The Role of Numbers in the Customer Journey

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Abstract

At each stage in customers' journeys, they encounter different types of numeric information that they process using different judgment strategies. Relevant numbers might include budgets, price, product attributes, product counts, product ratings, numbers in brand names, health and nutrition information, financial information, time-related information, and others. This manuscript provides a review of the vast array of numerical information presented to consumers at different stages of the customer journey. It also identifies several different types of judgment strategies that consumers use to evaluate numeric information. It includes a discussion of how consumers use these judgment strategies during the pre-purchase, purchase, and post-purchase stages of the customer journey, highlighting unanswered questions that identify new research opportunities. Implications for practice and research are identified.

Keywords: Numbers, Heuristics, Numerical Cognition, Pricing, Customer Journey

Number is the ruler of forms and ideas, and the cause of gods and demons

—Pythagoras

Customers encounter numeric information at every stage of their journeys—when they recognize the need for a product or service, when they search for information and evaluate relevant information, when they make the purchase decision, and even when they make their post-purchase evaluations. Our aim in this paper is to review and characterize the role of numeric information in different stages of the customer journey.

To bring to life the pervasive influence of numbers in customer journeys, consider the following three illustrative scenarios. Leanna overslept her alarm after a late night and is rushing to work. When she passes a 7-11 store, a sign in the window promoting coffee leads her to realize that she could really use a cup. She normally prefers to have breakfast at home to save money, but reasons that coffee at 7-11 is not expensive and will fit her budget. While in the store, she examines the coffee menu that outlines the different cup sizes and prices. She realizes that she is also hungry and notices that the store displays price and calorie information for various breakfast offerings. She selects a coffee and a breakfast offering that fit her health goals and financial budget. When she looks in her wallet, she sees she has several singles, a 20-dollar bill, and a credit card, and pays with the singles. She also gets loyalty points on her app. She is grateful that there was no line and the service time was fast since she is in a hurry. Later that day she thinks about how much she spent on breakfast in the store versus what it costs at home and resolves to be more diligent about leaving time in the mornings for breakfast at home.

Tyler is going away to school and realizes that he will need a new laptop computer. It has been a long time since he last bought one, so he thinks carefully about the type of laptop he needs and how much he is willing to spend. He researches different options and considers the size, weight, memory capacity, graphics capability, and price that best meets his needs. He also examines numeric product ratings and expert and user comments on a number of different websites. He then visits a retailer so he can visually examine the different laptops prior to making his decision. He decides to buy the Acer Nitro 7 version 10.1, but while in the store he checks his phone one last time and realizes he can get the same computer at a lower price from an online retailer, so he leaves the store and places his order. The online retailer offers free regular shipping but Tyler decides to pay more for expedited delivery. Once it arrives, Tyler provides online ratings for his new computer and the retailer.

Tushar has decided to organize a vacation to Ecuador. He first thinks about how many days he can take off and how much he is willing to spend, recognizing that this will be an expensive trip. He then gathers information from several sources to help make his decision. All provide some sort of numeric quality assessment – one of Tushar's friends described his trip as a perfect 10 – and all provide numeric information about the length of the trip, the price, and how many excursions and meals are included. Tushar then contacts several travel firms and compares their offerings based on the number of destinations included, the time at each destination, the overall number of days, the cost, any price promotions offered, when payment needs to be made, and any financing and payment plans offered. He makes his decision, books his trip and pays for it, and has the trip of a life time. During the trip and after he is back, several of the hotels, the airline, and the travel agency, all ask him to rate his satisfaction with their services.

As these scenarios illustrate, consumers are bombarded by all kinds of numbers throughout their customer journeys. The goal of this paper is to outline the role of numerical information and processing strategies at all stages of the customer journey, as summarized by

Figure 1. We start by reviewing the extant literature on the different types of numbers that customers encounter in their journeys. We then identify and describe several types of judgment strategies that consumers use when they evaluate these different forms of numeric information. Next, we discuss how consumers use these different judgment strategies during the different stages of the customer journey, and highlight some outstanding questions that remain open opportunities for research in this area (see Figure 2). We also highlight important implications for marketing practice and for policy makers.

Before proceeding, it’s important to state that we recognize that there are multiple types of customer journeys (Lee et al. 2018). In this review, we use a conventional four-stage model incorporating need recognition, information search and evaluation, purchase, and post-purchase behavior (Puccinelli et al. 2009). As such, we acknowledge that consumers may encounter, process, and incorporate numerical information differently if they are engaged in an alternative customer journey, a point that we identify as an area for future research.

TYPES OF NUMERICAL INFORMATION

We begin this review by summarizing ten common types of numeric information that customers encounter in their journeys: budget information, non-price product attribute information, product or brand identifying information, quantity information, nutritional/caloric information, financial information, time-related information, product evaluation information, loyalty program-related information, price information, and promotion information. Figure 1 maps these types of information into their predominant use during customer journeys.

Numbers that Convey Budget Information. The resources available for consumers to use to fulfill a need are often conveyed as numbers. The amount of cash in a wallet, the amount of money in a bank account, the remaining line of credit on a credit card, and the number of points allowed on a diet program are all examples of budgets that consumers manage. How these budgets are displayed (or recalled) can influence both the need recognition as well as the information search and evaluation stages. For example, if a consumer recognizes that they are hungry, but also on a diet, they may seek out alternatives that provide nutritional information that will allow them to stay within their desired caloric range. Alternatively, they may assign calories to a “snack” mental account instead of including them in a “lunch” mental account, if the latter’s budget has been met for the day but the consumer still wants to eat (Cheema and Soman 2006).

Numbers that Convey Price Information. Price information is a common type of numeric information that consumers encounter during their journey. The way in which a price is displayed, whether comparison prices are provided, the digits in the price, the price precision, and even the roundness of prices can affect consumers’ decisions. The currency used to convey price information (e.g., Dollars versus Euros) and whether the price is communicated using large denominations (e.g., $100 bills) or small denominations (e.g., coins) can affect consumer evaluations (e.g. see Mishra, Mishra, and Nayakankuppam 2006; Raghubir and Srivastava 2009; Raghubir, Morwitz, and Santana 2012; Wertenbroch, Soman, and Chattopadhyay 2007). The large and growing body of research on behavioral pricing has examined all these different ways in which consumers process numbers that convey price information (Cheng and Monroe 2013; Raghubir 2006) and their downstream effects, some of which we review in the next section.

Numbers that Convey Product Attribute Information. Numbers are also used to describe many non-price product attributes (e.g., calories, watts, gram, miles per hour). As we discuss in more detail in the next section, numeric product attribute information may be relied on more than other non-numeric attribute information because it is often easier to evaluate and compare, but consumers do not always accurately process this type of numeric information and are susceptible to scaling effects, the effects of numerosity, the impact of numeric roundness, precision, etc.

Numbers that Convey Product or Brand Identifying Information. Some products and services contain numbers as part of the brand name, and often these numbers do not contain any specific numeric magnitude (e.g., Three Musketeers, 7-Up). Gunasti and Ross (2010) demonstrated that even when they do not convey quantitative meaning, consumers are still affected by these numbers, for example by having greater preference for and being more likely to choose a brand that has a higher number as part of it, relying on a “the higher the better heuristic.” Yan and Duclos (2013) showed that not only do these numbers affect preferences and choice directly, but they also affect consumers’ assessments of other numeric product attributes (e.g., price, volume), because these numbers in the brand name can act as implicit anchors.

Products such as art or music are sometimes associated with serial numbers. Smith, Newman, and Dhar (2016) showed that these numbers can influence consumers’ preferences for otherwise identical products, as they more highly value those with earlier serial numbers. They do this because they view products with earlier numbers as being closer to the designer or artist who created them, even when holding their beliefs about market value and quality constant.

Numbers that Convey Quantity Information. In some online and retail shopping contexts, consumers are provided with information regarding how many units are left, which may signal scarcity or abundance to consumers. For example, when shopping for plane tickets, consumers may see that only five seats remain at that price; when shopping for tickets to an entertainment event, consumers may see that there are hundreds of tickets still available.

In other cases, consumers may see numbers that indicate the minimum purchase required or maximum number allowed for a specific price promotion. Inman, Peter, and Raghubir (1997) showed that sales restrictions (e.g., “limit 3 per customer”) lead to increased sales. Zhu and Ratner (2015) showed that numeric scarcity cues polarize consumers’ preferences for more versus less preferred items and increase the choice share of more preferred ones. Kristofferson, McFerran, Morales, and Dahl (2016) showed that these numeric scarcity cues can lead to more aggressive consumer behavior because it leads consumers to view other consumers as threats.

Numbers that Convey Calorie Information. Numbers also play a crucial role in regulating food consumption. With the obesity epidemic threatening to reduce the life-spans of people around the world, public policy officials as well as consumers have turned to quantification of calories as a means of regulating consumption. In fact, quantification of calories has been one of the first consumption regulation policies to be adopted by regulatory bodies in most developed countries. Researchers, policy analysts, and political leaders have been debating whether providing calorie count information can lower consumption and how such calorie information should be presented. While some researchers have found evidence for the effectiveness of such calorie labeling programs (Long et al. 2015), others have suggested that consumers might not use or understand numeric calorie system and have called for alternative types of calorie labeling (Bollinger, Leslie, and Sorensen 2011; Krukowski et al. 2006).

Numbers that Convey Financial Information. When consumers purchase insurance, take out a mortgage, buy and sell stocks, pay their credit card bill, apply for a student loan, or save for retirement, numbers influence their decision-making. However, research on consumer financial decision making has found that despite the frequency with which consumers make these decisions, they often make misguided or suboptimal choices. Stango and Zinman (2009) showed that consumers exhibit an exponential growth bias, or a tendency to linearize exponential functions. That is, they underestimate the future value of earning x% in annual interest because they assume savings grow linearly and not exponentially. As a result, they fail to recognize the value of saving money and thus do so at lower rates. In addition, Amar, Ariely, Ayal, Cryder, and Rick (2011) showed that consumers prioritize paying smaller debts over larger ones with higher interest rates, even though the latter strategy will save consumers more money.

Numbers that Convey Information about Time. For some products or services, time-related information is relevant. For example, some experiential products are described by their temporal length (e.g., a massage or an entertainment show), some service encounters may involve a wait time, and in other cases consumers may opt to pay more or less for faster or slower delivery service. Numeric information about time can influence consumers' judgments and choices, but consumers do not always evaluate this information normatively. For example, Yeung and Soman (2007) showed that consumers tend to evaluate services based on their temporal durations, even when longer durations are not necessarily better or worth a higher price, and even though other research has shown that people underweight duration in retrospective evaluations (Fredrickson and Kahneman 1993). In other cases, consumers compare numeric information related to obtaining a product now or in the future or that involves tradeoffs between future consumption and current dollars. Much research has shown that consumers have a present bias, display hyperbolic discounting, and therefore value options much less in the future than the present (Frederic, Loewenstein, and O'Donoghue 2002). However, the way in which numeric information about time is displayed can affect consumers' discount rates. For example, LeBoeuf (2006) showed that consumers discount the future more when the time until the considered event is described by the extent of time versus by the date.

Numbers that Convey Consumer Review Ratings and Ranking Information. With consumers' increased reliance on expert and consumer generated product reviews and rankings (Chevalier and Mayzlin 2006; Floyd, Freling, Alhoqail, Cho, and Freling 2014; Luca 2015), consumers are often exposed to a wide range of numeric information including average ratings, number of reviews, and numeric information that indicates a product's rank order in a list. De Langhe, Fernbach, and Lichtenstein (2015) showed that consumers heavily weight user ratings when inferring product quality (even though they do not correlate with more objective quality assessments) and they do not adequately account for the number of user ratings when making these assessments. Watson, Ghosh, and Trusov (2018) showed that consumers are more prone to use average product ratings than number of reviews in assessing product quality, but also outline situations in which the number of reviews is perceived to be diagnostic and will influence consumer assessments.

The manner in which numeric rating information is communicated can affect consumers' evaluations. For example, Kyung, Thomas, and Krishna (2017) showed that depending on their culture's norms, some consumers react more positively to quality rating information when the rating scale uses higher numbers to reflect more positive ratings (relying on the bigger-is-better heuristic) versus a scale where lower numbers reflect more positive ratings. Consumers also are influenced by a product's numeric rank in ordered lists. Isaac and Schindler (2014) showed that unit differences across ordinal ranks are not considered to be equivalent, and that consumers more favorably view an improvement that moves a product's rank past a round number (e.g., from 11^{th} to into the top 10) than equivalent shifts that do not cross a round number boundary.

Numbers that Convey Information Related to Loyalty and Reward Programs. Consumers also encounter numeric information regarding loyalty programs they are enrolled in. Various numbers are associated with the terms of the programs, their purchase requirements, and their associated rewards, and research has shown that various aspects related to these numbers affect consumers, their goal pursuit, and their goal success (Kivetz, Urminsky, and Zheng 2006; Nunes and Drèze 2006). For example, Bagchi and Li (2011) examined how two specific pieces of numeric information associated with reward programs, the reward distance (i.e., the points needed to obtain a reward) and the step size (i.e., the points earned per transaction unit) affect perceptions of progress toward the goal and overall evaluation of the reward program.

THE PSYCHOLOGY OF NUMERIC JUDGMENTS

Having listed various types of numerical stimuli customers encounter during their journeys, we now turn our attention to the judgment and decision making strategies that they use when they encounter these numerical stimuli. We will first review some of the extant theories of numerical cognition and then present a dual-process model that might be useful to explain and predict how customers react to numerical information in their journeys.

Extant Theories of Numerical Cognition

Adaptation Level. One of the oldest theories of perceptual judgments that consumer psychologists have used to explain numerical cognition effects, particularly pricing effects, is Helson's Adaptation Level Theory (Helson 1964). Although this theory was formulated to explain psychophysical stimuli such as weight, light, and sound, and later this theory was extended to social judgments, many consumer researchers have used Helson's theory to describe how consumers evaluate store prices and other numerical stimuli that they repeatedly encounter.

The central tenet of this theory is that new stimuli are evaluated relative to internal norms and adaptation levels. Helson (1948) proposed a quantitative framework to specify the adaptation level or the internal reference point that people use to evaluate new stimuli. In the marketing literature, Helson's Adaptation Level theory has been contrasted with Parducci's Range-Frequency theory (Parducci 1965) to test which of these two theories offers a better account of consumers' price comparisons (e.g., Janiszewski and Lichtenstein 1999). While the adaptation theory posits that people's evaluations of numerical stimuli are largely influenced by their internal reference point, the Range-Frequency theory posits that such evaluations are influenced by the end-points of the evoked range as well as the frequency distribution of the stimuli.

Triple-Code Model. Another numerical cognition theory that has found favor with consumer researchers is Dehaene's Triple-Code model (Dehaene 1992). This is primarily a theory of the mental representation of numbers. This theory posits that numbers can be mentally represented in terms of symbolic Arabic representations (e.g., $83), verbal representations (e.g., eighty-three) and analog representations (an approximate magnitude on a mental number line). This theory has been used by several consumer researchers (e.g., see reviews by Monroe and Lee 1999 and Thomas and Morwitz 2009b) to develop conceptual models of numerical cognition, particularly in the context of behavioral pricing.

The General Evaluability Theory. Although the General Evaluability Theory is not necessarily a theory of numerical cognition, several scholars have used it to explain how consumers process numerical information (e.g. Lembregts and van den Bergh 2018; Ma and Roese 2012). The General Evaluability Theory posits that some values can be more easily evaluated than others, and the evaluability of a value is influenced by three factors: mode of evaluation, the judge's knowledge, and nature of the stimuli. Mode of evaluation refers to whether the value is evaluated in isolation (separate evaluation) or in comparison to an explicit reference point (joint evaluation). For example, consumers' evaluation of a two carat diamond would depend on whether they are evaluating the diamond in isolation or side-by-side with another diamond. The second factor is based on the premise that experts have more knowledge than novices, and such knowledge can influence evaluations. For example, an expert diamond seller's sensitivity to differences in the carats of diamonds can be quite different from that of a novice. Lastly, some values are inherently more evaluable than others. For example, people may be more sensitive to differences in ambient temperature values than to differences in diamond carats because the former is inherently more evaluable than the latter.

In addition to the above, researchers have studied numerical cognition in the context of probability judgments (e.g., Keren and Tiegen 2001), mental accounting (Cheema and Soman 2008; Thaler 1985) and how confirmation bias and consistency goals influence the processing of numeric information (Russo et al. 2008; Carlson et al. 2009). While all of these models and theories have been immensely useful in explaining some numerical cognition effects, the applicability of these theories to the generalized consumer journey is somewhat limited. All of these theories have been motivated by specific narrow behavioral phenomena. The development of Adaptation Level theory and the Range Frequency theory was motivated by the desire to predict how the human mind responds to changes in psychophysical stimuli such as weight and light. The Triple Code model was proposed to explain non-linguistic numerosity judgments, in particular why the human mind maps numbers onto a logarithmic scale rather than a linear scale. The General Evaluability Theory was originally proposed to explain why people's evaluations and preferences change when they make joint versus separate evaluations. Overtime, the theory matured to identify not only evaluation mode but also knowledge of the judge and the nature of the stimulus as reasons for preference reversals. Importantly, while all these theories can account for some of the documented numerical phenomena, none of these theories can completely account for all the numerical cognition phenomena observed when consumers evaluate prices, product ratings, calorie information, length of duration, financial information, etc. throughout the customer journey. For example, these theories cannot explain why people judge the difference between 2.99 and 4.00 to be higher than that between 3.00 and 4.01 (Stiving and Winer 1997; Thomas and Morwitz 2005), or why partitioning of prices leads to underestimation of the total spend (Morwitz, Greenleaf, and Johnson 1998), or why quality ratings on a 1 to 5 scale (bigger-is-better) are more effective with U.S. consumers, but quality ratings in a 5 to 1 scale (smaller-is-better) are more effective in Germany (Kyung et al. 2017).

A Dual-Process Model of Numerical Cognition

In this review, we discuss a generalizable dual process model of numerical cognition that provides a basic framework that can explain several numerical cognition phenomena observed in the marketplace. Early ideas for this model were presented in Thomas and Morwitz (2009b) and were further refined in Thomas' (2013) critique of Cheng and Monroe's (2013) characterization of numerical cognition. In this approach, we combine insights from numerical cognition theories about mental representations of numbers (Dehaene 1992) and the hugely influential dual-process models of judgment and decision-making proposed by Kahneman and Tversky (see Kahneman 2011) to create a taxonomy of constructs that are relevant to many numerical cognition phenomena observed during the customer journey. The two foundational constructs in this dual-process model of numerical cognition are the types of *mental representations* and the types of *mental processes or heuristics* that operate on these representations.

Types of Mental Representations

Building on Dehaene's (1992) triple-code model and his subsequent focus on two neurological systems of numerical representations (Dehaene et al. 1999), we propose that everyday numerical cognition relies on two distinct types of mental representation of numbers—formal symbolic representations that are language dependent and intuitive analog representations that are language independent. The symbolic system is the language dependent system that people learn through formal education in schools. Arithmetic knowledge, the ability to add and subtract numbers, multiplication and division knowledge, are skills that are based on the symbolic representations of magnitudes. The symbolic representation system varies across individuals and cultures. In fact, most of the extant scales measuring individual differences in numeracy skills (e.g., Peters et al. 2006; Viswanathan 1993) tap into this language-dependent skill used to make judgments using such symbolic representations.

However, most everyday numerical cognition is also influenced by the intuitive language-independent representations of magnitude, referred to as analog representation. This type of mental representation is the same that is used to judge psychophysical stimuli such as sound and light. Infants have access to this mode of representation, suggesting that it is language independent and emerging evidence suggests it is also shared by other species such as monkeys and chimpanzees. Overtime this system has evolved to also inform our numeric judgments.

Judgment Strategies and Heuristics

Numerical judgments vary not only in the mental representations of numerical stimuli, but also in the processes—the judgment strategies and the heuristics—that operate on these mental representations. Various numerical properties influence consumers' judgments, often without their awareness. These include the specific digits that comprise numbers, the numbers' roundedness, precision, granularity and associated fluency, their numerosity, extremity, magnitude, whether they are a special number such as zero, whether they reflect linear, exponential, or other scales, and other associations including their sounds (if spoken) and perceived gender. In this section, we highlight some of the specific heuristics that have been documented in the numerical cognition literature.

Anchoring on Salient Numbers. The anchoring heuristic refers to the tendency to focus on the most salient information and ignore or adjust insufficiently for other information while making judgments. In the context of numerical cognition, a classic case of the anchoring heuristic is the left-digit effect (Thomas and Morwitz 2005; also see Stiving and Winer 1997). Consumers anchor their judgments of numerical difference on the left-most digits of multi-digit numbers and thus they mistakenly judge the difference between 3.99 and 2.00 to be smaller than that between 4.00 and 2.01. In a similar vein, Morwitz et al. (1998) showed that consumers tend to underestimate the magnitude of partitioned prices because they are prone to ignore or underweight the magnitude of surcharges relative to base prices. This effect, which has been labeled the partitioned pricing effect, may be caused by a shopper's propensity to use the base price as an anchor for their judgments and insufficiently adjust for the surcharge. Davis and Bagchi (2018) demonstrated that both presentation mode and the ordering of multiple percentage price changes (i.e., discounts and surcharges) on the same purchase results in consumers' anchoring on different numbers. Specifically, when, for example, two discounts (e.g., take 18% off, then take an additional 12% off) are presented simultaneously, consumers anchor on the first piece of information. However, when they are presented sequentially, consumers shift their attention to the latter percentage change, which serves as an anchor going forward.

Relatedly, Gourville (1998) showed that communicating a large one-time price in terms of a smaller but recurring expenditure (i.e., a pennies-a-day strategy) led to greater acceptance of an offer, presumably because it anchored consumer judgments on a small amount. More generally, Kim and Kachersky (2006) claimed that the attention consumers pay to a price component in a multidimensional price is related to the relative salience of that component compared to other components of the price. Estelami (2003) also noted that consumers tend to focus on a single, important component of a multidimensional price. He mentioned as an example that consumers evaluating an automobile lease might place disproportionate weight on the amount of each monthly payment and place little weight on the number of payments. Finally, scholars such as Navarro-Martinez et al. (2011) and Stewart (2009) demonstrated the counter-intuitive effect of providing minimum repayment amounts on credit card bills. They found that consumer repayments are actually lower when repayment minimums are provided versus when they are not, an effect they attribute to consumers anchoring on the repayment minimum.

Availability and Numeric Fluency. The availability heuristic refers to the tendency to rely on the subjective ease of memory retrieval as a heuristic cue while making numeric judgments. Although when this idea was first proposed it was presented as the availability heuristic (Kahneman 2011), subsequent refinements of this conceptualization suggests that this is more of a fluency heuristic wherein numerical judgments are influenced by the subjective experience generated by the fluency of cognitive operations. An illustration of the fluency heuristic is the ease-of-computation effect (Thomas and Morwitz 2009a), wherein the difference between 5.00 and 4.00 is mistakenly judged to be larger than that between 5.32 and 4.29 because the former calculation is easier and more fluent. In a similar vein, Biswas, Bhowmick, Guha, and Grewal (2013) showed that when comparing price information, consumers' evaluations of a lower price or sale offering is often greater when the smaller number is to the right of the larger number. They argue that this price ordering makes it easier for consumers to engage in a subtraction task, leading to higher evaluations when the subtraction process is beneficial. Likewise, Guha et al. (2018) found that when numeric attribute information is displayed in an aligned manner (i.e., lower calorie foods are displayed below higher calorie foods), shoppers assign more weight to the gap in numeric information, which affects subsequent preferences. Yan (2019) showed that the ease of evaluation leads consumers to compare numeric attributes based on their absolute rather than their relative differences which in turn affects the results and consequences of the comparative processes. Such metacognitive experiences can also interfere with arithmetic thinking; it has also been shown that consumers display insensitivity to magnitudes because they are difficult to evaluate or inhibit a reliance on feelings (Hsee, Rottenstreich, and Xiao 2005).

Some numbers are more fluently processed than others, which affects consumers' reactions. King and Janiszewski (2011) showed that numbers that are the result of commonly used, well-rehearsed math problems are more fluently processed and therefore more liked. For example, they showed that consumers had a higher likelihood to choose a product that used a common arithmetic problem result number in its brand name (e.g., Zinc 24) than one that did not (e.g., Zinc 31 or just Zinc). Similarly Coulter and Roggeveen (2014) found that prices are more fluent if they constitute an approximation sequence (a series of numbers that contain the same type of roundness; e.g., 5, 10, 15 or 20, 40, 60…) or are multiples of one another, which leads to more favorable reactions. However, Motyka, Suri, Grewal, and Kohli (2016) showed that sometimes when price information lacks fluency, consumers process the information more deeply, which, when that information is favorable, can lead to positive reactions.

Processing fluency has also been used to explain the effects of numeric roundness. Wadhwa and Zhang (2015) showed that whether numbers are rounded or not affects the process by which the numbers are evaluated. They argued that because rounded numbers are more commonly seen in everyday life (Schindler and Kirby 1997), they are more fluently processed. They provided evidence that since rounded numbers are processed more fluently, they provide a sense of feeling right, and this feeling-based process affects how they are evaluated. In contrast, non-rounded numbers, because they are less fluently processed are evaluated using more deliberative cognitive processes.

Representativeness and Other Similarity-Based Heuristics. Numbers not only differ in the inherent magnitudes they convey, but also in their digit patterns and their level of granularity. Sometimes consumers' magnitude judgments can be biased by heuristic thinking triggered by digit patterns and granularity. The representativeness heuristic refers to the propensity to rely on superficial properties of numbers such a digit patterns and granularity to make judgments. An example of the representativeness heuristic is the precision effect in negotiations. Thomas, Simon, and Kadiyali (2010) demonstrated using actual real estate transaction data, as well as laboratory data, that home buyers are likely to negotiate less if a house is listed for a precise list price, say $345,568, than if it is listed for a round list price, say $345,000. Consistent with these results, Janiszewski and Uy (2008) showed that people apply smaller adjustments to precise anchors than they do to round anchors. However, the precision advantage turns into a disadvantage when it comes to the probability of accepting an offer; Yan and Pena-Martin (2017) showed that since round numbers are associated with completion and goal end-points, in bargaining contexts, consumers are more likely to accept round offers.

Numerical precision effects manifest in a variety of other contexts. Schindler and Yalch (2006) showed that when less rounded numbers are used in advertising claims (e.g., a deodorant is claimed to last 47% or 53% longer than a competitor) those claims are deemed to be more accurate than those that use more rounded numbers (e.g., 50%). Pena-Marin and Bhargave (2016) showed that rounded numbers are viewed to be more stable and because of that, consumers' perceptions of attribute benefit duration will be greater when that attribute (e.g., grams of caffeine for coffee) is associated with a round versus a precise number. Zhang and Schwarz (2013) showed that when numeric information is communicated by a human, receivers' relative estimates are more strongly influenced by precise versus round numbers.

In consumer contexts, a product attribute might be described in more or less granular units (e.g., viewing time in minutes or hours, waiting time for product delivery in days or months) or a consumer might create a budget for more or less granular temporal periods (e.g., a month versus a year). Research has shown that the level of granularity influences consumers' thoughts and behavior. For example, Zhang and Schwarz (2012) showed that consumers consider product attribute descriptions that are more (vs. less) granular to be more precise, they believe the products will be more likely to deliver on their promises, and they are therefore more likely to choose them. Ülkümen, Thomas, and Morwitz (2008) showed that consumers create smaller and less accurate budgets for the next month than for the next year, but are more confident about the accuracy of monthly versus annual budgets.

Numerosity Heuristic. Numerical information can be presented in small units (e.g., 365 days) or in large units (e.g., 1 year). When larger units are used, the numerosity of the number is lower (i.e., 1 < 365) and this can bias consumers' judgments. Several studies have shown that people are prone to use a numerosity heuristic, especially when their cognitive resources are taxed, to estimate overall quantity, without properly weighting relevant information such as unit size (Pelham, Sumarta, and Myaskovsky 1994). As Adaval (2013) discussed, the reliance on the numerosity heuristic leads consumers to make inaccurate estimates in their decisions. Consistent with this, Pandelaere, Briers, and Lembregts (2011) found that when numeric attribute levels for competing options appear larger because they are communicated using units where numbers will be higher, consumers are more prone to select the option with the more favorable number. This happens because when the attribute difference appears more numerous, consumers perceive it to be larger. Related to this, Burson, Larrick, and Lynch (2009) found that the use of more expanded or contracted scales (e.g., dropped cell phone calls per 100 or per 1,000 or price per month or per year) affects consumers' preferences and their willingness to pay for products and services. They found that when a more expanded scale is used, consumers tended to inflate the perceived difference between products being compared on that attribute, which affected the weight they placed on that attribute in their evaluations. Bagchi and Davis (2016) discussed how the numerosity heuristic can lead to different perceptions of product size, height, or weight, and can affect consumers' quality and expensiveness perceptions, willingness to pay, and perceived progress toward a goal in a loyalty program.

A related heuristic that people often rely on is medium maximization (Hsee et al. 2003). The medium maximization heuristic refers to the observation that people sometimes tend to maximize the medium, even when the medium per se does not have any inherent value. For example, even though a customer might prefer vanilla ice cream over pistachio ice cream, when she is told that she will earn 60 loyalty or reward points for purchasing vanilla ice cream and 100 points for purchasing pistachio ice cream, she might prefer the latter to the former.

However, consumers do not always react more positively to the numerosity of product-related numbers; rather for some attributes, consumers are accustomed to and react more positively when products are described in default units, or units they prefer be used to describe an attribute (Lembregts and Pandelaere 2013). In a similar vein, numerosity effects are muted when consumers construe information at a higher level (Monga and Bagchi 2011) and when the personal relevance of the numerical information is high (Ülkümen and Thomas 2013).

Numeric Associations. Numbers can also carry other associations, even including gender, and sometimes people can rely on these associations to make heuristic evaluations. Wilkie and Bodenhausen (2012) demonstrated that odd numbers are associated with masculinity and even numbers with femininity. Yan (2016) similarly demonstrated that precise numbers are associated with masculinity while round ones are associated with femininity. Yan further showed that such irrelevant associations can have implications in consumer settings. Specifically, when there is a match between whether a product is associated as masculine or feminine and whether the numbers used to describe a product attribute are precise (and therefore associated with masculinity) or round (and therefore associated with femininity) product evaluations are more favorable than when there was a mismatch.

Another seemingly irrelevant property associated with numbers are the sounds associated with stating those numbers in one's own language. Coulter and Coulter (2010) showed that these sounds affect consumers' magnitude perceptions. Numbers, such as prices, whose auditory sounds when spoken in English are associated with front vowels and fricative consonants (e.g., 3 and 6) are underestimated while those associated with back vowels and stop consonants (e.g., 1 and 2) are overestimated. These perceptions in turn affect value perceptions and intentions.

In a similar vein, numbers may have personal associations for consumer, such as when a number matches the number of a favorite athlete, a home address, or a birthday. These associations in turn can affect consumers' perceptions and behaviors. For example, Coulter and Grewal (2014) showed that when prices contain cents digits that correspond to a consumer's name or to their birthday (e.g. $49.15 and April 15th), consumers like that price more and are more likely to purchase the product.

The associations with specific digits of a number, such as a price, can also affect how it is evaluated. In the domain of pricing, prices that end in the digit 9 are commonly used, a practice noted many decades ago (Twedt 1965). For example, Schindler (2006), showed the prices that end in 99 are often perceived as low prices, and that this association may come from firms' tendencies to link 99-price endings and low-price appeals in their advertising. Stiving and Winer (1997) discussed how the association between 99-endings and low prices can cause such image effects (i.e., an association with being on deal) independent of the left-digit effect discussed previously. In their analysis of scanner panel data, they found evidence for both the left-digit effect as well as image effects. Schindler and Kibarian (1996; also see Schindler and Wiman 1989) in a field experiment involving catalogues demonstrated that the use of 99-ending prices led to greater consumer spending compared to other endings such as 95.

The Number Zero Effect. The number zero is often considered a special number as it seems to be processed differently than other specific numbers. For example, in the price domain, Shampanier, Mazar, and Ariely (2007) showed that consumers derive positive affect from free offers and, because of that, the use of a free versus a trivially small price can lead to preference reversals. Chandran and Morwitz (2006) found that because a free price is highly salient and becomes focal, consumers are less sensitive to the effects of other negative information about the product than they are when equivalent monetary discounts are offered. Dallas and Morwitz (2018) showed that consumers treat what they call pseudo-free offers (i.e., those where the price is presented to the consumer as being free, but where consumers are required to make a non-monetary payment to obtain the good, such as completing a survey or providing personal information), similarly to how they treat truly free offers that have no costs. They show that consumers sometimes accept pseudo free offers even when their non-monetary costs outweigh their benefits. Consumers react positively to these pseudo-free offers because they tend to make neutral or positive attributions for why firms make these offers.

A zero deal price also affects consumers' perceptions and decisions even after the deal is over. For example, Raghubir (2004) showed that free gift with purchase promotions can have negative consequences as the promotion leads consumers to infer a low value for the item that was offered as a free gift. Similarly, Kamins, Folkes, and Fedorikhin (2009) showed that when an item in a product bundle is described as being free, consumers became less willing to pay for that item when considering it individually outside of the bundle. However, more recently, Palmeira and Srivastava (2013) showed that consumers are willing to pay more for a product after a free offer is completed versus a comparable discounted offer.

Consumers also react in non-rational ways when other non-price attributes are set at a level of zero. Palmeira (2011) argued that a zero value on a product attribute prevents consumers from being able to make relative comparisons. He showed that as a consequence, making an alternative worse by reducing the level of a desirable attribute to zero (e.g., the number of coffee pods that comes with a coffee maker), can lead to more favorable evaluations. The reverse can happen by increasing the level of an undesirable attribute from zero to a positive number (e.g., a number describing audio distortion for a stereo).

Comparison Heuristics. In many cases consumers do not evaluate numbers in isolation. Much research in pricing has discussed how consumers compare prices to internal and external reference prices, how external reference prices influence internal ones, and the effect that these comparison processes have on consumers' judgments and behavior (for example see Biswas and Blair 1991; Briesch, Krishnamurthi, Mazumdar, and Raj 1997; Greenleaf 1995; Grewal, Monroe, and Krishnan 1998; Hardie, Johnson, and Fader 1993; Kalyanaram and Winer 1995; Krishna, Wagner, Yoon, and Adaval 2006; Lichtenstein and Bearden 1989; Lichtenstein, Burton, and Karson 1991; Urbany, Bearden, and Weilbaker 1988; Winer 1986). While consumers often explicitly engage in comparison processes, purposely comparing a price to one of another product or an expected or recalled price, in some cases consumers are unaware that they are engaging in these processes or that contextual factors may influence what they use as a comparison standard (Adaval and Monroe 2002, Adaval and Wyer 2011; Nunes and Boatwright 2004).

The manner in which the numeric comparisons are communicated can influence how consumers react to numeric comparative information. For example, Chen, Monroe, and Lou (1998) showed that price reductions were perceived more favorably when they were communicated in dollar terms for high-price products, but for low-priced products evaluations were more favorable when the price reduction was communicated in percentage terms. González, Armida, Roggeveen, and Grewal (2016) similarly found that dollar off promotions were more effective for higher-priced items. Retailers sometimes use multiple percent discount (e.g., 25% off after the first 20% off) strategies. Consumers have difficulty processing this type of numerical information and because of that, they often react more positively to sequential percentage discounts than to an equivalent single percentage discount (Chen and Rao 2007).

Janiszewski and Lichtenstein (1999) show that numbers are not only evaluated relative to single references, but also to the end points of the range on which such numbers extend. Cunha and Shulman (2011) showed judgments depend not just on these end points but on both the range and the rank of a number in its distribution. Niedrich, Sharma, and Wedell (2001) and Niedrich, Weathers, Hill, and Bell (2009) provide evidence that Range-Frequency Theory provides a more complete picture of the ways in which consumers compare numbers like prices to references.

Numeric product-related information is used differently when consumers compare product offerings versus when they evaluate a single product separately or in isolation. For example, Nowlis and Simonson (1997) showed that compared to separate evaluations, consumers were more likely to use numeric price or attribute information in product comparisons than they were to use non-numeric information such as brand or country of origin. They argued that this happens because it is easier for people to compare numeric information than non-numeric information. This is consistent with Hsee's (1996) evaluability hypothesis and Hsee and Zhang's (2010) General Evaluability Theory.

Evaluating Numeric Rates. Consumers often encounter or have to mentally compute rates—mileage per gallon or dollar per day—and extrapolate that information to make judgments and decisions. In such situations, they typically assume numeric information is linear in nature and this assumption, in turn, can influence their judgments. For example, Larrick and Soll (2008) showed that consumers hold the inaccurate belief that the amount of gas consumed by a car decreases in a linear fashion with changes in its miles per gallon. This in turn leads to false perceptions of the value that can be gained by replacing a car that gets very low miles per gallon with a more fuel efficient one, versus replacing a more fuel efficient car with one that looks to be much more fuel efficient based on its high miles per gallon.

Framing Effects. Numbers can be communicated in a variety of different ways, and while economic theories assume that consumers should display descriptive invariance, and not be affected by how the same objective information is framed, a large body of research has shown that people react differently to different ways of describing the same information, including numeric information (Tversky, Sattath, and Slovic 1988). Numbers can also be communicated in a way that creates a positive or a negative frame. For example, Levin and Gaeth (1988) showed that people reacted more positively to ground beef that was framed as 75% lean than to the same meat described as 25% fat (negative frame), even with actual product consumption. Similarly, two printers can be described as having a 99.997% and 99.990% percent reliability rates or .003% or .010% failure rates (Kwong and Wong 2006). Kwong and Wong (2006) showed that when consumers engage in product comparisons, they react more positively to an option if its superior attribute is expressed in such a way that the ratio difference between the options appears larger versus smaller because of the framing. Similarly, Guha et al. (2018) showed that when the depth of a price discount is framed relative to the sale price (versus the original price) it leads to increased discount depth perceptions and purchase intentions.

Other aspects of how numeric information is framed can also affect customers throughout their journeys. For example, Coulter and Coulter (2005) showed that the font size used to convey numeric information affects consumers' perception of the number's magnitude. Consumers reacted more favorably to sale prices displayed in small versus large fonts, because of the associations between font size and magnitude. Coulter and Norberg (2009) showed that when there is a greater horizontal physical separation of prices, consumers perceive a larger difference between the numbers. Bagchi and Davis (2012) showed than when consumers encounter a multi-item product package, the order in which the price and the number of units is displayed (e.g., $29 for 70 items or 70 items for $29) affects how those packages are evaluated because of the heighted salience of the first piece of information. Consistent with this, Dallas, Liu, and Ubel (2019) found that in U.S. food settings, displaying numeric calorie count information to the left of food items led to ordering of lower calorie food, while displaying calorie counts to the right of food items in Israel did the same. They argued this occurs because Americans read left to right and Israelis read right to left. Thus, in each setting, the caloric information is processed first.

THE CUSTOMER JOURNEY

In this section we overlay various types of numerical information that consumers encounter at different stages of the customer journey with the different strategies they might use to process that information. In doing so, we not only offer an organizing framework for the role of numerical information along the customer journey (Figure 1), but we also highlight a number of areas for future research (Figure 2).

The process through which consumers express the need or desire for a product/service through its selection, consumption, and retrospective evaluation has been referred to in a number of ways, including customer buying behavior (Farley and Ring 1970; Howard and Sheth 1969), the customer journey (Lee et al. 2018; Lemon and Verhoef 2016), the path to purchase (Bell, Corsten, and Knox 2011), and the consumer decision process (Puccinelli et al. 2009). Although these terms are different, they all describe a similar core set of activities that consumers perform when deciding to make a purchase. Some of these activities occur before a purchase is made, some occur within the purchase context itself, while others occur after purchase and consumption have been completed. For this reason, and consistent with prior research (Puccinelli et al. 2009) we consider the role of numerical information—and how consumers process numerical information—at four stages: need recognition, information search and evaluation, purchase, and post-purchase, and we collectively refer to these stages as the customer journey.

Stage 1: Need Recognition

Customers begin their journey when they recognize that their current need state differs (negatively) from their desired need state, and that the acquisition of some product or service will restore the balance between the two. It is at this *need recognition* stage that many consumers process their first piece of numerical information—a budget. Existing research on budgeting has largely focused on the ways in which consumers recall, calculate, and manage their expenses (Sussman and Alter 2012; Ülkümen et al. 2008; Ülkümen and Thomas 2013) and shows how biases in spending recall and confidence in spending projections impact the accuracy of budgets. Even so, additional research opportunities remain.

For example, the way in which consumers mentally account for or establish a budget could have significant effects on their need recognition (as well as subsequent behavior). If a consumer uses broad budget categories (e.g., clothes), then the opportunities for need states to arise may be higher, as a larger budget is unlikely to be exhausted very easily. However, if they use narrow budget categories (e.g., short sleeve t-shirts), then opportunities for need states to arise may be lower. Although prior research on malleable mental accounting (Cheema and Soman 2008) shows that consumers demonstrate a substantial amount of flexibility in their mental accounting when they encounter an attractive product, less is understood about whether consumers exhibit similar levels of malleability with the setting of budgets themselves. This interplay between budgeting and mental accounting is a promising avenue to explore.

Much of the current research on budgeting assumes that consumers set and manage budgets only for themselves. However, consumers frequently have to set and manage budgets for others. When setting up a healthcare savings account to cover out-of-pocket expenses, an employee might need to predict and calculate expenses not just for themselves, but for the entire family. When planning for a family vacation, the planner might need to estimate the food, lodging, transportation and souvenir expenses for each person traveling. Or if a consumer is managing a parent's expenses, they might need to estimate their monthly expenditures to ensure that the retirement income is sufficient. Although these and similar scenarios are commonplace, research on whether and how budgeting behavior differs for others (vs. for one's self) is scant.

A third area where additional research would be welcome is whether consumers use different processes to budget for material versus experiential, or hedonic versus utilitarian purchases. To date, much of the existing research on budgeting has focused on the category level (e.g., entertainment, food), with far less attention paid to the type of purchase made (other than planned vs. unplanned, Iyer 1989; Stilley, Inman, and Wakefield 2010). Given the sizable literature on material versus experiential, and hedonic versus utilitarian purchases (Nicolao et al. 2009; Thomas and Millar 2013; Van Boven and Gilovich 2003), how consumers budget for these types of expenditures is an important opportunity to pursue.

A fourth area where additional research is needed concerns how (or indeed whether) consumers budget for the growing proportion of purchases that now occur on a subscription basis. According to a recent Forbes article, the subscription e-commerce market has grown by more than 100% per year over the past five years and exceeded $2.6 billion in 2016 (Columbus

2018). Existing research on price framing and anchoring (Gourville 1998) might explain why consumers initially sign up for a subscription (the monthly or weekly cost appears small, perhaps even trivial), but it doesn't explain whether consumers budget accurately for those subscriptions in advance or whether they accurately recall their total expenditures retrospectively.

Another area where additional research on budgeting would be helpful is with respect to the various time frames over which consumers budget. When Ülkümen et al. (2008) demonstrated the importance of the temporal frame on budget accuracy, they considered two timeframes—monthly and annually. However, in reality, consumers often budget different categories of expenditures differently. Gas/fuel might be budgeted on a weekly basis, cell phone expenses on a monthly basis, and property taxes on an annual basis. Two questions arise from this reality. First, what is the relationship between temporal frame, budget accuracy, and budget reconciliation? That is, are consumers better at setting budgets for items with temporally matched purchase frequencies (e.g., weekly grocery budget and weekly grocery shopping) than for those that are not matched (monthly grocery budget and bi-weekly shopping)? Second, how do consumers approach creating a total budget across categories and items that are billed over different time periods and how (and how often) do they reconcile these expenditures?

Finally, more research on how consumers process budget feedback and reconciliation information is warranted. Thus far, extant research has yielded important insight into the cognitive and perceptual processes consumers use to generate and manage budgets. However, insight into how affective and situational factors influence consumer budget estimates and management would be welcome. For example, when a consumer realizes that he has overspent his budget, does he experience sadness, anger, guilt, fear, or some other emotion? How does this emotional response influence his subsequent budget setting and management process, if at all? It is also possible that future budget setting is influenced by the context in which a consumer's actual versus budgeted expenditures become known. For example, if a consumer learns that his expenses exceeded his budget/available funds in private (e.g., via a notification from a budgeting app), then the feedback might be perceived and processed differently than if the consumer learns this information in public—like via a declined credit card at a retail point-of-sale.

Pursuing these research avenues might prove useful to managers as well. For example, having a better and more holistic understanding of how consumers budget would provide insight into how best to frame certain expenditures and replacement costs—e.g., $X per month vs. $Y per year, which might increase consumers' budget accuracy. In addition, firms that cater to group or family expenditures (e.g., insurance providers) could develop expense estimation tools to aid those consumers that need to make financial decisions for people beyond just themselves.

Stage 2: Information Search and Evaluation

The information search and evaluation stage follows the need recognition stage in the customer journey. During these two stages, consumers rely on a wide range of numerical information to help them organize, sort, compare, and choose the set of products, brands, and/or services from which they will make their final choice. It is at this point that many consumers consult user-generated ratings/reviews, and compare how other consumers (or professionals) rate the quality of the focal product or service. They may also compare numerical information across different products/brands, such as calories, annual percentage rates on credit cards, promotions/discounts, available memory on laptops, and of course prices.

Similar to the need recognition stage, additional questions remain unanswered in the information search and evaluation stage, particularly with respect to the role of product ratings.

Consumers consult user generated product/service reviews for everything from automobile purchases to cotton balls, and nearly 9 out of 10 consumers trust an online review as much as a personal recommendation (Saleh 2018). While prior research has explored important questions such as how the display order of reviews affects consumer choice (Ghose et al. 2012, 2014), and what rating information consumers actually use in their decision making (Watson et al. 2018), to our knowledge no one has examined whether ratings presented as numerical information (e.g., 4 out of 5) or as symbols (e.g., 4 out of 5 stars) are processed differently by consumers and if so, whether it affects consumer judgment and choice. Similarly, research examining whether and how precision in customer ratings (e.g., 3.73 out of 5) affects consumer perceptions and judgments would be an interesting question to pursue.

As consumers become more health conscious, manufacturer provided nutritional information is beginning to play a larger role in purchase and consumption behaviors. As such, research examining whether numeric or semantic descriptions that convey the same or similar information (e.g., 0% fat vs. fat free; 2% fat vs. "low" fat) differentially affect consumer evaluation and choice would be valuable. Relatedly, research could examine whether the robust left digit effect (Manning and Sprott 2009; Thomas and Morwitz 2005) that affects price, quality ratings, and calorie perceptions (Choi, Li, and Samper 2019) extends to other relative numerical values such as computer memory, remaining credit limit, and price per ounce.

Finally, as consumer participation in loyalty programs accelerates, researchers should examine how consumers operate within this unique sub-economy. Many loyalty programs reward their members with proprietary currency that is converted to cash before it can be used (e.g., Macy's Star Rewards), and some reward their members with proprietary currency that can only be used with the issuing manufacturer (e.g., Starbucks Rewards). In even more sophisticated arrangements, loyalty currency from some programs can be converted into the currency of other programs and used there. Furthermore, sellers often list product prices in these proprietary currencies both with and without the dollar equivalent listed. In each of these cases, the consumer must perform a conversion process either implicitly or explicitly, and then assess the perceived value of the deal.

Clearly in this stage consumers process a variety of different types of complex numerical information and a better understanding of how consumers navigate numbers in this stage would benefit managers, policy makers, and scholars alike. For example, if consumers process “0% fat” and “fat free” differently, and that difference leads to changes in purchase and consumption behavior, regulators may want to intervene. If consumers exhibit different price elasticity when products are priced in dollars vs. the equivalent value in reward currency, then marketers may want to post prices in one or the other currency. And if consumers evaluate a product with 4 out of 5 stars differently than one rated 4 out of 5 numerically, then ratings sites would want to change how they display product reviews.

Stage 3: Purchase

Upon deciding which alternative best meets their needs, consumers then purchase that item. Perhaps the most salient numbers encountered at this stage are price and price promotions. Research shows that the setting in which prices and promotions are presented is a critical factor in consumer choice (Hardesty and Bearden 2003; Krishna et al. 2002). That said, the extant research that focuses only on a few price/promotion attributes in either off-line or online purchase contexts fails to capture the dynamic shopping environment of the modern consumer. Take, for example, online grocery shopping. When grocery shopping online, consumers might receive discounts presented in different ways (now $3.99 was $4.99) for specific items ($.20 off for a specific brand of ketchup) or for making multiple purchases (5 for $1.00 or $.25 each). The discounts might be applied at the start or at the end of the transaction, and prices might be shown as fixed ($2.99) or variable ($2.99/lb), and product ratings are frequently displayed beneath each product. And all of this information might be presented on a single screen.

This context, which millions of consumers encounter on a daily basis, involves a staggering amount of numbers, calculations, and cognitive resources. How consumers navigate this environment online, how that compares to their offline processing strategies, and how that affects their behavior awaits further inquiry. Even more broadly, how consumers process numerical information in an omni-channel (and/or omni-device) retail environment deserves more attention. Specifically, how does a consumer who conducts research on her mobile device and finds a product for $29.99 respond if she subsequently finds the product in-store for the same price, but the font, size, or color of the price is displayed differently? Is it perceived to be a better deal? A worse deal? Does it matter at all? Having insight into these matters could help firms and consumers alike navigate the increasing convergence of digital and brick-and-mortar retailing.

A related phenomenon is the emergence of pay-what-you-want strategies and other forms of participative pricing strategies in online settings. In an attempt to widen their reach and to extract consumer surplus, more and more retailers are allowing consumers to offer bids on their products or services. Some examples are Priceline, an online travel aggregator that allows shoppers to bid on hotel rooms; winebid.com, an online wine store that allows buyers to bid on different wines; and e-bay where anybody can auction anything to a global audience. Recently, Thomas and Kyung (2018) demonstrated that buyers' purchase decisions on pay-what-you-want websites can be influenced by response formats; slider scales increase the salience of endpoints, prompting consumers to pay more than what they would have paid if they were using a textbox. Their findings highlight the need to study how other types of response formats—vertical versus horizontal scales, discrete scales versus slider scales—would change consumer responses.

Stage 4: Post-Purchase Evaluation

Finally, after a consumer makes a purchase, they enter the *post-purchase evaluation* stage. Here firms often encourage buyers to rate the product or service they just purchased using a numerical scale (e.g., 1-5) or symbols (e.g., stars), and they even sometimes suggest specific ratings (e.g., "anything less than excellent makes us sad"). However, this is not the only context in which consumers process numerical information after making a purchase. When rating a restaurant online, consumers might be asked to categorize the price of the establishment (e.g., $, $$, or $$$). This is essentially equivalent to asking for a price perception. A relatively large body of research has examined the antecedents of retailer price image perceptions (Cox and Cox 1990; Hamilton and Chernev 2013; Schindler 2001; Simester 1995), but several questions still remain. For example, current research shows that price image perceptions can be shaped by average prices paid in the past, the range of product prices in the establishment, and even the appearance of the other patrons in the establishment. But other possibilities exist. It is possible that consumers simply recall roughly how much they paid for their own most recent meal and then make their evaluation. Alternatively, they may recall how they paid for their purchase (e.g., cash, credit, mobile) and infer how expensive the meal/item must have been based on their payment mode. They also might recall only the food they purchased without accounting for beverages, which might reduce their price perceptions. It would also be interesting to understand whether additional numeric information other than price influences consumers' price perceptions. For example, consumers may associate fewer menu options with more expensive restaurants and more menu options with less expensive restaurants, which could result in dramatically different price perceptions of the same establishment. While prior research has examined the role of assortment size and product attractiveness on retailer choice (Chernev and Hamilton 2009), to our knowledge, no one has examined how assortment size affects price perceptions.

In addition to being asked about price, consumers might be asked to recall the promotion/discounts they received from a seller; that is how much money they saved at a specific store in the past year. If the findings from partitioned pricing research (Morwitz, Greenleaf, and Johnson 1998) extend to promotions, it is possible that this promotion recall process would be biased as well and could influence other price or store-related perceptions. For example, if consumers simply remember the final price paid and not the full price, the discount applied, and final price separately, then they might mistakenly underestimate the value of their discount, which could affect their future shopping behavior.

ADDITIONAL AREAS FOR RESEARCH

The areas for future research presented thus far have focused largely on single-stage opportunities, but ample opportunity also exists to examine the role of numerical information and processing strategies across multiple stages of the customer journey. For instance, scholarly research examining the cumulative effect that different numerical processing strategies have on consumer decisions from one stage of the customer journey to the next represents a substantial opportunity. Such an approach has significant merit, as it likely better reflects how consumers actually make decisions and may shed light on the broader effects of inter-stage and intra-stage numerical processing strategies. For example, research on drip pricing (where a firm first presents a base price, but then later reveals mandatory or optional fees) shows how price presentation affects perceived value and consumer choice in the early stages of the customer journey, and how when consumers receive information that disconfirms value perceptions later in the journey, they fail to change their initial decision (Santana, Dallas, and Morwitz 2019). Relatedly, Carlson and Guha (2011) demonstrate how consumers begin to form preferences and how that affects information search. If consumers employ a leader-supporting search strategy, they may subsequently seek numerical information that supports their emerging preference (e.g., fewer calories, less time), even if that information is less credible. Similarly, consumers have been shown to distort new information received in order to maintain consistency with a tentatively preferred option (Carlson, Meloy, and Lieb 2009; Russo, Meloy, Carlson, and Yong 2008). Thus, how a price is presented at one stage of the customer journey has a significant impact on choices made in future stages of the journey.

Second, although Figure 1 associates certain types of numeric information with different stages of the customer journey, empirical research confirming such associations marks another area for scholars to pursue. For example, while it’s feasible that budgets are salient in the need recognition phase (as depicted), it’s also possible (and indeed likely) that budgets are salient at every other stage of the customer journey as well, but to a different degree. So a more accurate depiction of the role of budgets might be to demonstrate empirically how prominent and influential they are at each stage, and whether they are a primary or secondary factor. As such, the contents of Figure 1 should be interpreted as illustrative rather than as a generalizable description of how customers process numerical information across all journeys. Similarly, we did not map the different types of processing strategies into the stages of the customer journey, as we believe that these strategies likely operate in all stages, but future research should examine whether different strategies are more likely in different stages.

Finally, the examples of consumer decisions outlined in this research make two important assumptions. First, we (implicitly) assume that consumers are making a decision for the first time and/or in a one-shot environment. However, as consumers make the same or similar decisions on a repeated basis (e.g., routine purchases), it’s likely that their customer journey is abbreviated and/or changes entirely. As such, the role of numerical information, how that information is processed, and the heuristics employed by consumers could change considerably. This marks another area of future research. Additionally, as we stated at the outset of the paper, we assume that all consumers progress through a similar four-stage customer journey. However, research shows that as many as 12 customer journey archetypes are possible (Lee et al. 2018). Thus, it is possible that the role of numerical information in the customer journey varies according to the relevant archetype. We see this as a promising area for future research.

CONCLUSION

This review summarizes the wide range of numerical information that consumers encounter throughout the customer journey and the different strategies they utilize to process that information. In doing so, we also highlight the complexity of everyday consumer decision making as well as avenues for future research. As the retail landscape continues to evolve and consumers embrace new ways to recognize, search, compare, purchase, and evaluate goods and services, scholarly research will need to evolve as well.

Notably, our recommendations for future research address public policy, managerial and individual consumer issues. For example, having a deeper understanding of how numerical information presented at one stage of the customer journey affects decision making at a later stage may help policy makers design and deploy interventions at different (and more critical) points in the choice environment. Likewise, knowing whether and what non-price information affects consumers' price and promotion perceptions can help sellers alter the environment accordingly. Finally, if consumers realize that they systematically underestimate their expenditures on subscription services such as Netflix, Harry's, and Blue Apron, perhaps they will modify their enrollment behavior. We look forward to more research on these important topics.

Figure 1 – Examples of Numerical Information and Processing Strategies Utilized Throughout the Customer Journey

Decision Stage	**Need Recognition**	**Information Search and Evaluation**	**Purchase**	**Post-Purchase Evaluation**
Types of Numeric Information	• Budgets	• Product Ratings • Product Rankings • Product Attribute Information • Price Information • Brand Identifying Information • Calorie Information	• Price Information • Promotion Information • Quantity Information • Time Information • Financial Information	• Consumer Ratings • Price Recall • Promotion Recall
Mental Representations	• Symbolic Representations • Intuitive Analog Representations			
Judgment Strategies and Heuristics	• Anchoring • Availability • Numeric Fluency • Representativeness • Numerosity • Numeric Associations • The Number Zero • Framing Effects • Comparison and Evaluation Heuristics			

Figure 2 – Future Research Opportunities

Need Recognition	**Information Search & Evaluation**	**Purchase**	**Post-Purchase**
• How do consumers budget for others? • How do consumers budget for utilitarian and hedonic purchases? • Interplay between budgeting and mental accounting?	• Are symbolic ratings (e.g., stars) processed differently than numeric ratings? • Are semantic and numeric representation of nutrition information processed differently?	• How do online price evaluation strategies different from offline strategies? • How do various response formats change online payments?	• What factors influence consumers' post-purchase price recall? • What factors influence consumers' post-purchase satisfaction ratings?
Multi-Stage Impact of Numerical Information and Processing Strategies Throughout the Consumer Journey			

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