that these three in turn simultaneously drive sales, and that sales may reinforce experience (Vakratsas & Ambler, 1999). Based on this framework, later empirical models of marketing, mindset metrics, and sales choose flexible models with dual causality of each mindset metric with sales (Hanssens, Pauwels, Srinivasan, Vanhuele, & Yildirim, 2014; Pauwels, Erguncu, & Yildirim, 2013; Srinivasan et al., 2010). However, none of them examined which advertising effect sequence operates across brands, nor which category or brand characteristics moderate this sequence.

The integrated sequence of effects framework augments advertising-sales response models by integrating the sequence, dynamic evolution, and purchase reinforcement of mindset factors (Bruce et al., 2012). For the one studied brand, Bruce et al. (2012) find the best fit for the integrated framework over the classical and simultaneous models, with a sequence of effects from advertising to experience, then cognition, and then affect, which shows dual causality with sales (experience → cognition → affect, or ECA sequence). Additionally, advertising ignites both the mindset factors and sales.

However, it is unlikely that the ECA sequence applies across FMCG brands. First, research applying the classical sequence of effects framework, focusing on differences by product category, indicates that no single sequence applies (Assael, 1987). Ray et al. (1973) proposes three different sequences: the learning sequence (cognition → affect → experience, or CAE), the dissonance attribution sequence (experience → affect → cognition, or EAC), and the low-involvement sequence (ECA); this perspective on sequence is still disseminated in contemporary marketing textbooks (e.g., Kotler & Armstrong, 2018). By contrast, Vaughn (1980) presents four possible sequences based on a classification of types of consumer decisions for different product types: rational (CAE), habitual (ECA), feeling-driven (ACE), and imitative (EAC). More recently, consumer behavior studies have shown affect often precedes cognition, especially for everyday stimuli, such as TV advertising and magazine pictures (Pham, Cohen, Pracejus, & David Hughes, 2001) and for low-involvement decisions such as those pertaining to FMCGs (Shiv & Fedorikhin, 1999). Finally, the sequence could also differ among brands in the same category, as consumer reaction to brand advertising differs by brand size (e.g., Ehrenberg, Uncles, & Goodhardt, 2004) and by brand differentiation (e.g., Keller, 1993).

In sum, little agreement exists on the prevalence of the different frameworks and sequences and whether there is variation across brands and categories. Table 1 summarizes the contributions of the present paper compared to the extant literature in general and over Vakratsas and Ambler (1999), Srinivasan et al. (2010), and Bruce et al. (2012) in particular.

3. Conceptual framework

We propose that advertising's sequence of effects follows an integrated framework, with the ACE sequence being the most likely to operate for FMCG brands. Moreover, we propose that brand characteristics of differentiation and market share negatively moderate the likelihood of the ACE sequence. Finally, we offer competing expectations for the moderating role of the product category characteristic of utilitarian vs hedonic on the likelihood of the ACE sequence. Fig. 1 summarizes our conceptual framework and expectations.

First, we hold that, for FMCG brands, advertising's sequence of effects follows the integrated framework as proposed by Bruce et al. (2012). In this framework, sales reinforces the three mindset factors. This reinforcement is especially relevant for FMCGs, for which brand consumption happens soon after purchase. Furthermore, the integrated framework accounts for

Table 1
Panel A: Summary of Studies on Advertising's Sequence of Effects.

	Classical Model	Simultaneous Model	Integrated Model	This paper
Conceptual Framework	Advertising sets in motion a linear sequence of effects through the mindset metrics of cognition, affect and, ultimately, behavior	Advertising simultaneously triggers the three mindset factors, which in turn simultaneously drive sales	Augments the advertising-sales response models by integrating sequence, dynamics, and mindset factors purchase reinforcement	Affect, Cognition, Experience (ACE) is the dominant integrated hierarchy, moderated by both brand and category factors
Methodology	Range of econometric methods	Literature synthesis and Vector Autoregressive Models	Dynamic factor model linking advertising, mindset metrics, and sales	Restricted Vector Autoregressive models and Dynamic Factor Models
Substantive Findings	Linear hierarchy of advertising effects on sales, including cognition, affect and, ultimately, behavior. The hierarchy differs by category	Linear hierarchy is not supported. Instead, advertising effects manifest in three-dimensional space of experience, affect and cognition	Experience, Cognition, Affect (ECA) is the sequence for the analyzed brand, dynamic and purchase reinforcement effects exist for all intermediate effects, and advertising simultaneously contributes to sales and brand building	Affect, Cognition, Experience (ACE) is the dominant integrated hierarchy across brands and categories. This sequence is even more likely for utilitarian products and less differentiated brands
Managerial Implications	Primary goal of advertising campaign is to move the needle on the initial mindset metric of the sequence	Ads may contain informational content that appeals to cognition, emotional stories that evoke affect, and product demonstration that connects with consumers' experiences	Managers should consider using the proposed framework to capture advertising's dual contributions of building brands and growing sales	The last mindset factor in the sequence is the most important in driving sales, with cognition being most responsive to advertising. In utilitarian categories, highly differentiated brands can expect about seven times higher advertising responsiveness of affect than less differentiated brands
Representative Papers	Colley (1961); Lavidge and Steiner (1961); Vaughn (1986)	Vakratsas and Ambler (1999); Srinivasan et al. (2010)	Bruce et al. (2012); Hanssens et al. (2014)	Current paper

Panel B: Contribution to Advertising's Sequence of Effects

	Advertising Models			Advertising's Sequence Identified	Brand and Category Moderators	Empirical Generalization
	Classical	**Simultaneous**	**Integrated**			
Colley (1961)	✓					
Lavidge and Steiner (1961)	✓					
Palda (1966)	✓					
Vaughn (1980; 1986)	✓				✓	✓
Ratchford (1987)	✓				✓	✓
Barry and Howard (1990)	✓					
Vakratsas and Ambler (1999)		✓				
Srinivasan et al. (2010)		✓				✓
Bruce et al. (2012)	✓	✓	✓	✓		
Hanssens et al. (2014)		✓				✓
This Paper	✓	✓	✓	✓	✓	✓

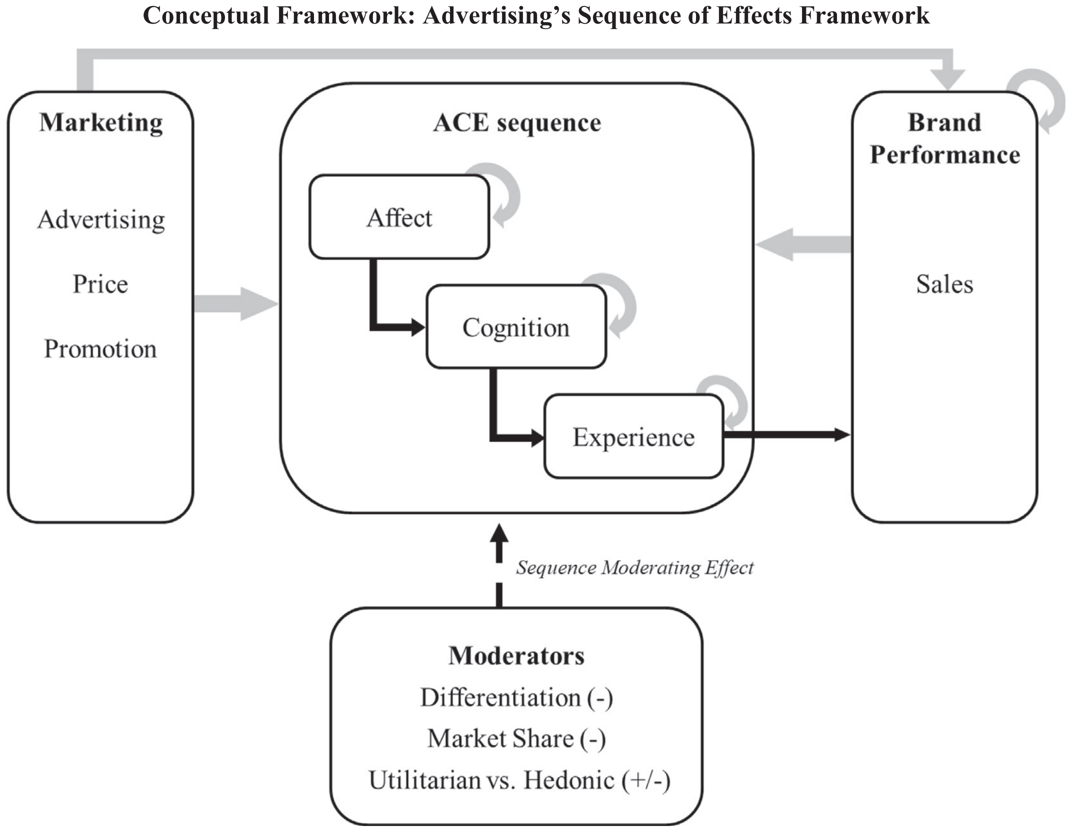


Fig. 1. Conceptual Framework: Advertising's Sequence of Effects. Notes: The black lines and arrows show the relationships that consider the sequence: The solid black arrows show the relationships that capture the sequence of the mindset factors (ACE sequence), and the dashed black arrow shows the effect of the moderators on the sequence (differentiation, market share, and utilitarian vs hedonic). The solid gray arrows denote purchase reinforcement, mindset and sales dynamics, and marketing effects on sales and mindset.

previous findings on dual causality among sales and intermediate metrics (Bruce et al., 2012; Hanssens et al., 2014; Srinivasan et al., 2010) and on the presence of carryover effects (Leone, 1995). Hence, we expect that the results from Bruce et al. (2012) on the *superiority of the integrated sequence of effects framework* over the classical and simultaneous models will generalize to FMCG brands.

We next delve into our expectations on the *sequentiality among mindset factors* for FMCGs. The exact sequence has been highly debated and remains controversial, as noted in our literature review. We begin with which mindset factor should be last in the sequence. Experience comes last in the classical framework (Palda, 1966) and its variations (Vaughn, 1986), as well as in the most recent models of the online consumer decision journey (Pauwels & Van Ewijk, 2020), in which it feeds back into the next purchase and/or word-of-mouth occasion. Experience should be especially powerful in directly driving brand sales for FMCGs, as (1) the short purchase cycles enable experiential information to be used effectively, and (2) consumers are less likely to be motivated to attend to advertising, let alone change their minds as a result of their ad exposure. More uninvolved consumers are less willing to spend time processing information and evaluating brands (Zaichkowsky, 1986). Experience is thus most likely to positively influence consumers' responses to advertising in low-involvement conditions by increasing the credibility of the advertising and decreasing purchase risk. Finally, Sharp (2016) also suggests that experience is the factor with a direct effect on sales. Hence, for FMCG brands, we expect e*xperience to be the last mindset factor in advertising's sequence of effect*s.

This leaves the question of which mindset factor should generally come first in the sequence. Consumer behavior insights favor affect being triggered first, especially for low-involvement decisions such as those pertaining to FMCGs (Shiv & Fedorikhin, 1999). Zajonc (1989) holds that affective reactions can occur relatively automatically without an active role of higher-order cognitive processes. According to the affect-as-information framework (Schwarz, 1990; Schwarz & Clore, 1996), people rely on their feelings because they perceive these feelings to contain valuable judgmental information. Indeed, Pham et al. (2001) show that in responses to everyday stimuli (magazine pictures and TV commercials), immediate affective responses precede and dictate evaluative cognitions, rather than the other way around. In a study of 1000 ads, Pham et al. (2013) report a strong influence of affect evoked by the ad on brand attitudes. Hence, for FMCG brands, we expect *affect to precede cognition in the advertising's sequence of effect*s. In sum, we expect the *affect → cognition → experience (or ACE) sequence to be the most common advertising's sequence of effects for FMCG brands.*

Next, we examine the role of *brand and product category characteristics in moderating* the sequentiality among mindset factors for FMCGs. We base our expectations on the seminal paper by MacInnis and Jaworski (1989) on brand information processing from advertisements. These authors develop a framework on how consumer ability, motivation, and opportunity to process advertising determine the direction of that processing and the resulting purchase outcomes. If ability, motivation, or opportunity are lacking for any reason, consumers' processing of advertising will be affected (Batra & Ray, 1986; MacInnis, Moorman, & Jaworski, 1991; Petty, Cacioppo, & Schumann, 1983). Table 2 outlines the brand and category moderators used in previous studies, describes insights from previous work, and summarizes our expectations and findings on these moderators.

At the brand level, both the ability and motivation to process brand information are higher for brands that are more *differentiated*, since consumers can and want to perceive the differences across brands themselves. Consumers do not perceive differentiated brands as substitutes, and thus they will be motivated to compare and evaluate differences (Zaichkowsky, 1986). Consistently, Assael (1987) and Ray et al. (1973) argue that cognition comes before affect in the sequence when the brand is highly differentiated. By contrast, the lower the ability and motivation to process information, the less complex are consumers' processing operations (MacInnis & Jaworski, 1989). Therefore, the lesser the differentiation among brands, the more likely cognition will follow affect in the sequence of mindset factors. Hence, for FMCG brands, we expect that *the less differentiated, the more likely the sequence is affect → cognition → experience (or ACE).*

Similarly, both the ability and opportunity to process brand information are likely higher for higher market share brands, because more information can be shared and compared across customers and purchase occasions (Ehrenberg, Barnard, Kennedy, & Bloom, 2002; Sharp, 2016). As a result, for low market share brands (compared to high market share brands), the simpler processing of information by consumers will increase the likelihood of affect preceding cognition in the sequence of advertising effects. Hence, for FMCG brands, we expect that *the lower the market share, the more likely the sequence is affect → cognition → experience (ACE).*

At the category level, needs of consumers (Li, Abbasi, Cheema, & Abraham, 2020; MacInnis & Jaworski, 1989) are typically classified as *utilitarian* (e.g., detergent, feminine hygiene, shaving products) *or hedonic* (e.g., beer, candy, snacks). The impact of this classification on the sequentiality of the mindset factors is unclear, as different schools of thought point to either cognition or affect initiating the sequence for utilitarian products.

On one hand, Vaughn (1986) proposed that for utilitarian products, consumers need to first learn about a product and process information cognitively before evaluating it and developing affection, leading to purchase and experience. In other words, the greater the utilitarian need, the more consumers' attention is focused on how the brand solves their problems. Following this reasoning, cognition is more likely to precede affect in the sequence in utilitarian vs hedonic categories. Hence, for FMCG brands, we would expect that *the more hedonic (as opposed to utilitarian) the category, the more likely the sequence is affect → cognition → experience (ACE).*

On the other hand, more recent consumer behavior research finds in lab experiments that consumers deliberate more about hedonic products because of their higher perceived preference uniqueness (Botti & McGill, 2011; Okada, 2005). Higher perceived preference uniqueness for hedonic (vs utilitarian) purchases leads consumers to anticipate having greater difficulty in finding a product to match their unique preferences, resulting in a desire to review a larger assortment of alternatives in the hope of finding a preference-matching product (Whitley, Trudel, & Kurt, 2018). For utilitarian products, consumers may deliberate less about the products and choose products from lower-order affective reactions. For hedonic products, Shiv and Fedorikhin (1999, p. 289) note that increasingly "more shopping situations are likely to involve presentation modes that are symbolic, which in turn is likely to result in choices being based less on affect and more on cognition." This perspective suggests that cognition is more likely to precede affect in the sequence in hedonic vs utilitarian categories. Hence, for FMCG brands, we have the competing expectation that *the more utilitarian (as opposed to hedonic) the category, the more likely the sequence is affect → cognition → experience (ACE).*

Finally, we identify additional brand and category factors used in previous studies for which we do not have expectations on their moderating effects on the sequentiality among mindset factors. Srinivasan et al. (2010) propose that expensive categories have higher levels of consumer involvement relative to inexpensive categories, and a greater role for the consumer's state of mind, as reflected in advertising awareness, consideration, and liking. Similarly, whether the category is food vs non-food and a necessity vs discretionary results in behavioral differences based on stockpiling ability, increased consumption ability, and consumer needs vs wants (Blattberg, Briesch, & Fox, 1995; Narasimhan, Neslin, & Sen, 1996; Nijs, Srinivasan, & Pauwels, 2007; Srinivasan et al. 2004, 2008). However, how these category factors would influence the mindset sequence is an open question.

4. Methodology

4.1. Model requirements

Our research objectives impose four modeling requirements. First, the model should accommodate multiple equations simultaneously, that impose a causal structure to capture the sequence at the brand level (e.g., advertising → affect → cognition → experience → sales). Second, the model should treat cognition, affect, experience, and sales as endogenous. Third, the model should incorporate intertemporal dynamics of cognition, affect, and experience. Con-

Table 2
Summary of Moderator Effects – Brand and Category Characteristics.

Brand and Category Characteristic	Description	Related literature	Our expectations	Our findings
Brand differentiation	Ability and motivation to process brand information are higher for brands that are more *differentiated* since consumers can and want to perceive the differences across brands	Assael (1987); Ray et al. (1973); Zaichkowsky (1986)	The less differentiated the brand, the more likely that the sequence is affect → cognition → experience	Confirmed
Brand market share	Ability and motivation to process brand information are higher for brands with higher *market share* since more information can be shared and compared across customers and purchase occasions	Ehrenberg et al. (2002); Sharp (2016)	The lower the market share, the more likely that the sequence is affect → cognition → experience	Directionally Confirmed
Hedonic vs Utilitarian categories	For *utilitarian* products, consumers need to first learn about a product and process information cognitively before evaluating it and developing affection, leading to purchase and experience	Cheong and Cheong (2021); Li et al. (2020); Pham, Geuens, and De Pelsmacker (2013); Vaughn (1980)	The more hedonic the category, the more likely that the sequence is affect → cognition → experience	Confirmed
	Higher perceived preference uniqueness for *hedonic* (vs utilitarian) purchases leads consumers to anticipate having greater difficulty in finding a product to match their unique preferences, resulting in a desire to review a larger assortment of alternatives in the hope of finding a preference-matching product	Botti and McGill (2011); Okada (2005); Whitley et al. (2018)	*Competing expectation*: The more utilitarian the category, the more likely that the sequence is affect → cognition → experience	Rejected
Category expensiveness and involvement	*Expensive* categories have higher levels of consumer *involvement* relative to inexpensive categories, and a greater role for the consumer's state of mind, as reflected in ad awareness, consideration, and liking	Srinivasan et al. (2010)	Control variables	Not significant
Food or nonfood, necessities or discretionary categories	Used as category variables to account for behavioral differences based on stockpiling ability, increased consumption ability, and consumer needs vs wants	Blattberg et al. (1995); Narasimhan et al. (1996); Nijs et al. (2007); Srinivasan, Pauwels, Hanssens, and Dekimpe (2004, 2008)	Control variables	For necessity categories, the more likely the sequence is affect → cognition → experience

sumers' thoughts and feelings are not static but are dynamically updated and interact over time. For example, a certain level of experience with a brand may increase consumers' cognitive ability and learning in subsequent periods. Therefore, the model should allow for dynamics and dependencies among cognition, affect, and experience. Finally, the model should be flexible in treating marketing decisions (advertising, price, and promotion in our application) as either endogenous or exogenous.

These requirements lead us to consider the state-space model class (Hamilton, 1994). Within this class of models, dynamic factor models have been used by Bruce et al. (2012) to show the superiority of the integrated framework for their studied brand. However, dynamic factor models, though flexible in linking the observed metrics to unobservable constructs, present model identification and convergence issues that call for researcher intervention at the individual-model level (Stock & Watson, 2010). Therefore, dynamic factor models are not appropriate for our large-scale analysis, whose objective is to establish generalizations on advertising's sequence of effects across many brands and categories (see the 'Robustness Check' section for an estimation with dynamic factor models on a subset of brands). Instead, we specify restricted vector autoregressive models, also a subclass of state-space models, in which the mindset factors are taken as measured, rather than unobserved. As a result, better model identification and convergence allows for large-scale comparison across brands. We formulate our models by imposing constraints on the model parameters for the 13 different configurations (Lutkepohl, 2005).

Although the conceptual framework follows how an individual consumer moves through a mindset sequence to eventually purchase the product, model estimation is only possible at an aggregate level due to tracking feasibility. Asking the same individual the same question about the same brand weekly would lead to annoyance and fatigue, and would be subject to a mere-measurement effect, i.e., the mere fact that a respondent indicates during a panel survey that a brand is in her consideration set may increase the subsequent intention to purchase (Morwitz & Fitzsimons, 2004; Zwane et al., 2011). Commercially collected aggregated mindset data circumvent these two problems by interviewing a given respondent less than once a year about a particular product category. This avoids fatigue and allows time for the measurement effect to dissipate. Thus, brand managers use mindset metrics that track the aggregate response at regular time intervals (e.g., monthly) of a representative sample of different consumers. We use such data in our analysis.

4.2. Model specification

Our model has the following general form for each brand:

$$y_t = \sum_{p=1}^{P} A_p y_{t-p} + Bx_t + v_t, \tag{1}$$

where y_t is a $k\times 1$ vector of endogenous variables, p denotes the number of lags, A_p is a $k \times k$ matrix of parameters for the autoregressive terms at lag p, x_t is an $n \times 1$ vector of the exogenous variables of marketing actions and time trends, B is a $k \times n$ matrix of parameters, and v_t $N(0,\Omega)$ is the error term. In the main empirical application, the endogenous variables are sales, cognition, affect, and experience. Our results are robust to treating the marketing actions as endogenous, to allowing for direct lagged effects of advertising on sales, and to incorporating competitive effects (see 'Robustness Check' section).

For ease of exposition, we can express the general form of the model using one lag ($p = 1$) in the following matrix–vector form (see the 'Model Estimation and Comparison' section for the optimal lag length selection procedure):

$$\begin{bmatrix} C_t \\ A_t \\ E_t \\ S_t \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \begin{bmatrix} C_{t-1} \\ A_{t-1} \\ E_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix} \begin{bmatrix} Adv_t \\ Price_t \\ Promo_t \\ Trend_t \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \end{bmatrix} \tag{2}$$

where *C*, *A*, *E*, and *S* stand for cognition, affect, experience, and sales, respectively, and *Adv*, *Price*, *Promo,* and *Trend* stand for advertising, price, promotion, and time trend, respectively.

To accommodate the different sequences, we impose constraints on the parameters of the model in Eq. (2). Our model formulation can account for the carryover effects, sales dynamics, purchase reinforcement, and marketing effects. Thus, the three advertising frameworks proposed in the literature—classical, simultaneous, and integrated—and the six possible sequences are nested within our specification. We test the operating sequence for each brand on the basis of the three frameworks.

Classical framework. According to this framework, advertising triggers one of the mindset factors (C, A, or E) to initiate the sequence, and the last factor in the sequence drives sales. For example, for the ECA sequence, our Model 1, the equation is

$$\begin{bmatrix} C_t \\ A_t \\ E_t \\ S_t \end{bmatrix} = \begin{bmatrix} 0 & 0 & \alpha_{13} & 0 \\ \alpha_{21} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \alpha_{42} & 0 & 0 \end{bmatrix} \begin{bmatrix} C_{t-1} \\ A_{t-1} \\ E_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} 0 & \beta_{12} & \beta_{13} & \beta_{14} \\ 0 & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ 0 & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix} \begin{bmatrix} Adv_t \\ Price_t \\ Promo_t \\ Trend_t \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \end{bmatrix} \tag{3}$$

where β_{31} captures advertising affecting experience (E_t); prior experience (E_{t-1}) influences current cognition (C_t), captured by α_{13}; prior cognition (C_{t-1}) influences current affect (A_t), captured by α_{21}; and prior affect (A_{t-1}) drives sales (S_t), captured by α_{42}. Hence, prior experience (E_{t-1}) does not influence current period experience (E_t). The β_{k2}, β_{k3}, and β_{k4} parameters control for price, promotion, and time effects, respectively. Similarly, we formulate Model 2–Model 6 for the other five possible sequences of the classical framework: Model 2 for CEA, Model 3 for EAC, Model 4 for CAE, Model 5 for AEC, and Model 6 for ACE (see Web Appendix W1 for the formulations of these models).

Simultaneous effects. This framework states that advertising influences all mindset factors (C, A, and E) simultaneously and that all of them drive sales jointly (Vakratsas & Ambler, 1999). Therefore, we formulate the model for this framework, our Model 7, as

$$\begin{bmatrix} C_t \\ A_t \\ E_t \\ S_t \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & 0 \end{bmatrix} \begin{bmatrix} C_{t-1} \\ A_{t-1} \\ E_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ 0 & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix} \begin{bmatrix} Adv_t \\ Price_t \\ Promo_t \\ Trend_t \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \end{bmatrix} \tag{4}$$

where β_{11}, β_{21}, and β_{31} capture the simultaneous effect of advertising on the three mindset factors. Prior cognition (C_{t-1}), prior affect (A_{t-1}), and prior experience (E_{t-1}) drive sales, captured by the parameters α_{41},α_{42} and α_{43}, respectively. Parameter α_{34} captures purchase reinforcement from prior purchases (S_{t-1}) to current experience (E_t). Finally, the β_{k2}, β_{k3}, and β_{k4} parameters control for price, promotion, and time effects, respectively.

Integrated framework. This framework posits that advertising increases sales and builds brands simultaneously, that mindset exhibit dynamics, and that purchase reinforcement occurs not only for experience but for all three mindset factors as well (Bruce et al., 2012). Thus, for ECA sequence, we formulate the model, our Model 8, as

$$\begin{bmatrix} C_t \\ A_t \\ E_t \\ S_t \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & 0 & \alpha_{24} \\ 0 & 0 & \alpha_{33} & \alpha_{34} \\ 0 & \alpha_{42} & 0 & \alpha_{44} \end{bmatrix} \begin{bmatrix} C_{t-1} \\ A_{t-1} \\ E_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix} \begin{bmatrix} Adv_t \\ Price_t \\ Promo_t \\ Trend_t \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \end{bmatrix} \tag{5}$$

where advertising evokes all three mindset factors and sales jointly, determined by the β_{k1} parameters, and the β_{k2}, β_{k3}, and β_{k4} parameters control for price, promotion, and time effects, respectively. The parameters α_{11}, α_{22}, α_{33}, and α_{44} capture the mindset carryovers and sales dynamics, while α_{14}, α_{24}, and α_{34} measure purchase reinforcement. Finally, similar to Model 1 of the classical framework, parameters α_{13}, α_{21}, and α_{42} capture the ECA sequence. In addition, we formulate Model 9–Model 13 for the other five possible sequences: Model 9 for CEA, Model 10 for EAC, Model 11 for CAE, Model 12 for AEC, and Model 13 for ACE. Table 3 summarizes the characteristics of the 13 models, and Web Appendix W1 provides model specifications.

4.3. Model estimation and comparison

4.3.1. Estimation

To ensure model stability, we check whether the roots of the autoregressive polynomial are outside the unit circle. We also check that the models do not show violation of autocorrelation or heteroskedasticity. We allow the mindset factors to be correlated, i.e., the variance–covariance matrix of the model has nonzero elements in the off-diagonal positions. Because we use constraints in a system of structural equations, we estimate the models by an iterated seemingly unrelated regression algorithm (Zellner & Theil, 1962).

4.3.2. Model comparison

We use log-likelihood and Akaike (AIC) and Bayesian (BIC) information criteria to compare the models and determine for each brand which framework and which sequence of advertising effects operate. Our main criterion is BIC, given its asymptotic consistency and small sample performance (Lutkepohl, 2005). In our empirical application, BIC has 96 % and 95 % agreement with AIC and log-likelihood, respectively, in identifying the best model fit. We identify a model as statistically superior to another if the improvement in BIC exceeds two units (Burnham & Anderson, 2002).

4.3.3. Unit root, time trends, and structural breaks

For each brand, we check whether any of the four endogenous variables (cognition, affect, experience, and sales) presents a unit root with the Phillips-Perron unit-root test. If necessary, we keep the time trend in the models (β_{k4} parameters in Eqs. (2)–(5)) to test the presence of unit roots. We also visually inspect the variables to assess whether they present any structural break, and include controls, if necessary, to account for these structural breaks.

4.3.4. Lag length

We select the lag length of the model (p in Eq. (1)) based on the model fit criterion of BIC and autocorrelation in the residuals. If the results remain unchanged (i.e., best framework and sequence) with higher order lags, we use the lowest lag length for parsimony.

Table 3
Classical, Simultaneous, and Integrated Model Specifications.

Model	Advertising Framework	Sequence	Advertising Triggers	Price and Promotion	Dynamics	Purchase Reinforcement
1	Classical	ECA	Only E	Yes	None	None
2		CEA	Only C			
3		EAC	Only E			
4		CAE	Only C			
5		AEC	Only A			
6		ACE	Only A			
7	Simultaneous	None	C, A, E	Yes	None	Only E
8	Integrated	ECA	C, A, E, Sales	Yes	C, A, E, Sales	C, A, E, Sales
9		CEA				
10		EAC				
11		CAE				
12		AEC				
13		ACE				

4.3.5. Endogeneity

With the exception of the three marketing-mix variables and the time trends, we treat all variables as endogenous; that is, variables can be influenced by their own past and the past of other variables in a system of equations (see Eqs. (2)–(5)). All three advertising frameworks (classical, simultaneous, and integrated) assume that advertising initiates the sequence (i.e., advertising is an input and therefore serves as an exogenous variable in the model). However, from an empirical standpoint, advertising and the mindset may be determined simultaneously. To check this, we estimate the models with endogenous marketing variables. We discuss these results in the 'Robustness Check' section.

4.4. Relationship between ACE sequence and category and brand characteristics

To assess whether the incidence of the ACE sequence depends on the product category (utilitarian vs hedonic) and the brand-level characteristics (brand differentiation and market share), we conduct a second-stage analysis with the moderators as independent variables. We estimate a brand-level logit regression, where the dependent variable is whether the brand follows the ACE sequence or not. Eqs. (6) and (7) present the logit model specification, where for each brand i, y_i takes the value of 1 if the brand follows the sequence ACE and 0 otherwise. So if brand i follows the ACE sequence (Model 13), y_i takes the value of 1 for the ACE sequence and 0 for the other 12 models. $Hedonic_i$, $Differentiation_i$, and $MarketShare_i$ capture the three moderating variables of interest. To control for potential confounds, we add category- and brand-level variables used in the literature. In the 'Robustness Check' section, we examine whether our results hold up to the inclusion of these controls.

$$Prob(y_i = 1|\boldsymbol{x}_i) = \frac{exp(\boldsymbol{x}_i\boldsymbol{\theta})}{1 + exp(\boldsymbol{x}_i\boldsymbol{\theta})} \tag{6}$$

$$\boldsymbol{x}_i\boldsymbol{\theta} = \theta_1 Hedonic_i + \theta_2 Differentiation_i + \theta_3 MarketShare_i + Controls \tag{7}$$

5. Data

We obtain data from two sources. First, Kantar Worldpanel's brand-level performance tracker includes consumer attitude metrics, purchases, and marketing-mix data between January 2003 and July 2010 on a four-week basis for all 178 brands in 18 product categories in France. We analyze all brands present throughout the entire observation period. Thus, we have a complete set of 98 time-series observations per measure for each brand. Table 4 details the empirical measures and their operationalization.

For consumer mindset metrics, a nationally representative panel of households is surveyed weekly with a rotation method, such that a given household is only interviewed at most once a year about a given product category. This ensures that the previous survey does not influence a respondent's answers on a new survey for a given product. The brand performance tracker reports four-week averages of the responses for each metric (more than 8,000 surveys are conducted each year for each category in France). Brand managers receive these metrics to track the performance of their brands in the purchase funnel. We use these metrics to measure the three mindset factors.

For cognition, we average the metrics of advertising awareness and aided brand awareness because they capture the "thinking" dimension as a possible result of an advertising campaign. While brand awareness has a long history as a cognition measure (Murphy & Zajonc, 1993; Pauwels & Van Ewijk, 2020; Phelps, 2005), aided brand awareness is often at a ceiling for well-known brands. Therefore, advertising awareness is used as an additional proxy of awareness both by practitioners (e.g., Coca Cola in Pauwels, 2014) and academic researchers (e.g., Hanssens et al., 2014; Lautman & Pauwels, 2009; Pauwels et al., 2013; Srinivasan et al., 2010). In combination, these awareness measures reflect cognition. For affect, we use the metric

Table 4
Variables and Their Operationalization.

Variable	Operationalization
Sales volume	Sales (quantity sold)
Advertising	All advertising media expenditures (in euros)
Average price	Average price paid (in euros)
Promotion	Distribution-weighted average promotion in percentages
Advertising awareness	"For which of these brands have you seen, heard, or read any advertising in the past two months?"; (Respondent is given a list of brands and replies YES or NO to each); % of respondents indicating "yes" for the particular brand
Aided brand awareness	"Which of the following brands have you heard of?"; (Respondent is given a list of brands and replies YES or NO to each);% of respondents indicating "yes" for the particular brand
Liking	"Please indicate how much you like brand X."; (1 = "I don't like at all," 7 = "I like a lot")
Past purchase	"Which of these brands have you purchased in the past?"; (Respondent is given a list of brands and replies YES or NO to each); % of respondents indicating "yes" for the particular brand
Purchase intention	"Which of these brands are you willing to buy in the future?"; (Respondent is given a list of brands and replies YES or NO to each);% of respondents indicating "yes" for the particular brand
Category hedonic nature	We obtain respondents' scores on 'feeling' and 'thinking' items and then calculate, as a continuous metric, the extent to which a category is hedonic vs utilitarian measured as the difference between 'feeling'and 'thinking' (Ratchford, 1987). Details are in Web Appendix W3.
Brand differentiation	"Is the brand original?"; (Respondent is given a list of brands and replies YES or NO to each); % of respondents indicating "yes" for the particular brand
Brand market share	Market share in value
Involvement (1 to 7)	Survey questions with three-item scale (see detail on Web Appendix W3)
Category expensiveness	Market share–weighted average of the maximum prices of all brands in the category in euros
Food category	Dummy variable (Yes or No)
Necessity category	Dummy variables (Yes or No)
Dynamism	% respondents agreeing that brand is dynamic
Trust	% respondents agreeing that brand inspires trust
Quality	% respondents agreeing that brand offers quality
Spending per buyer	Average spending per buyer in euros
Quantity per purchase	Average quantity per purchase in volume or weight
Higher price would be ok	% respondents agreeing that a higher price would be justifiable
Frequency	Average number of purchase occasions per period

liking because it describes the "feeling" dimension. The term experience has been used in the literature to refer both to memories of brand experience (Vakratsas & Ambler, 1999) and to conation (Bruce et al., 2012 equate experience with purchase intention). We average the metrics of past purchase and purchase intentions because they capture in combination, respectively, consumers' positive "memories" of previous interactions and anticipations of future interactions with the brand.

All metrics are expressed as percentages of respondents, except for degree of liking, which is expressed as an average score across respondents obtained from a 7-point Likert scale. The measures of the mindset factors show reliability and discriminant validity: the Cronbach's alpha for cognition and experience are 0.71 and 0.93 (affect is measured with a single metric); and cognition, affect, and experience have greater correlation coefficients with their component metrics than those computed with the other metrics (see Web Appendix W2 for discriminant validity details). We normalize all variables for the empirical application.

We use brand differentiation and market share, from the brand performance tracker in the second-stage analysis as moderators of interest. This data also includes metrics on brand dynamism, brand trust, brand quality, spending per buyer, 'higher price would be ok', purchase quantity, and purchase frequency, which we use as controls. Moreover, we calculate and use category expensiveness as a control by computing the market share–weighted average of the maximum prices of all brands in the category (Raju, 1992). We measure purchase data with a nationally representative household panel (12,000 households in France) using hand-held scanner device information. Finally, we obtained advertising expenditure, brand prices, and promotions from Kantar Worldpanel.

Our second data source is a survey that we conducted among an online panel with each of the 18 categories to measure the utilitarian or hedonic nature of the category (a moderator) and involvement (a control variable). Our sample of 100 French respondents is stratified on the basis of sociodemographic criteria. The survey instruments are the Ratchford (1987) scales translated into French. Each respondent answered the survey for ten categories to minimize respondent fatigue (see Web Appendix W3 for survey measurement details).

Our sample consists of 178 brands in the categories of beer, candy, canned meals, cereal, cleaning, coffee, detergent, facial cream, feminine hygiene, frozen meals, makeup, milk, snack, shampoo, shaving, shower, soft drink, and yogurt. These brands represent a mix of food and nonfood categories, storables and perishables, and necessities and discretionary items, allowing us to generalize our findings across FMCG categories. Table 5 provides descriptive statistics averaged across brands on all variables (see Web Appendix W4 for correlations between variables).

Overall, with a temporal duration of seven years and a wide coverage of brands across 18 consumer product categories, the data are uniquely suited to address our research objective of assessing advertising's sequence of effects on aggregate metrics of affect, cognition and experience, its generalizability, and the impact of moderating variables.

Table 5
Variables: Definition and Descriptive Statistics.

Variable type	Definition	M	SD	Min.	Max.
Sales	Sales in volume or weight (100 households)	12.39	26.47	0.02	160.27
Marketing	Advertising (in thousand euros)	449.00	557.14	0.07	2,733.74
	Average price (in euros)	3.55	5.29	0.07	43.10
	Promotion (%)	30.16	19.41	0.00	81.68
Mindset metrics	Ad awareness (%)	17.98	10.36	1.32	50.52
	Aided awareness (%)	80.97	14.10	21.65	96.72
	Liking (1 to 7)	5.64	0.66	3.65	6.76
	Purchase intention (%)	5.72	5.07	0.45	33.32
	Purchase past (%)	19.34	11.85	0.78	72.16
Moderators	Hedonic nature (−7 to 7)	−0.18	0.23	−0.65	0.20
	Differentiation (%)	11.66	5.25	3.46	29.50
	Market share (%)	4.79	4.95	0.05	34.88
Control Variables	Involvement (1 to 7)	3.01	0.18	2.69	3.36
	Category expensiveness (in euros)	4.16	5.21	0.18	19.19
	Food category (dummy)	0.49	0.50	0.00	1.00
	Necessity category (dummy)	0.58	0.49	0.00	1.00
	Dynamism (%)	14.61	4.60	5.47	29.82
	Trust (%)	34.59	6.48	21.88	50.61
	Quality (%)	34.66	7.39	20.64	51.88
	Spending per buyer (in euros)	6.48	6.62	0.85	54.75
	Quantity per purchase (volume or weight)	3.71	6.13	0.49	37.13
	Higher price would be ok (%)	7.98	5.31	1.70	34.82
	Frequency (#)	1.19	0.20	0.44	1.76

Notes: Average across brands and periods.

6. Results

For model stability, we confirm that the roots of the autoregressive polynomial are inside the unit circle for all models and brands. The models show no violation of autocorrelation or heteroskedasticity (see Web Appendices W5 and W6). We use a lag length of one for all brands because it either yields better fit or presents the same result as with more lags.

We proceed as follows to explore the endogenous variables in the model (cognition, affect, experience, and sales) and assess whether time trends and structural break controls are needed. First, for 52 of the 178 brands, the tests without time trends reject the presence of unit root for all four variables. Hence, we estimate the models without time trends for these brands, i.e., we set to zero the β_{k4} parameters in Eqs. (2)–(5). Second, for 106 brands, some variables require a time trend to reject the presence of unit root. Hence, we estimate the models with time trends for these variables and brands. Finally, we visually inspect the remaining 20 brands and identify that all present structural breaks for some variables. Taking into account these structural breaks and time trends when needed, the test rejects the presence of unit root for all the variables.

Table 6
Estimates for an Illustrative Brand in the Coffee Category.

A: Model Comparison: Classical, Simultaneous, and Integrated					
Model	**Advertising Framework**	**Sequence**	**LL**	**AIC**	**BIC**
1	Classical	ECA	−429.9	883.8	914.7
2		CEA	−430.2	884.4	915.3
3		EAC	−433.7	891.4	922.3
4		CAE	−432.0	888.0	918.9
5		AEC	−428.8	881.6	912.5
6		ACE	−431.8	887.7	918.6
7	Simultaneous	None	−428.0	886.1	924.7
8	Integrated	ECA	−372.9	789.7	846.3
9		CEA	−369.6	783.2	839.9
10		EAC	−373.7	791.3	848.0
11		CAE	−375.6	795.2	851.8
12		AEC	−373.6	791.2	847.9
13		ACE	**−367.7**	**779.4**	**836.1**

B: Model Estimates for the ACE Sequence Model.
$$\begin{bmatrix} C_t \\ A_t \\ E_t \\ S_t \end{bmatrix} = \begin{bmatrix} \mathbf{.751} & \mathbf{-.095} & 0 & \mathbf{.101} \\ 0 & -.108 & 0 & -.119 \\ \mathbf{.359} & 0 & .037 & \mathbf{.132} \\ 0 & 0 & .111 & \mathbf{.162} \end{bmatrix} \begin{bmatrix} C_{t-1} \\ A_{t-1} \\ E_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{.079} & \mathbf{-.130} & -.030 \\ \mathbf{.176} & .042 & .099 \\ .058 & -.018 & -.018 \\ .046 & \mathbf{-.203} & \mathbf{.386} \end{bmatrix} \begin{bmatrix} Adv_t \\ Price_t \\ Promo_t \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \end{bmatrix}$$

Notes: In Panel A, criteria (LL [log-likelihood], AIC, BIC) significantly superior to other models are in bold. In Panel B, significant coefficients at p <.1 are in bold.

Hence, we include controls in Eqs. (2)–(5) for these brands to account for the structural breaks. Note that when comparing the 13 models for each brand, all models include the same time trends and structural change variables.

6.1. Is there a sequence of effects in Advertising?

For each brand, we identify the model that best fits the data within each framework—classical, simultaneous, and integrated—and then compare the resulting three models across frameworks to evaluate which one describes the brand best. For illustration, we display the comparisons among models for a coffee brand in Panel A of Table 6. We compare the model fit statistics of Model 13 (the best model of the integrated framework) with those of Model 5 (the best model of the classical framework) and Model 7 (the simultaneous framework). We find that the integrated framework operates for the coffee brand, as it statistically outperforms the other two frameworks because the differences in BIC exceed two units (Burnham & Anderson, 2002). Web Appendices W7 and W8 present the fit criteria and estimation coefficients for all brands and models.

Overall, for 96 % of the brands (171 of 178), the integrated framework is statistically superior, while for 3 % of the brands (5 of 178), the classical framework is statistically superior. For the remaining 1 % of brands (2 of 178), the integrated and classical models are statistically indistinguishable from each other but are superior to the simultaneous model. The simultaneous model does not operate for any of the 178 brands in our sample. Statistically testing these differences, we find that the integrated framework is the predominant one ($z = 17.76$, $p < .01$).

Thus, as predicted in our conceptual framework and consistent with Bruce et al. (2012), *we find that the integrated advertising's sequence of effects framework operates across brands and categories in FMCGs*. We conclude that there is a sequence of effects from advertising through mindset effects to sales.

6.2. Is there a predominant sequence in Advertising?

Next, we compare the incidence of sequences in the integrated framework. This involves five pairwise fit comparisons among models within this framework. For our illustrative coffee brand, we compare Model 13 with Models 8–12 (Table 6, Panel A). We find that Model 13 (ACE) is the operating sequence because its fit statistically outperforms the other five sequences. Table 7 shows our results across all the studied brands.

For 92 of the 178 brands (52 %), one model is statistically superior to all other models. Among these 92 brands with an identifiable best model, Model 13 with the ACE sequence operates for 41 % (38) of the brands. In distant second and third place are the AEC and CEA sequences (Models 12 and 9), which operate for 21 % (19) and 18 % (17) of the brands, respectively. Finally, the ECA and CAE sequences operate for 5 % (5) of the brands while the EAC sequence is present for only 3 % (3) brands.

Of the 86 brands for which no single model is statistically superior to the others, 59 have two models that outperform the other 11 models but are statistically indistinguishable from each other. For 33 (56 %) of these 59 brands, one of the two superior models is the ACE sequence. For 32 (54 %) of these 59 brands, one of the two superior models is the CEA sequence while the AEC and the EAC sequences are one of the two superior models for 17 (29 %) and 16 (27 %) of the brands, respectively.

Table 7
Incidence of Sequences.

Model	Framework	Sequence	Brands with Statistically Superior Sequence		Frequency for Brands without Single Superior Sequence (# of Brands)		
			Frequency (# of Brands)	**%** (of Brands)	**Two Superior Sequences**	**Three Superior Sequences**	**>Three Superior Sequences**
1	Classical	ECA	1	1 %	1	0	1
2		CEA	1	1 %	1	1	1
3		EAC	1	1 %	0	0	0
4		CAE	1	1 %	1	0	0
5		AEC	1	1 %	1	0	0
6		ACE	0	0 %	0	0	0
7	Simultaneous	None	0	0 %	0	0	0
8	Integrated	ECA	5	5 %	7	8	5
9		CEA	17	18 %	32	8	10
10		EAC	3	3 %	16	10	7
11		CAE	5	5 %	9	4	9
12		AEC	19	21 %	17	6	9
13		ACE	38	41 %	33	8	10
Total Number of Brands			**92**	**100 %**	**59**	**15**	**12**

Note: For brands without single superior sequence, the incidence of sequences are double counted for "two superior sequences", triple counted for "three superior sequences", etc. Hence, the "total number of brands" cell divides the incidence of sequences by a factor of two, three, etc., respectively.

Table 8
Logit Regression Estimation Results on Moderating Effects of the Sequence.

	Dependent Variable (Sequence)					
	ACE	ECA	CEA	EAC	CAE	AEC
Hedonic nature	−2.59**	3.62	1.55	−1.89	0.45	2.29
	(1.23)	(3.12)	(1.5)	(2.56)	(2.35)	(1.49)
Differentiation	−0.19**	0.17**	0.08	0.13	−0.18	0.00
	(0.06)	(0.08)	(0.05)	(0.08)	(0.15)	(0.05)
Market Share	−0.07	0.06	0.07	−0.35	−0.07	0.07
	(0.06)	(0.14)	(0.06)	(0.38)	(0.16)	(0.06)
Constant	1.36*	−4.92**	−2.47**	−4.40**	−0.77	−1.22*
	(0.71)	(1.48)	(0.78)	(1.76)	(1.36)	(0.72)
Obs	92	92	92	92	92	92
LL	−52.889	−15.647	−41.721	−11.288	−18.028	−45.421
Pseudo R2	0.152	0.194	0.052	0.146	0.072	0.031

Notes: Standard errors are in brackets, ** Coefficients at p <.05, * Coefficients at p <.1. Variables in the model are normalized.

Next, 15 brands have three models that are statistically superior to the rest but are indistinguishable from one another. Of these 15 brands, 8 (53 %) have the ACE sequence as one of the superior models. In addition, 10 (67 %) have the EAC sequence, while 8 (53 %) each have the ECA and CEA sequences. Finally, 12 brands have four or more models that are statistically superior to the rest but are indistinguishable from one another. Of these 12 brands, 10 (83 %) have the ACE sequence as one of the superior models. In addition, 10 (83 %) have the CEA sequence while 9 (75 %) have the CAE and AEC sequences as one of the superior models.

Integrating the results across all cases, we find that no sequence performs better than the ACE sequence for 89 out of the full sample of 178 brands (50 %). We conclude that the *affect → cognition → experience (or ACE) sequence is the most common advertising's sequence of effects for FMCG brands.*

6.3. Do hedonic Nature, Differentiation, and market share moderate the ACE Sequence?

Table 8 reports the estimations for Eqs. (6) and (7). Column 2 shows the results for the predominant ACE sequence. We find that the ACE sequence is negatively associated with the hedonic nature of the product and with brand differentiation (–2.59, p <.05; –0.19, p <.01, respectively). Therefore, we conclude that the ACE sequence is even more likely to occur for utilitarian products and less differentiated brands. The relationship between market share and the ACE sequence is negative, but not statistically significant (–0.07, p >.1). Even though we did not formulate expectations for other sequences, we checked whether our moderators have an influence on their occurrence. Columns 3 through 7 in Table 8 show no significant effects, with one exception: the ECA sequence is more likely to occur the more differentiated the brand is (0.17, p <.05; Column 3).

Thus, as predicted in our conceptual framework, *the lower the brand differentiation, the more likely ACE is the sequence for FMCGs.* Of the two opposing views on the moderating effect of the hedonic vs utilitarian nature of the category, our results are consistent with the expectations that *the more utilitarian (as opposed to hedonic) the category, the more likely ACE is the sequence for FMCGs.* Finally, although directionally the lower the brand market share the more likely ACE is the sequence for FMCGs, our results do not statistically support this expectation.

6.4. Robustness checks

We perform seven robustness analyses to assess the validity and generalizability of our results. Details are available in the Web Appendix (and from the authors upon request).

6.4.1. Dynamic factor model estimation

We were able to estimate dynamic factor models for a subset of brands, allowing all mindset metrics to load on the three mindset factors in the observation equation and include identification constraints. We had to search for a suitable optimization algorithm and appropriate starting values to achieve estimation convergence, which required several interventions. This labor-intensive process took multiple days for each brand and model. Despite these efforts, some models did not fully converge. For the 18 fully converging brands, we find the same results as in our main analysis; that is, the integrated framework is the dominant one and ACE is the most common sequence, being the single superior model for 39 % of the brands (see Web Appendix W9).

6.4.2. Endogenous marketing variables

In our model specification and main analysis, we follow the frameworks proposed in the literature that consider advertising and marketing exogenous. However, we check the robustness of our results to account for dual causality effects for the marketing variables by treating them as endogenous in the model. We adapt our model specifications to accommodate eight endogenous variables instead of five. The results confirm the main results that advertising's sequence of effects operates across all brands and that the ACE sequence is most common.

6.4.3. Lagged marketing effects

The use of marketing variables as contemporaneous in the model may lead to biased estimates due to possible simultaneity with sales and mindset factors. To address this possible endogeneity concern, similar to Bruce et al. (2012), we estimate the models with lagged effects of marketing (advertising, price, promotion). The results of this estimation remain unchanged from our main analysis; that is, the integrated framework is the dominant one and ACE the predominant sequence.

6.4.4. Competitive effects

In our main analysis, we only consider marketing effects of the focal brand. However, one might expect that advertising's sequence of effects could be also affected by competitors' marketing. We adapt our model specifications to incorporate competitors' advertising, price, and promotional effects as exogenous variables. To measure competitors' marketing we use the data of the remaining brands in the same category of the focal brand (Dekimpe & Hanssens, 2000). The results confirm that advertising's sequence of effects operates across all brands and ACE is most common sequence (Web Appendix W10).

6.4.5. Inclusion of controls in examining the moderators of the sequence

To evaluate the robustness of the results we include control variables in Eq. (7). We use four variables examined in the literature and seven additional variables for which we have data. The results confirm that the ACE sequence is more likely to occur for utilitarian products and for less differentiated brands. Of the controls, only whether the category is a necessity (vs discretionary) is significantly positively related to the prevalence of ACE sequence. See Web Appendix W11 for a detailed explanation of this analysis.

6.4.6. Adding dynamics and purchase reinforcement to the simultaneous framework

In our model specification and analysis, we compare the frameworks and models proposed in the literature. However, we can extend the simultaneous model by incorporating mindset and sales dynamics and purchase reinforcements to all three mindset factors. We adapt the restrictions in Eq. (4) to accommodate for these relationships. The empirical comparison with this new model yields the same results of our main analysis in that the advertising's sequence of effects operates across all brands.

6.4.7. Brands with low market share

While we studied market share as a moderator, a question remains whether our results would hold up for small brands that have had little opportunity to build experience at the market level. Slotegraaf and Pauwels (2008) showed that brands with under 3 % share experience different marketing effectiveness than large brands do. Our data set contains an even wider range of market share, from 0.00 % to 47.65 % (Table 5), with 26 (15 %) brands with a market share below 1 %. The robustness analyses confirm that ACE is the predominant sequence, both for the group of brands with more than 1 % and for the group of brands with market share below 1 % (see Web Appendix W12).

7. Managerial Implications

Our findings reveal robust support for the advertising's sequence of effects across all brands and for specific sequences for different brands, with the ACE sequence being the most common. To what extent are these findings actionable for managers? We address this question in three ways by showing (1) which mindset factor is the most important in driving brand sales, (2) which factor has the greatest responsiveness to advertising, and (3) what is the mediation effect of the mindset factors from advertising to sales. Thus, we help brand managers assess the impact of cognition, affect, and experience on sales, evaluate their responsiveness to advertising, and assess which mindset factor to focus on.

7.1. Importance of the mindset factors in driving sales

To advise managers on which mindset factor is the most important in driving sales over time, we compute the long-term forecast error variance decomposition (FEVD) for 32 weeks. The FEVD decomposes how much of the variation of an endogenous variable of interest—sales in our application—is explained by changes in other endogenous variables of interest in the system (e.g., Nijs et al., 2007)—cognition, affect, and experience. Similar to the dynamic R-square, the FEVD quantifies the dynamic explanatory value on sales of each endogenous variable. Because our model imposes a causal structure to advertising and mindset factors, we perform a Cholesky decomposition for the FEVD (Lutkepohl, 2005).

Fig. 2 shows the importance of each mindset factor in driving sales, organized by the sequence. Intuitively, we find that for each of the six sequences the last mindset factor in the sequence is the most important in driving sales (58 % of sales variation), followed by the middle factor (25 %), and then the first factor (18 %). For the ACE sequence, the last, middle, and first factors explain 48 %, 37 %, and 15 % of the sales variation, respectively.

Importance of First, Middle, and Third Mindset Factor for Each Sequence in Driving Sales

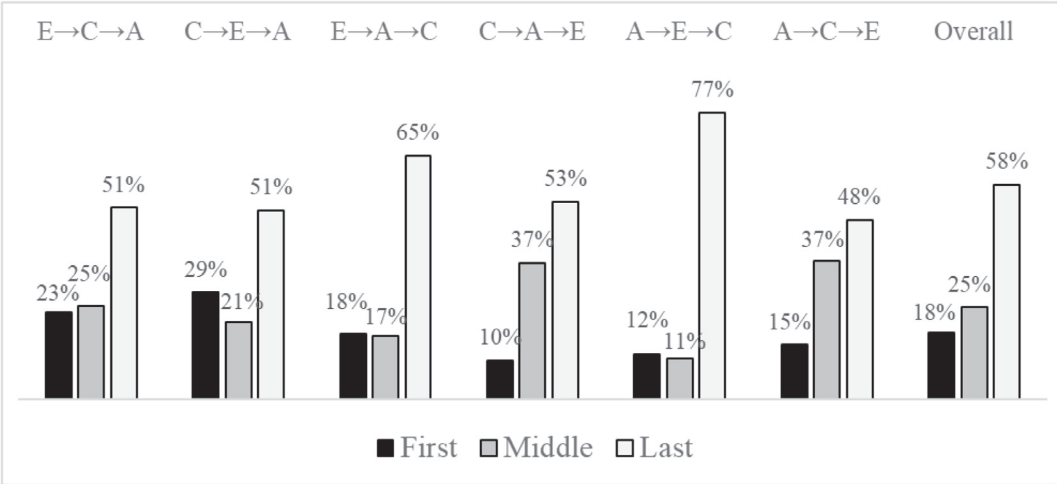
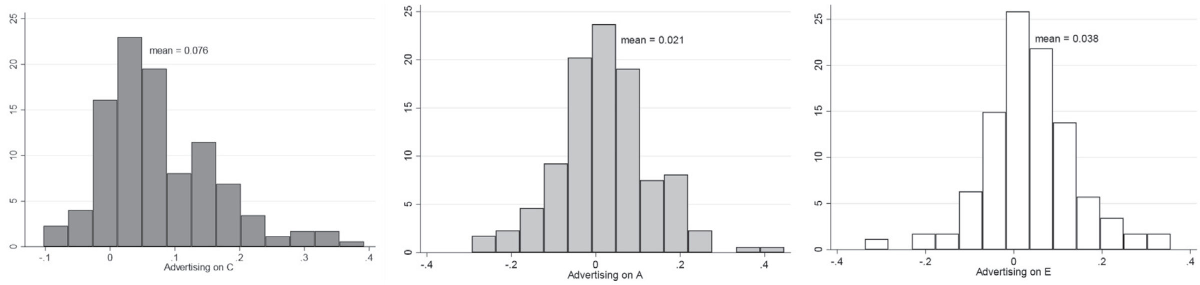


Fig. 2. Importance of First, Middle, and Third Mindset Factor for Each Sequence in Driving Sales, Note: The figure presents the relative importance among cognition, affect, and experience, excluding the effect of past sales, with long-term FEVD estimates.

Responsiveness of Mindset to Advertising

A: Distribution of Responsiveness of Mindset Factors to Advertising



B: Responsiveness of the Mindset Factors to Advertising for each Sequence

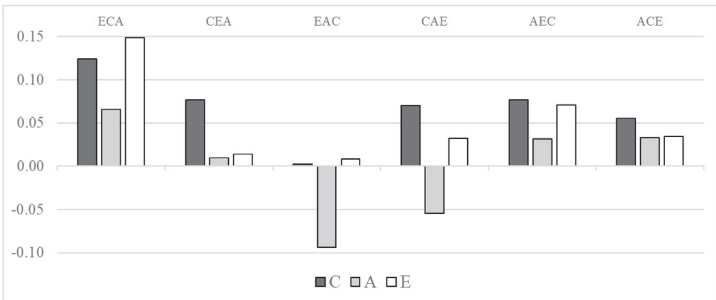


Fig. 3. Responsiveness of Mindset to Advertising. Note: In panel B, for brands with ECA sequence, the responsiveness of cognition, affect, and experience to advertising is 0.12, 0.07, and 0.15, respectively.

7.2. Responsiveness of the mindset factors to advertising

Managers also need to assess the extent to which advertising moves the needle on cognition, affect, and experience. To this end, we collect the coefficients of the operating model and their standard errors for the 92 brands with a dominant sequence. For the remaining 86 brands without a dominant operating sequence, we average the coefficients and obtain the pooled standard errors for the top models that are statistically undistinguishable. Panel A of Fig. 3 shows the large variation in responsiveness. Cognition, affect, and experience have a mean elasticity to advertising of 0.076, 0.021, and 0.038, respectively. Thus, while advertising lifts all three mindset factors, it moves the needle the most on cognition. Possible explanations include advertising content and cognition measures. First, the advertising appeals in our sample may be rational rather than emotional (Belch & Belch, 2018). Second, the cognition factor most directly reflects advertising as it is partly measured through advertising awareness. More generally, this finding is consistent with the view that advertising mostly serves as information to increase brand salience (Ehrenberg et al., 2002).

Panel B of Fig. 3 shows the advertising response averaged across brands with the same sequence. For the ECA sequence, advertising elasticity is highest for experience (0.15), followed by cognition (0.12). For all other sequences, advertising responsiveness is the highest for cognition. For the predominant ACE sequence, cognition, affect, and experience have a mean elasticity to advertising of 0.055, 0.033, and 0.034, respectively.

7.3. Mediation effect of mindset factors from advertising to sales

To advise managers on which mindset factor to focus on, we compute the mediation effects of advertising through the mindset on sales. For each brand with a superior model, we collect the advertising and sequential effects' coefficients. We compute the mediation effect of each factor by multiplying the coefficients of advertising through the respective sequence. For example, for a brand with the ECA sequence, we obtain the mediation effect of experience by multiplying the coefficients of advertising effects on experience, effect of experience on cognition, effect of cognition on affect, and effect of affect on sales (β_{31}, α_{13}, α_{21}, and α_{42} from Eq. (5)). Similarly, for the ECA sequence, we obtain the mediation of cognition by multiplying the coefficients of advertising effects on cognition, effect of cognition on affect, and effect of affect on sales (β_{11}, α_{21}, and α_{42} from Eq. (5)). Finally, for the ECA sequence, we obtain the mediation of affect by multiplying the coefficients of advertising effects on affect and effect of affect on sales (β_{21} and α_{42} from Eq. (5)).

Overall, cognition, affect, and experience have an average mediation effect of advertising on sales of 48 %, 26 %, and 25 %, respectively. For highly differentiated brands in utilitarian categories, cognition, affect, and experience have an average mediation effect of advertising on sales of 32 %, 59 %, and 9 %, respectively. For less differentiated brands in utilitarian categories, cognition, affect, and experience have an average mediation effect of advertising on sales of 60 %, 13 %, and 27 %, respectively. For highly (less) differentiated brands in hedonic categories, cognition, affect, and experience have an average mediation effect of advertising on sales of 34 % (55 %), 61 % (−23 %), and 4 % (67 %), respectively.

The mediation effect of cognition ranges from 32 % for more differentiated brands to 60 % for less differentiated brands in utilitarian categories. For more differentiated brands, affect has a higher mediation effect: 59 % and 61 % for utilitarian vs hedonic categories, respectively. The highest mindset mediation effect is for experience in hedonic categories for less differentiated brands (67 %). In hedonic categories, the high positive mediation of affect for more differentiated brands (61 %) con-

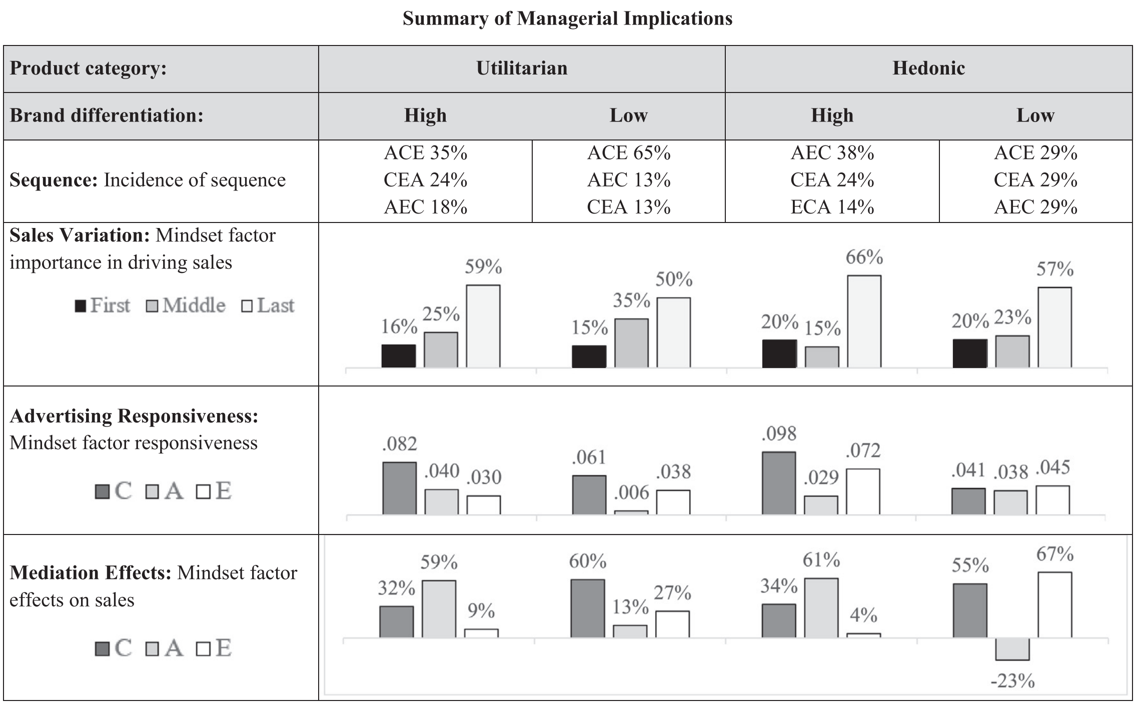


Fig. 4. Summary of Managerial Implications. Note: Brands in our study are placed in each condition using a median split for each of the two dimensions.

trasts with the negative mediation effect of affect for less differentiated brands (–23 %). Similarly, in utilitarian categories, the mediation of affect is larger for more differentiated brands (59 %) than for less differentiated brands (13 %). These results indicate that brand differentiation is important for advertising to build up an emotional connection (see last row on Fig. 4).

7.4. Visualizing the Implications

Ideally, managers would identify the specific sequence operating in their own brands. Our model can then guide their advertising allocation by indicating the impact of the mindset factors on sales and also assess the responsiveness of the mindset factors to advertising.

When such own analysis is not feasible, our findings can be used directly to predict the likely sequence and advertising responsiveness depending on the level of the moderating factors of brand differentiation and hedonic vs utilitarian nature of the category. We place the analyzed brands in four conditions in Fig. 4 according to the median values of differentiation and hedonic vs utilitarian nature. We show in each condition, the 1) incidence of each sequence, 2) average importance of each mindset in explaining sales, 3) average advertising responsiveness of each mindset factors, and 4) average mediation effect of each factors.

Following up with our opening example of managers, their brand's differentiation indicates which condition among the utilitarian product (detergent) applies. If Ariane managed a less differentiated brand, her situation would be in the second quadrant of Fig. 4. As a result, her brand will likely operate under the ACE sequence (65 % of the brands in the second condition in Fig. 4 operate under this sequence). Experience, the last mindset factor in the sequence, explains 50 % of the sales variation; and advertising elasticity is 0.038 for experience, 0.061 for cognition and 0.006 for affect. Thus, doubling advertising spending is expected to increase experience by 3.8 %, cognition by 6.1 % and affect by only 0.6%. Finally, for Ariane's brand, experience is projected to account for 60 % of the effect of advertising on sales, while cognition and affect would account for the remaining 27 % and 13 %. In contrast, if Victor managed a highly differentiated brand, the brand would fall in the first quadrant of Fig. 4. As a result, doubling advertising spending for the brand is expected to increase experience by 3.0 %, cognition by 8.2 % and affect by 4.0 %. Such a highly differentiated brand is less likely to operate under the ACE sequence (35 % of the brands in the first condition in Fig. 4 operate under this sequence), and the last mindset factor in the sequence explains 59 % of the sales variation. Finally, for Victor's brand, affect is projected to account for 59 % of the effect of advertising on sales, while experience and cognition would account for the remaining 32 % and 9 %. Comparing Ariane's and Victor's brands, highly differentiated brands in utilitarian categories can expect about seven times higher advertising responsiveness of affect than less differentiated brands (0.04 vs 0.006). However, for hedonic categories, a highly differentiated brand can expect about double higher advertising responsiveness of cognition than less differentiated brands (0.098 vs 0.041).

8. Discussion and conclusions

The advertising's sequence of effects has received considerable attention by both academics and practitioners, yet solid empirical evidence for the sequence was limited to one brand (Bruce et al., 2012). Our study addresses this gap by analyzing how cognition, affect, and experience mediate advertising effects on sales using data for 178 FMCG brands in 18 categories. Moreover, the moderating effects of brand and category characteristics had not been examined yet in an empirical comparison. Several new findings emerge from our work.

The *integrated model* introduced by Bruce et al. (2012) holds up well. With longitudinal mindset metrics data sets that are effectively used by brand managers, we perform a large-scale empirical comparison of sequential models. We conclude that advertising's sequence of effects is validated empirically, at least for FMCGs. Importantly, the sequence varies across brands, with the *ACE sequence* being the most common; it is statistically superior for *half of all studied brands*. While different sequences operate for different brands, the incidence of the predominant ACE sequence is greater for *undifferentiated brands and utilitarian products*. Only for highly differentiated brands in hedonic categories is ACE not the predominant sequence. Our findings (summarized in Fig. 4) provide managers conditions under which each sequence is more likely to occur.

Having established advertising's sequence of effects, we provide insights for managers into which mindset factor is most important in driving sales. The last mindset in the sequence has the greatest importance in driving sales, followed by the middle and first (58 %, 25 %, and 18 %, respectively). By applying our approach, managers can understand of how to move the needle on the mindset factors. Importantly, all three mindset factors (cognition, affect, and experience) respond positively to advertising with mean elasticities of 0.076, 0.021, and 0.038, respectively. Taken together, these findings offer insights into advertising expenditure that influences all mindset factors to result in long-term sales lift.

Limitations of our study suggest useful directions for further research. Advertising content, for which we had no data, may play a role in the sequence, with emotional appeals likely to trigger affect before cognition, while rational appeals may trigger cognition first (e.g. Belch & Belch, 2018). The classical advertising's sequence of effects framework was originally developed for new brands, while our data set consists of existing brands in mature FMCG categories. Further research could aim to collect data on newer brands (e.g., "challenger" or "disruptor" brands) and compare their sequence with that of established brands. In addition, consistent with the perspective that firms take a longer-term horizon to managing their brands' advertising (e.g., Lodish & Mela, 2007), we use 4-week data at the brand level. We encourage future research to consider using data that are at a finer level of aggregation (e.g., weekly or daily). Other data limitations include the unexplored market, company, and additional brand metrics that may influence the studied effects. We encourage researchers to examine potential drivers such as economic and cultural differences (Pauwels et al., 2013), the company's market sensing, brand management, and customer relationship management capabilities (Morgan, Slotegraaf, & Vorhies, 2009), and the quality of the brand experience, as captured in, for example, online reviews and offline word-of-mouth conversations (Fay, Larkin, Pauwels, & Keller, 2017).

Although our work provides support for a sequence of effects, we note the complexity of the models that receive the strongest statistical support. Advertising not only operates through the mindset but also has a direct effect on sales, which may indicate that the available metrics do not fully capture the more immediate effects of advertising and/or that advertising leverages the existing mindset without necessarily changing it in a measurable way (Srinivasan et al., 2010). In addition, each of the mindset factors exhibits dynamics, in that it is influenced by previous states. We also observe purchase reinforcement for all mindset factors. Therefore, the sequence of advertising effects as currently taught, even if variations in the sequence are acknowledged, is simplified. The time has come in today's data-rich world to change the way the model is presented in marketing courses as its relevance lies in its richness. While our research demonstrates that the integrated framework is relevant to guide advertising decision-making, given the complex interactions among the mindset metrics, we encourage brand managers to investigate the operating sequence for their brands and the actionable recommendations that arise. We urge academics and practitioners to incorporate the integrated model in their theoretical and empirical investigations of advertising and to consider its potential value in understanding advertising effects.

Data availability

The data that has been used is confidential.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2022.12.002.

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