BEHAV ANALYST (2017) 40:329–342
DOI 10.1007/s40614-017-0100-2

BEHAVIORAL ECONOMICS IN CONSUMER BEHAVIOR ANALYSIS

Progress of and Prospects for Hypothetical Purchase Task Questionnaires in Consumer Behavior Analysis and Public Policy

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Published online: 4 April 2017

Abstract Based on the conceptual, methodological, and analytical framework of operant behavioral economics, hypothetical purchase task (HPT) questionnaires provide a low cost, scalable, and quantitatively rich source of empirical insights on consumer motivation, preferences, and decision-making. Here, we briefly summarize the history of HPT development and validation in clinically oriented research in addiction through to recent work with more conventional consumer goods and services. We discuss several possible novel applications of HPT methods to consumer behavior analysis for business, marketing, and public policy formulation and evaluation, as well as emerging best practices, limitations, and additional directions for future research and development.

Keywords Behavioral economics · Hypothetical purchase task · Consumer behavior analysis · Marketing · Public policy

A Behavioral Economic Approach to Consumer Behavior

An interest in consummatory behavior spans myriad social and behavioral sciences. Economists, marketing researchers, psychologists, and retailers use insights from

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consummatory behavior research to better understand factors that influence decisions guiding consumption. Common techniques in consumer decision science to quantify resource/product utility include stated preference surveys (e.g., Adamowicz, Boxall, Williams, & Louviere, 1998; Louviere, Hensher, & Swait, 2000) and discrete choice models (Berry, 1994) as well as controlled field and laboratory studies on consumer preferences to reveal actualized preferences (Houthakker, 1950; Richter, 1966). Despite rich histories within each consumer research approach, these various methods deviate substantially from the behavior analytic tradition of within-subject repeated measures designs. The discipline of consumer behavior analysis emerged in the mid-1990s and integrates the goals of consumer research with behavior analytic principles and theory (see Foxall, 2010; Hantula & Wells, 2013).

Consumer behavior analysis has been defined as "the application of behavioral economics to the sphere of human consumer choice, particularly in the context of advanced marketing-oriented economies" (Foxall, 2010, p. 92) while adhering to behavior analytic principles and considerations. Applied behavioral economists integrate behavioral psychology with consumer demand theory to understand human decision making (Hursh, 1980; Jarmolowicz, Reed, DiGennaro Reed, & Bickel, 2016), especially regarding the quantification of human demand persistence in the face of behavioral constraint-challenges (i.e., prices by way of financial or time costs). A major divergence between neoclassical/standard and behavioral economic theory is the presumed rationality of decision making. Whereas neoclassical/standard economists assume rational decision making (e.g., discrete choice models) evidenced by linear functions and constant discount/elasticity rates, behavioral economists view decision making as a context-specific process rendering dynamic behavioral profiles (i.e., inconsistencies). Fortunately, such apparent irrationalities are systematic and orderly in behavioral economic models of choice and decision making (Hursh & Silberberg, 2008; Hursh & Roma, 2016) and do so using subject-level repeated measures, in accordance with the behavior analytic tradition.

Operant demand curve modeling is grounded in the law of demand, which posits that the consumption of a commodity decreases as the price of that commodity increases (Samuelson & Nordhaus, 2010; Stigler, 1954). This relation is captured in a demand curve containing several noteworthy features and has been refined across studies employing numerous species over the last several decades (see Hursh, Madden, Spiga, DeLeon, & Francisco, 2013). *Demand intensity*, or the maximum level of demand, refers to the level of consumption when a commodity is available for free or extremely low price. Consumers will defend this maximum level of consumption to some extent as price increases up to the *breakpoint,* the price at which the organism refuses to "pay" and thereby ceases consumption. *Elasticity* is a quantitative measure that captures the sensitivity of consumption to price increases (Hursh, 1984). When a demand curve is inelastic, consumption declines slowly as price increases such that a one-unit logarithmic increase in price results in a less than one-unit logarithmic decrease in consumption. Unit elasticity at $\text{Price}_{\text{max}}$ (i.e., P_{max}) refers to the price at which demand shifts from inelastic to elastic, such that a one-unit logarithmic increase in price yields a one-unit logarithmic decrease in consumption. The corollary metric of O_{max} is the maximum total output or expenditure at P_{max}. Beyond P_{max}, demand is elastic such that price increases result in increasingly disproportionate reductions in consumption. The exponential model of demand first introduced by Hursh and

Silberberg (2008; also see Hursh, 2014; Hursh & Roma, 2013, 2016) is a non-linear regression based model for analyzing demand curve data that quantitatively separates demand intensity from demand elasticity, with the latter expressed as a rate constant (α) for decreasing consumption across the entire range of increasing prices. Demand elasticity is inversely related to the theoretically constant "essential value" the commodity holds at any given time and/or under a particular set of conditions (i.e., reinforcing strength independent of unit size), and the exponential model's rate constant term (and derivative essential value metrics) quantifying demand elasticity is a novel and heuristically informative means of comparing value and motivation within and across individuals, populations, conditions, and qualitatively different commodities (Hursh, 2014; Roma, Hursh, & Hudja, 2016).

Development and Application of Hypothetical Purchase Task Questionnaires

The behavioral economic approach to quantifying demand differs from traditional behavior analytic approaches by focusing on consummatory responding (i.e., units of a commodity consumed in an economic system), rather than response rate or allocation (see Hursh & Silberberg, 2008 for a discussion on the evolution of such focus). Behavioral economists first demonstrated the translational utility of demand curve models in the field of addiction and substance use disorders (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014; Hursh, 2000; Jarmolowicz, Reed, & Bickel, 2015). Due to ethical and logistical concerns of delivering drug reinforcers to generate demand curves, behavioral economists began using *hypothetical purchase task* (HPT) questionnaires to simulate subject-level models of demand in human populations (Jacobs & Bickel, 1999; MacKillop et al., 2008a, b; Murphy & MacKillop, 2006; Murphy & MacKillop, 2005; Petry & Bickel, 1998). Such HPTs impose some constraint-challenge to respondents' stated preference (often in a willingness-to-pay approach) at each level of constraint in a within-subject repeated-measure design. The prototypical HPT format begins with a description of the basic hypothetical scenario the respondent is asked to imagine (e.g., "Imagine a typical mid-afternoon weekday when you are hungry for a snack"), a series of assumptions and limitations either as part of the vignette or a bullet-point list (e.g., commodity unit/size, availability of alternatives, budget), the response instructions specifying consumption modality (quantity purchased or probability of single purchase) and applicable temporal frame (e.g., quantity purchased per week), and finally the list of prices and corresponding spaces for the participants or researcher to enter the respondents' hypothetical purchase data. Although superficially similar in some ways to other hypothetical purchase tasks used in marketing research (cf. Murray, 1991), by design, HPT procedures rooted in the operant behaviorist tradition permit the modeling of full within-subject demand curves across a wide range of prices, thereby providing a rich suite of standardized metrics and unique behavioral account of consumer motivation and decision-making.

From a behavior analytic perspective, the use of verbal reports on hypothetical economic systems raises natural concerns regarding the validity of HPT approaches. Indeed, the practical strengths of the HPT method that served as the impetus for its

development are simultaneously its most questionable feature—even in a controlled laboratory setting, HPTs by definition do not measure actual consumption. Fortunately, the existing validation work is encouraging. A number of studies have found that hypothetical demand via HPTs significantly predicts alcohol use (e.g., MacKillop & Murphy, 2007), cigarette cessation (e.g., Madden & Kalman, 2010), and correlates with actual purchasing of alcohol drinks in a controlled market (e.g., Amlung, Acker, Stojek, Murphy, & MacKillop, 2012). Additional studies on construct validity of HPTs have documented sensitivity of hypothetical demand to real-world environmental cues (cue-reactivity; e.g., MacKillop, Brown, Stojek, Murphy, Sweet, & Niaura, 2012; MacKillop, O'Hagen, Lisman, Murphy, Ray, Tidey, & Monti, 2010), while other work has demonstrated convergence between hypothetical demand metrics and clinical assessments using already established clinical scales (e.g., MacKillop et al., 2008a, b; Murphy, MacKillop, Tidey, Brazil, & Colby, 2011; Murphy & MacKillop, 2006; Reed, Kaplan, Becirevic, Roma, & Hursh, 2016). Finally, in addition to demonstrating significant validity, behavioral economists have also documented adequate reliability of HPTs across a number of studies (e.g., Few, Acker, Murphy, & MacKillop, 2011; MacKillop et al., 2008a, b; Murphy, MacKillop, Skidmore, & Pederson, 2009; Reed, Kaplan, Roma, & Hursh, 2014).

HPTs for Conventional Consumer Products and Services

As described above, the HPT methodology originated and has undergone considerable development and expansion within the field of behavioral pharmacology and addiction. Not surprisingly, the use of HPT questionnaires for goods and services beyond conventional drugs of abuse has been quite limited; however, the existing data support the generalizability of behavioral economic principles and HPTs across commodities, and the implications for consumer behavior analysis and public policy applications are promising.

In countries where pharmaceutical advertising to the general public is legal, prescription medications often occupy a precarious space between consumer product and drug of abuse. The work in this domain includes that of Pope, Kean, Nash, Kanayama, Samuel, Bickel, and Hudson (2010), who developed a clinical diagnostic interview for detecting dependence on anabolic-androgenic steroids in weightlifters with a history of steroid use. As part of their validation research, they included a modified 15-price HPT and found significant differences between dependent and non-dependent users in demand intensity (100 vs. 10 bottles, respectively, at £1/bottle) and maximum expenditure (£525 vs. £150.5, respectively) on steroids hypothetically purchased for long-term personal use. Similarly, Pickover, Messina, Correia, Garza, and Murphy (2016) modified the alcohol purchase task to assess the value of non-prescribed use of prescription sedatives, stimulants, and pain relievers in college students, and found significant correlations between HPT demand metrics and past year and lifetime reported use variables, with stronger correlations among stimulants and pain relievers compared to sedatives.

Shifting to more common everyday commodities, albeit still within an addiction framework, several investigators have used HPTs to assess the reinforcing value of various foods. First, Epstein, Dearing, and Roba (2010) modified the cigarette purchase

task to assess the reinforcing efficacy of obese and non-obese adults' preferred snack foods (67–103 kcal portion [14–20 g]) established during a prior ad libitum eating session, which including Wavy Lay's potato chips, Cooler Ranch Doritos, M&Ms, Twix, Kit Kat, and Butterfinger. As with drug HPTs, the resulting demand data were consistent with microeconomic principles, and importantly, maximum expenditures and elasticity in the HPT correlated significantly with multiple demand metrics from an operant laboratory consumption task (absolute *R*s from 0.44–0.47). More recently, Chase, MacKillop, and Hogarth (2013) also modified the cigarette HPT to develop a chocolate purchase task, using Cadbury Dairy Milk bars as the target commodity. This study also yielded orderly demand data and revealed lower intensity of demand and higher elasticity of demand for chocolate compared to cigarettes in the subject pool of regular smokers.

Additional consumer commodities that may best be categorized as either services or access to reinforcing activities, but have also been examined within an addiction framework using HPTs, include internet access (Broadbent & Dakki, 2015), sex (Jarmolowicz, Lemley, Mateos, & Sofis 2016), gambling (Weinstock, Mulhauser, Oremus, & D'Agostino, 2016), and ultraviolet indoor tanning (Reed, Kaplan, Becirevic, Roma, & Hursh, 2016). Broadbent and Dakki (2015) found that demand for paid hourly internet access during a hypothetical 5-h flight was highly elastic, but still significantly greater in all demand metrics among users classified as problematic vs. non-problematic. After having participants rank order hypothetical sexual partners from a standardized set of sexual orientation-appropriate images, Jarmolowicz and colleagues (2016a) used a modified sex HPT and observed significantly greater demand for sex with high- and medium-preferred vs. low-preferred partners. When asked how many times per month respondents would gamble at various cover charge prices, Weinstock et al. (2016) found that individuals with a gambling disorder did not differ from healthy controls in demand for alcohol (via alcohol purchase task) but showed significantly higher intensity of demand, maximum expenditure, and breakpoint for access to gambling through a modified gambling HPT. In a similar spirit, Reed et al. (2016) assessed demand for a standard monthly indoor tanning package using a novel HPT based on increasing excise taxes, and found that all demand metrics significantly increased as a function of reported real-world tanning consumption (recent > non-recent > never).

Additional examples of HPTs for non-drug goods focus on motor vehicle fuel, a commodity that unambiguously operates beyond a conventional individual biomedical addiction framework. Examining recreational driving, Reed et al., (2014) asked participants how many miles they would be willing to drive for a vacation at various prices per gallon of fuel, which produced orderly demand curves and metrics, with median intensity of demand at 1000 mi and median breakpoint for forgoing vacation altogether when fuel was $7 per gallon. Additional work comes from Daley, Nangle, Boeckman, and Miller (2014) who surveyed demand for E85 ethanol fuel among drivers in the US Federal fleet equipped with flex-fuel trucks. In this case, because fleet drivers do not pay for fuel themselves, the increasing "price" of the fuel was defined in terms of convenience, i.e., additional time and additional distance to an E85 station relative to a conventional fuel station, ranging from <5 min to >15 min and <1 mi to >5 mi. Intensity of demand for alternative fuel was comparable at the lowest time and distance prices (79% likelihood of purchase) and both curves were characteristically elastic; however, demand was more sensitive to additional time price than to additional distance price. Finally, perhaps the most comprehensive use of HPTs explicitly and

purposely for consumer goods beyond drugs of abuse comes from Roma et al., (2016), who constructed purchase tasks in multiple formats for a variety of generic consumer goods, services, and experiences and assessed hypothetical demand in ~1000 members of the Amazon Mechanical Turk online crowdsourcing community (Buhrmester, Kwang, & Gosling, 2011). This work involved separate HPTs for the small-ticket commodities of a hamburger or sandwich, a roll of toilet paper, and a pay-per-view movie, show, or event and the big-ticket commodities of a fine-dining restaurant meal, a refrigerator, and a vacation package. All HPTs produced prototypical demand curves and superb model fits (mean $R^2 = 0.98$) for small-ticket (Fig. 1) and big-ticket (Fig. 2) commodities, and there was significantly concordant rank-ordering of the various commodities' essential values across the various HPT formats and procedural manipulations (Kendall's $\overline{W} = 0.82$, $p < 0.01$). Taken together, the existing findings suggest that data generated by HPTs for consumer goods and services yield orderly demand curve functions, and further underscore the broad applicability of the HPT method across commodities while supporting commodity specificity and sensitivity to individual and group preferences.

Opportunities, Gaps, and Challenges for HPTs in Business, Marketing, and Public Policy

We envision behavioral economic hypothetical purchase task questionnaires as a broadly applicable, metric-rich, and cost-efficient means of gathering empirical insight on consumer behavior and decision-making, whether for products and services or broad public policy campaigns aimed at increasing public health, safety, and prosperity. Indeed, the sensitivity of HPTs and their suitability for repeated administration procedures make them a promising methodology for consumer behavior analysis. Regardless of scientific or organizational goals, or whatever specific commodity the respondents are "consuming," it is helpful to consider the potential value of HPTs from a product lifecycle perspective, which generally includes research and development, market entry, growth, maturity, decline, and market exit (Dhalla & Yuspeh, 1976; Klepper, 1996). For example, customized HPTs could save considerable time, effort, and resources by evaluating demand for multiple product ideas in the very early brainstorming stages to provide quantitative guidance on which products and ideas to further develop before investing in costly manufacturing processes and test market roll-out campaigns. Once prototypes are made, HPTs could be crafted to continuously evaluate consumer interest in the prototypes and competing products throughout the research and development process. Indeed, it is worth noting that similar to investigators who have utilized an operant demand approach to assess the value of food items (Geisen, Havermans, & Jansen, 2010; Reslan, Saules, & Greenwald, 2012), or the work of Oliveira-Castro, Foxall, and colleagues examining consumer panel data (Oliveira-Castro, Cavalcanti, & Foxall, 2016; Oliveira-Castro, Foxall, Yan, & Wells; 2011), both Chase et al., (2013) and Epstein et al., (2010) used genuinely branded "mature" food products for their HPT assessments. Although they did not explicitly assess the effects of branding, their work

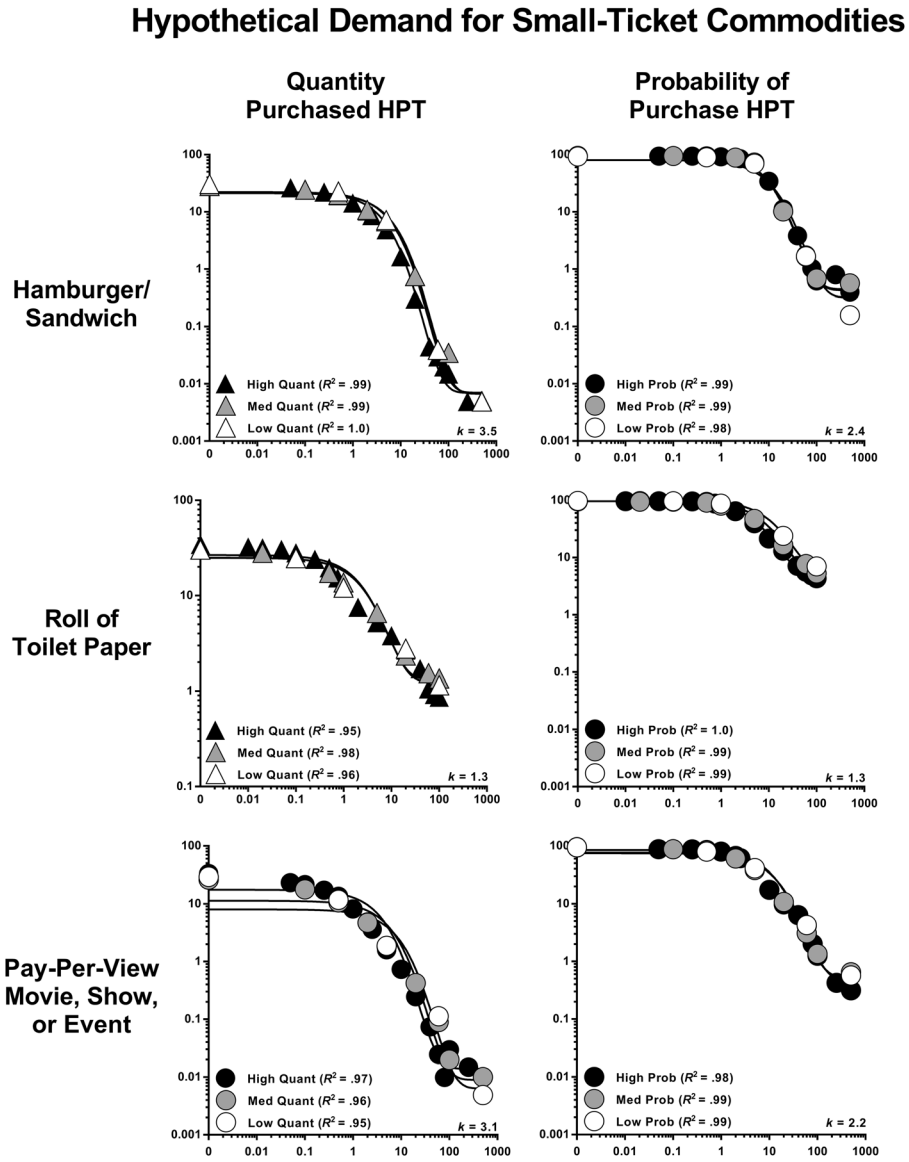

Fig. 1 Demand for small-ticket commodities. Demand curves derived from hypothetical purchase task (HPT) questionnaires for several generic consumer goods and services based on quantity purchased (left column) or probability of a single purchase (right column) response format at multiple price densities. Figures adapted from Roma et al. (2016)

supports the notion that HPT methods could provide a rapid and cost-efficient approach to quantifying the effectiveness of branding and various marketing strategies at multiple stages of the product lifecycle. Once in the market, carefully designed HPTs could be incorporated with minimal logistical or financial burden into more conventional focus

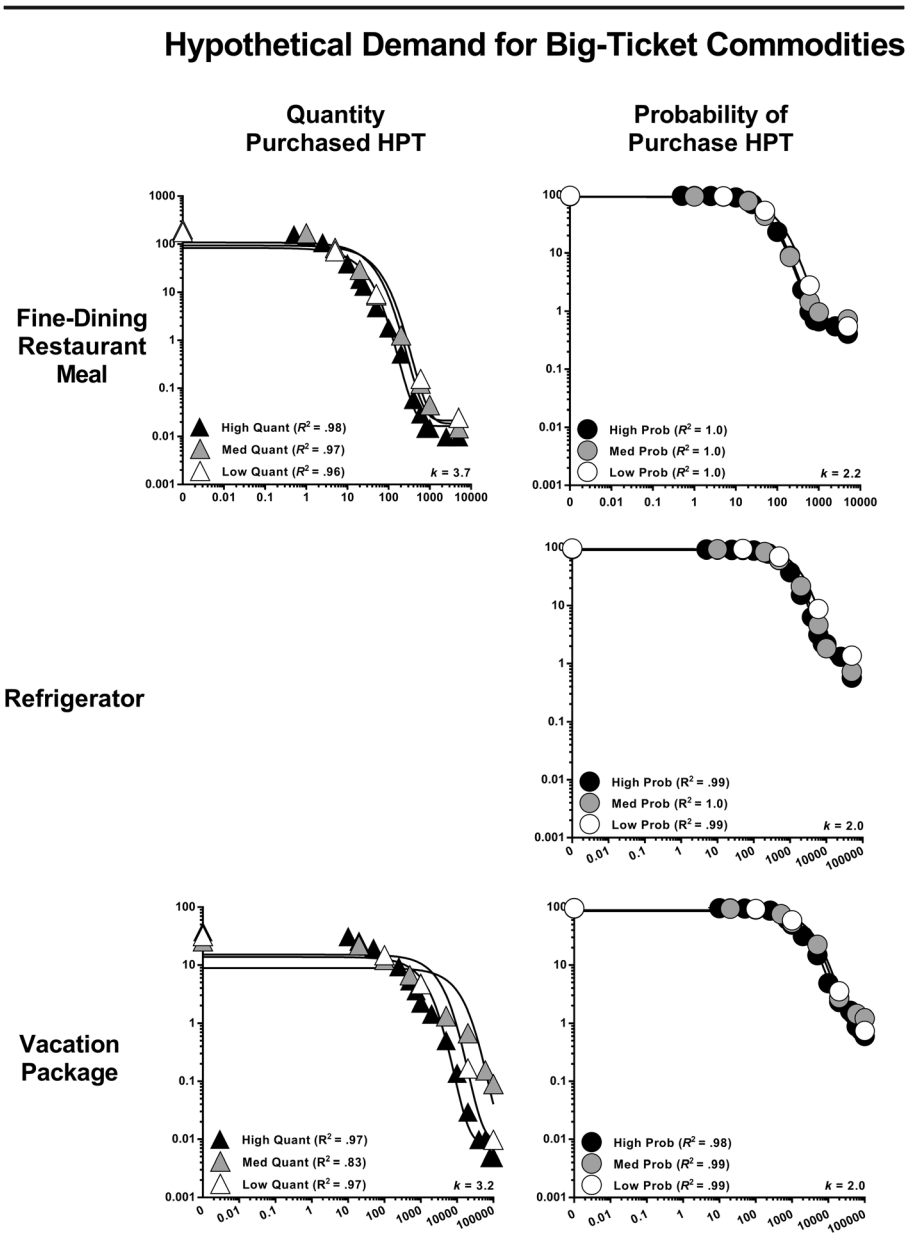

Fig. 2 Demand for big-ticket commodities. Demand curves derived from hypothetical purchase task (HPT) questionnaires for several generic consumer goods and services based on quantity purchased (left column) or probability of a single purchase (right column) response format at multiple price densities. Figures adapted from Roma et al. (2016)

group procedures, standing consumer panels, or large sample online administration efforts (e.g., Amazon Mechanical Turk; Bickel, Wilson, Franck, Mueller, Jarmolowicz,

Koffarnus, & Fede, 2014; Buhrmester et al., 2011; Roma et al., 2016). In this context, HPTs could potentially serve as sentinel measures for predicting a product's growth and maturity, thereby supporting continued investment, or for predicting the transition from maturity to decline and market exit, thereby supporting innovation initiatives, price adjustments, or voluntary market withdrawal to minimize losses.

As with a traditional business perspective where the goal is to increase consumption, we believe the potential for HPTs still holds in broader policy domains where the goals are often to decrease consumption of commodities considered cumulatively detrimental to public health, safety, or financial stability, or increase the consumption of substitutes that confer less cumulative public risk. Much more work needs to be done in this area, but the notable examples above from Reed et al., (2016) who assessed demand for ultraviolet indoor tanning as a function of increasing hypothetical excise taxes (to offset the public costs of cancer education, screening, and treatment) and Daley et al., (2014) who assessed demand for alternative fuels as a function of time and distance costs (indirectly assessing US transportation infrastructure's capacity to support alternative fuels) illustrate how HPTs could be applied to a variety of publically relevant issues both prospectively and continuously to empirically inform policy development.

Whether assessing differences in demand among various clinical or demographic groups, different variations of the same product or policy in development, or competing commodities with which consumers have more extensive natural exposure or experience, much of the existing research using HPTs—experimental or otherwise—focuses on identifying differences as a function of an independent variable or set of variables. This focus on how input variables and qualitative categories affect consumers' demand is appropriate and useful in the various research contexts in which it appears, but belies the value of HPTs for estimating revenue for those providing the goods, services, and experiences being consumed. Theoretically, the essential value of a commodity for any given individual at any given time is stable and independent of the commodity's unit size (Hursh & Silberberg, 2008; Hursh & Roma, 2013, 2016), but is not independent of price, because a core tenet of operant behavioral economics is that subjective "value" cannot be separated from objective price. This latter point is important for business, marketing, and policy applications that may only focus on a single commodity and demand curve at a time, and would be less interested in abstract constructs of value (however quantitatively precise) and more interested in the resulting revenue (however hypothetical). To this end, the outcome variables based on the *x*-axis of the demand curve may be most informative, with O_{max} representing the maximum revenue (at unit price P_{max}) and breakpoint representing the lowest unit price to yield zero revenue.

Regardless of context, novel applications of HPT methods will likely require adaptation of existing questionnaires or construction of new ones that are appropriate for the commodity being tested, the various situations in which consumption is expected, and the price range. The general HPT format of vignette, limitations/assumptions, and price-response list to build a demand curve is consistent across all HPTs developed to date, and the popular alcohol and cigarette purchase tasks are frequently used without modification; however, there are almost literally as many variations in HPT structure as there

are HPTs. To provide some empirical guidance to researchers developing novel HPTs and to determine whether structural and purchase format variations can systematically affect behavioral economic demand metrics, Roma et al. (2016; cf. Reed et al., 2014) recently tested the effects of price density (17, 9, or 5 prices) and purchase type (quantity purchased or probability of single purchase) in the generic small-ticket and big-ticket consumer goods described above. Although the rank-ordering of commodities by essential value was significantly consistent despite the HPT structural variations, there were notable effects that can inform best practices for novel HPT construction. Specifically, across all commodities and purchase types, the 17-price high density HPTs produced the highest elasticities and thus the lowest essential values as well as the lowest P_{max}, O_{max}, and breakpoints. Low density 5-price HPTs are efficient, effective, and provide orderly data that may qualify as a "minimum effective price density," but still provide relatively inflated estimates of demand compared to higher-density HPTs whose higher resolution allows respondents to more precisely estimate their shift from inelastic to elastic demand. Based on these results, we recommend a 17-price HPT when feasible and appropriate, or at least be acutely aware of potential confounds in comparing demand measures across different price densities. In terms of purchase format, HPTs built upon the estimated probability of a single purchase at each price operate virtually identically to the classic HPT format based on quantity of units purchased at each price. The important points to consider are that essential values are systematically higher for probability versus quantity HPTs, and despite the superficial similarities between them and common methods to analyze their data, the two formats ultimately ask very different questions about demand, consumption, and value and should be used and interpreted with due care and thoughtfulness.

Perhaps both the biggest challenge and opportunity for HPT development is that which all questionnaire methods face, regardless of their providence, and that is validation—most importantly predictive or ecological validity. Simply put, to what extent do responses on HPTs predict behavior in the real world? This question is particularly relevant to inherently applied fields such as consumer behavior analysis, business, marketing, and public policy. The laboratory and clinical validation work described above is very encouraging, but even if HPT and real-world consumption are highly statistically correlated, that only means that those with relatively high HPT demand values will have relatively high real consumption values, not necessarily that the amount actually consumed is the same as the amount hypothetically purchased. Indeed, to provide more meaningful elasticity measures, HPTs typically include far more prices across a far wider range than a single consumer would ever encounter in the marketplace (although see Koffarnus, Wilson, & Bickel, 2015 for a notable exception). Moreover, even if HPT scales precisely match the array of real-world prices, phenomena such as "hypothetical bias" (Loomis, 2014) where respondents overestimate real consumption could limit predictive power. However, we do not consider these issues to be insurmountable through research. Recent advances in mobile and wearable technology and the management of "big data" that offer potentially transformative

opportunities for the behavioral and social sciences underlying public health (Collins & Riley, 2016) also represent an opportunity to better understand consumer behavior, and could contribute to the field validation of HPTs and better understanding of the relationship between hypothetical and actual demand. Indeed, as long as HPT prices encompass the expected (or actual) real-world range, and biases inherent to estimating consumption are consistent as a function of any number of variables (e.g., age, gender, income, experience with product, etc.), then HPT data could be adjusted or weighted accordingly to provide more accurate predictive models of consumption and projections of revenue calibrated against increasingly accurate objective field measures.

Conclusion

In this non-exhaustive review, we summarized the history of behavioral economic hypothetical purchase task (HPT) questionnaire development and validation in clinically oriented research in addiction through to recent work with more conventional consumer goods and services. We also considered several possible novel applications of HPT methods to consumer behavior analysis, as well as emerging best practices, limitations, and additional directions for future research and development of HPT-based tools.

An important contribution and overarching theme of this work is the generalizability and broad applicability of the operant behavioral economic approach and HPT methodology. The conceptual, methodological, and analytical framework of behavioral economics continues to grow. Even with its development history, validation, and expansion in clinically oriented research on addictions, an emerging body of work supports the applicability of the HPT approach across a broad range of consumer products, services, experiences, and public policy-relevant issues. This is evident in the emerging literature using HPTs for commodities as widely varied as food, prescription medications, health and beauty services, alternative fuels, and household appliances. Continued research and development addressing a number of methodological and scientific considerations is necessary for expanded HPT use, but represents an exciting opportunity to advance this behavior analytic-inspired approach to the broader consumer behavior analysis community. Taken together, the operant behavioral economic framework and novel methods such as hypothetical purchase task questionnaires can complement existing research methods targeting biological, behavioral, and cognitive mechanisms, or stand on their own as cost-effective, scalable, and quantitatively rich sources of empirical insights on consumer motivation, preferences, and decision-making for business, marketing, and public policy formulation and evaluation.

Acknowledgements PGR and SRH's contributions to this work were supported by intramural funds from the Institutes for Behavior Resources.

Compliance with Ethical Standards All research protocols described in this paper were reviewed and approved by the responsible committees on such research, or determined to be exempt from review by the respective committees.

Conflict of Interest The authors declare that they have no conflicts of interest.

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