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Twenty-five years of simulated demand: A bibliometric and systematic review of hypothetical drug purchase tasks

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Abstract

Since its introduction by Jacobs and Bickel (1999), the hypothetical purchase task (HPT) has emerged as a frequently used methodology in behavioral economics research, particularly in studies of substance use and public health decision making. The HPT represents an approach that seeks to quantify the reinforcing value of drugs and other commodities through parametric, scalable methodology measured via self-reported consumption across escalating prices. Despite its increasing use in research settings, no comprehensive evaluation of its scientific influence has yet been undertaken. To address this gap, we conducted a two-part review of the HPT's empirical legacy. In Study 1, we conducted a bibliometric analysis of all peer-reviewed documents citing Jacobs and Bickel (1999) through mid-2025. In Study 2, we conducted a systematic review of empirical HPT studies employing operant demand analyses to assess drug consumption. We conclude with a discussion on the legacy of Jacobs and Bickel (1999), an evaluation of the present state of the field of operant behavioral economic science in addiction, and a call for critical areas of inquiry in the use of HPTs to measure drug abuse potential.

Keywords

behavioral economics; demand curve; drug; operant; purchase task

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> Even though a report of behavior in a hypothetical situation may not be a perfect substitute for observations of behavior in those actual situations, self-report data are in many ways preferable to no data
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> (Jacobs & Bickel, 1999, p. 424).

In the 1980s and 1990s, Dr. Warren K. Bickel pioneered the application of behavioral economic principles to the study of addiction (Bickel et al., 1993, 1998). Leveraging the groundbreaking work in operant demand popularized in the nonhuman laboratory by Dr. Steven Hursh (Hursh, 1980, 1984, 1991), Bickel translated operant assays of drug abuse potential assessment to study how humans interact with addictive commodities within a behavioral economic framework. His early work directly translated concepts such as fixed-ratio (FR) or progressive-ratio (PR) schedule responding to objectively quantify the relative reinforcing efficacy of drugs (Bickel et al., 1990, 1991, 1992; DeGrandpe et al., 1992).

Much of the enthusiasm behind applying behavioral economics to drug consumption is the multifaceted view of "demand" afforded by demand-curve modeling. Unlike typical operant investigations that focus on reinforcement rate at varying unit prices (i.e., amount of reinforcement per response requirement), demand curves focus on reinforcer *consumption* (see Reed, Graham, et al., 2025). Specifically, demand curves (see left panel of Figure

1) plot the quantity of reinforcers consumed (on the *y*-axis) as a function of reinforcer unit price (on the *x*-axis); these scales are typically used in log–log coordinates to focus on the percentage of change in consumption against the percentage of change in price—an approach commonly employed to interpret demand elasticity in microeconomics. The primary dependent variable in this approach is the rate of change in demand elasticity across the demand curve (also known as alpha [α]; see Gilroy et al., 2020). In log–log space, the demand curve can be visualized as biphasic: It begins with *inelastic* demand where one unit increase in unit price results in less than one unit decrease in reinforcer consumption, until it switches to *elastic* demand where one unit increase in unit price results in greater than one unit decrease in consumption. In log–log space, a behavioral economist can examine the demand-curve function to isolate the unit price with exact unit elasticity, where a one unit increase in price is met with exactly one unit decrease in consumption—put simply, the point where demand shifts from inelastic to elastic. The point of *unit elasticity* (i.e., where 1% unit increase in price is met with exactly 1% unit decrease in consumption) is known as P_{max} (i.e., price yielding maximum output; Gilroy et al., 2019). Mathematically, the responses emitted by an organism to defend consumption at P_{max} result in maximum output, known as O_{max} (where O_{max} can be solved by multiplying consumption at P_{max} by the unit price associated with P_{max}). The notion of O_{max} is best visualized in a work curve, where response output—that is, the number of responses emitted to earn the total number of reinforcers consumed—is plotted as a function of unit price (see right panel of Figure 1).

Demand curves also permit analysis of demand intensity, which is the amount of reinforcer consumed with no or little unit price (i.e., the *y*-intercept of the demand curve; similar to the notion of a reinforcer bliss point; see Kagel et al., 1985). Note that formal models of demand can derive these indices as fitted parameters (see discussion by Kaplan et al., 2019) or by simply reporting observed values in the raw data (e.g., calculating the maximum product of unit price and reinforcers consumed at that experienced unit price provides an observed O_{max}, where the unit price at which observed O_{max} occurs defines observed P_{max}). Finally, the common metric of breakpoint used in PR self-administration studies can also be obtained through demand-curve analysis (i.e., the last price associated with reinforcer consumption [BP_1] or the first price without reinforcer consumption [BP_0]), rendering the demand-curve approach highly adaptable and conceptually consistent with traditional approaches to quantifying relative reinforcer efficacy. This demand curve approach can be applied across both human and nonhuman studies.

As noted above, traditional assays employing self-administration of the study drug by humans match the direct operant-testing protocols used in nonhuman experimental analyses of behavior. While self-administration protocols are the “gold standard” in drug abuse potential testing (Gauvin et al., 2018; Henningfield et al., 1991; O’Connor et al., 2011), these procedures may not be well suited to scalable clinical research due to resource constraints, such as costs and time. These procedures also present practical and ethical barriers when conducting work among adolescent populations or people seeking treatment for a substance use disorder—those groups to which primary prevention and treatment research ideally generalizes. Self-administration methods emerged from the nonhuman laboratory, where subjects are largely homogeneous and both inter- and extra-experimental variables are nearly exclusively under researcher control. However, as the cocaine epidemic

raged in the United States during the late 20th century (Hamid, 1992), the need for human clinical research became critical. Policy makers and researchers alike recognized the importance of individual differences in drug-seeking behavior (see Budney et al., 1992), which necessitated larger sample sizes and community-dwelling participants to permit proper analyses of covariates and capture the nuances of the diverse backgrounds of drug users. These needs render self-administration studies impractical for addressing many research questions—especially those concerned with behavioral variability, treatment engagement, or broader contextual influences rather than pharmacological mechanisms of action per se.

Concurrent to Bickel's development of behavioral economic tasks, the field of experimental economics had been actively developing and refining its own methods. Just as self-administration tasks predominated in behavioral pharmacology research, the use of live auctions emerged as the task du jour for experimental economics (Kagel, 2020; Smith, 1989). In the auction methods, researchers would invite relatively homogenous samples—often undergraduate students—to participate in a live auction for a good to render its valuation. Through bidding and competition, the realized price proxied the market value, permitting the assessment of demand elasticities. However, as with addiction research, experimental economics began to recognize the limits on external validity imposed by the tightly controlled nature of auction methods. To that end, experimental economics began using *posted price* methods, where participants indicate their willingness to pay varying costs for target commodities, circumventing the need for resource-intensive auction procedures (Plott, 1986). The posted price method showed consistency with auction methods and expanded the scale at which experimental economic research could be conducted.

In the early 1990's, Griffiths and colleagues similarly began experimenting with a *multiple-choice procedure* as a form of a posted-price task to quantify the relative reinforcing efficacy of drugs. In the novel multiple-choice procedure (Griffiths et al., 1993), participants with a history of recreational drug use sampled the effects of ingesting each of the three choice options—a placebo and two different doses of sodium pentobarbital. The participants were blinded to the identity of each option; however, each of the three options was associated with a particular color code (red, blue, or yellow). They then responded in choice tasks where each color-coded option was presented as an alternative to an ascending financial reward and the participants selected either the drug option (based on color) or the financial reward amount. Upon completion, one of their choices was selected for actual experience—that is, either consuming the chosen drug or receiving the indicated financial reward. The multiple-choice procedure thereby served as a form of a posted-price task, where crossover points (from drug to money) quantified the financial value of the drug, much like a PR task quantifies value based on breakpoint.

The multiple-choice procedure, similar to a PR assay and its breakpoint, was limited in that the crossover value provided only a single facet of reinforcer efficacy. As articulated by Johnson and Bickel (2006), such single crossover values and PR breakpoints provide only a single-point estimate of reinforcing efficacy, which is limited to the price values assessed and fails to provide a comprehensive and fully parametric evaluation across all potential price points. As Johnson and Bickel later demonstrated, the demand-curve

approach provides a superior account of relative reinforcing efficacy. But such demand-curve modeling requires a measure of consumption quantity at each price point—not just a binary choice. The multiple-choice procedure was not readily amenable to demand-curve analyses; this was a major limitation, as demand analyses had begun to emerge as a leading approach to behaviorally quantifying abuse potential and relative reinforcing efficacy of drugs.

In the late 1990s, Petry and Bickel (1998) published the first simulated purchasing task for drugs with demonstrated abuse potential, directly translating the idea of posted-price research to build on Griffiths and colleagues' simulated approach to relative reinforcing efficacy of drugs (Griffiths et al., 1993; Kidorf et al., 1995). Specifically, Petry and Bickel used a structured, simulation-based purchasing task to model polydrug decision making among outpatient participants with opioid dependence. They supplied participants with imitation money and asked them to hypothetically purchase drugs—heroin, valium, cocaine, marijuana, and alcohol—based on realistic street prices and constrained budgets. In Experiment 1 of their study, heroin prices varied across trials ($3, $6, $11, and $35 per bag), whereas the prices of other drugs remained fixed: valium at $1 per pill, cocaine at $15 per 1/8 gram, marijuana at $5 per joint, and alcohol at $1 per drink. Participants had a constant income of $30 per trial and made purchasing decisions accordingly. In Experiment 2, both heroin and valium prices varied independently, allowing for a detailed examination of cross-price elasticity. Heroin prices again ranged from $3 to $35 per bag, whereas valium prices ranged from $0.33, $1, $3, to $10 per pill. Experiment 3 manipulated income levels ($30, $100, $156, $300, and $560) while keeping all drug prices constant. This allowed assessment of income elasticity for each drug class. The task's design enabled estimation of behavioral economic indices—own-price and cross-price elasticity coefficients—that captured substitution and complementarity patterns across drug classes.

Petry and Bickel's (1998) use of finely calibrated and ecologically valid price points provided a novel depiction of drug-demand dynamics, advancing the feasibility of hypothetical simulations in substance use research. Yet, this task did not fully yield demand data in a format directly analogous to that produced by preclinical nonhuman self-administration studies. Specifically, their task emphasized cross-commodity choice under varying price and income constraints but lacked the fine-grained, continuous assessment of consumption as a function of unit price. Behavioral economists at the time—including Bickel—had written extensively that the multifaceted view of relative reinforcing efficacy rendered by the parametric evaluation of a reinforcer's unit price in isolated consumption arrangements served as the core advantage of operant demand-curve procedures in animal models (Allison, 1979; Bickel et al., 1993; Hursh, 1993; Kagel et al., 1981). Thus, additional translation was necessary to arrive at a simulation procedure that was analogous to operant demand in preclinical assays.

In 1999, Jacobs and Bickel addressed the aforementioned limitations of earlier simulated purchasing tasks by introducing a streamlined, questionnaire-based methodology that more closely mirrored the structure and output of operant self-administration studies in nonhuman models. Rather than assessing cross-drug substitution under constrained budgets, cigarette smokers with opioid dependence reported how many units of a single drug—heroin or

cigarettes, in isolation—they would purchase at each of 15 escalating unit prices, ranging from $0.01 to $1,120. This approach yielded dense, within-subject consumption data (i.e., quantity purchased) across a continuous unit-price range, enabling the construction of individualized demand curves. To that end, the task produced parameter estimates such as demand intensity, elasticity, P_{max}, and O_{max}, which paralleled the quantitative indices being popularized in preclinical studies on drug abuse potential. By translating these operant principles into a human self-report format, Jacobs and Bickel provided the first fully parametric human drug demand curves, effectively bridging the methodological gap between hypothetical simulation and operant self-administration, laying the groundwork for a rapidly expanding literature in human operant behavioral economics.

The publication of Jacobs and Bickel (1999) permitted a new wave of clinical research in substance use and addiction (see discussion on hypothetical purchase tasks [HPTs] for clinical models of substance use by Koffarnus & Kaplan, 2018). Beyond addressing the abuse potential of drugs in clinical populations, the formulation of a HPT (see also Roma et al., 2016) paved the way for behavioral economics to become both a feasible and scalable framework to address a range of human concerns. The general HPT developed by Jacobs and Bickel has since been translated to address a range of other drugs, leading to substance-specific tasks such as the alcohol purchase task (APT; Kaplan et al., 2018; Murphy et al., 2006), cigarette purchase task (CPT; MacKillop et al., 2008; Reed et al., 2020), and marijuana purchase task (MPT; Aston & Meshesha, 2020; Collins et al., 2014), to name a few.

Hypothetical purchase tasks not only advanced the field's understanding of the relative reinforcing efficacy of drugs in clinical samples but also provided a framework for studying the behavioral economics of other issues of societal concern such as behaviors serving as risk factors for skin cancer (Reed et al., 2016), medication adherence (Jarmolowicz et al., 2020), sustainable actions for addressing climate change (Gelino et al., 2023), vaccine acceptance (Hursh et al., 2020), and factors influencing distracted driving (Hayashi et al., 2019). Moreover, the HPT can serve as a tool for experimental public policy, where the vignettes and contexts embedded in the task can be manipulated to safely test policy proposals such as happy-hour laws for alcohol consumption (Kaplan & Reed, 2018), dosing restrictions in nicotine products (Higgins et al., 2017), late night transportation options on college campuses (Gelino et al., 2024), and availability of contraception (Strickland et al., 2020)—each of these would be ethically concerning to test in the field without prior simulations. Indeed, the HPT has been increasingly applied to examine potential behavioral effects of policy considerations well beyond the field of addiction and pharmacology (Reed, Gelino, et al., 2022; Roma et al., 2017).

Despite the proliferation and success of HPTs in and beyond behavioral economics, critics warn that the hypothetical nature of the tasks compromises their validity (e.g., Hausman, 2012; Lloyd, 1994).[1] Worse still, others view the HPT as antithetical to the tenets of

[1]Note that recent reviews have documented robust psychometric performance in HPTs (e.g., Miller, Reed, et al., 2023; Strickland, Campbell, et al., 2020), including important empirical demonstrations that hypothetical tasks (a) perform consistently with incentivized versions (e.g., Amlung & MacKillop, 2015; Gelino et al., 2025), (b) appear to capture macrocontingencies (see Glenn,

behavior analysis, where free-operant responding and concomitant experiential outcomes remain the gold standard. To outsiders, these concerns appear well founded. Yet from a radical behaviorist perspective, such concerns overlook a fundamental assumption: “Private events such as thinking, although not publicly observable, are observable to one person, are behaviors, and are controlled by the same stimulus-response relations as other behaviors” (Hake, 1982, p. 23).

An important but underappreciated aspect of Jacobs and Bickel’s (1999) approach was that their HPT embedded components of verbal behavior that sought to control covert verbal responding related to other stimulus–response relations known to be implicated in operant demand. Their approach thereby directly aligned with the broader goal of human operant research put forward by Hake (1982): to test whether principles discovered in nonhuman contexts hold in humans under experimentally controlled verbal contexts, treating self-report as a bona fide operant and not merely introspective data. For example, the initial vignette instructed participants to “assume that you have no other drugs available to you” and “you cannot get drugs or cigarettes through any other source, other than those you buy here” when completing the task. This language controlled the availability of potential substitutes/complements (Imam, 1993; Kearns, 2019), effectively closing the virtual economy. Additional language instructed them that “Everything you buy is, therefore, for your own personal consumption within a 24-hour period,” which imposed a temporal budget. The full Jacobs and Bickel (1999) vignette is provided in the Appendix, along with a contemporary example of the current CPT (Reed et al., 2020) vignette language based on the Jacobs and Bickel model.

The HPT shares some characteristics with actual consumer behavior in that responses may be influenced by reinforcement histories, with the operant of interest—purchasing—occurring in the absence of direct reinforcement.[2] That is, in both simulated and actual purchasing events, the putative consumer response to a purchase occurs before the consequence is engaged. Moreover, while HPTs may sacrifice some degree of ecological precision by removing direct contingencies, they compensate by allowing for experimental manipulations that would be ethically or practically infeasible in naturalistic contexts (see the quote at the opening of this article). The hypothetical format enables researchers to examine price sensitivity, access restrictions, and drug substitution effects without exposing participants to pharmacological risk or reinforcing maladaptive behavior. In this way, the HPT represents one approach that extends experimental options, affording control and flexibility that complements rather than contradicts the foundational goals of behavior analysis.

The resulting HPT procedure, introduced by Jacobs and Bickel (1999), represented a pivotal methodological development; still, the empirical influence and scope of its legacy have

2004) from active cultural contexts (e.g., Acuff et al., 2023; Reed et al., 2023), and (c) result in responses sensitive to real-world manipulations to subject-level contexts such as acute withdrawal or cue reactivity (see Acuff et al., 2020; e.g., Becirevic et al., 2017).

[2]Conceptually, simulated demand is much like hypothetical delay discounting assays in which the participant’s “self-report” response is a valid verbal operant under the control of the verbal context programmed by the experiment (see discussion by Odum, 2011). From the perspective of the experimental analysis of behavior, such self-reports *are* operant behavior in their own right—subject to antecedent control, reinforcement histories, and contextual variables like any other measurable response (Critchfield et al., 1998).

not yet been comprehensively documented. Given the widespread adoption, versatility, and critiques surrounding the HPT since Jacobs and Bickel's seminal 1999 publication, a comprehensive evaluation of its scientific influence is timely and warranted. To that end, this article systematically examines the legacy of Jacobs and Bickel's original hypothetical drug purchase task using two complementary review methodologies. In Study 1, we conducted a bibliometric analysis to quantitatively map the academic influence of Jacobs and Bickel (1999) by identifying patterns of citations and coauthorship networks across 25 years of scholarship. In Study 2, we conducted a systematic review to qualitatively synthesize empirical findings from studies employing HPTs to assess drug demand. Collectively, Studies 1 and 2 provide both a quantitative depiction and qualitative synthesis of how this methodological innovation reshaped research trajectories, informed public health policies, and expanded behavioral economic research into diverse domains.

STUDY 1: BIBLIOMETRIC LEGACY

The purpose of Study 1 was to quantitatively assess the scientific influence of Jacobs and Bickel's (1999) introduction of the HPT by mapping its citation patterns and intellectual diffusion over the past 25 years. We used bibliometric analysis and bibliographic coupling to identify the fields, journals, and scholarly networks that have integrated the HPT, revealing both the chronological trajectory and disciplinary breadth of its influence.

Method

To evaluate the bibliometric legacy of Jacobs and Bickel's (1999) introduction of the HPT, we first collected citation data by identifying all peer-reviewed articles that cited Jacobs and Bickel through June 2025. Citation data were retrieved on July 8, 2025, from Digital Science's Dimensions platform, available at https://app.dimensions.ai (see also Hook et al., 2018). We then analyzed the rate of citations in relation to major milestones in the history of the HPT. We next performed a bibliographic coupling analysis on those articles that cited Jacobs and Bickel. Articles citing Jacobs and Bickel (1999) were exported for bibliographic coupling analysis using VOSviewer (version 1.6.20; van Eck & Waltman, 2010), a standard tool for mapping and visualizing bibliometric networks. Bibliographic coupling quantifies intellectual overlap by assessing the number of shared references between documents. Unlike cocitation analysis, which examines how often two articles are cited together, coupling focuses on commonalities among references in the citing documents themselves —an approach particularly apt for delineating contemporary thematic clusters anchored to a common scholarly source.

VOSviewer computed coupling strengths based on the count of shared cited references between each document dyad. To enhance the stability and interpretability of the coupling network, we restricted the analysis to documents sharing at least two references. The resulting similarity matrix was visualized using a force-directed layout algorithm, where proximity among nodes—each representing a journal—reflected the degree of shared citation patterns.

Clusters were identified through modularity optimization, a community detection algorithm akin to the Louvain method (see Blondel et al., 2008; van Eck & Waltman, 2010). This

technique maximizes the density of intracluster links relative to intercluster links. Cluster identity was visually encoded through color, whereas node size reflected total link strength —that is, the sum of coupling ties to other journals. Edge thickness corresponded to the magnitude of coupling between journal pairs. The visualization was limited to journal-level nodes to highlight the diffusion of Jacobs and Bickel's (1999) contribution across disciplines.

Results and discussion

We identified 287 unique documents that cited Jacobs and Bickel (1999). The first citation of Jacobs and Bickel (1999) was by Carroll (2000), who evaluated Meisch's (2000) proposed measure of relative persistence as a way to quantify the reinforcing effectiveness of drugs. Carroll specifically cites Jacobs and Bickel (1999) to support the validity of behavioral economic metrics, noting that P_{max} has been shown to correlate highly with breaking points on PR schedules and highlighting the utility of behavioral economics in assessing drug reinforcement. The next two citations came from articles on delay discounting, using the Jacobs and Bickel study to underscore the importance of using hypothetical measures as behavioral proxies to understand the strength of drug dependence.

The first article to cite Jacobs and Bickel (1999) methodologically came from Murphy and MacKillop (2006), who translated Jacobs and Bickel's general HPT approach to assess alcohol demand in college students. The Murphy and MacKillop HPT for alcohol became known as the APT, which in retrospect constituted a watershed moment in HPT methodology (see Kaplan et al., 2018). As depicted in Figure 2, the publication of the APT was an inflection point in the bibliometric legacy of Jacobs and Bickel's article. From 1999 to 2006—the first epoch in the history of the HPT for quantifying drug demand—the rate of citations to Jacobs and Bickel was 1.0 citation per year. We view the period from 2006 to 2016 as the second epoch of HPT development. In this translational period, tasks such as the APT and the CPT (MacKillop et al., 2008; see Reed et al., 2020) became mainstays in the behavioral economic study of human drug dependence and demand. Over this period, the rate of citations increased to 9.4 per year (see Figure 2). This translational epoch concluded in 2016, with the publication of Roma et al.' (2016) concise yet authoritative overview of HPTs within behavioral economics.

The Roma et al. (2016) article provided the first thorough account of HPT methodological advantages, empirical validity, and practical utility in assessing the demand for both licit and illicit commodities. The article was particularly important for establishing best practices and clarifying the conceptual foundations of HPTs, positioning them as efficient and reliable tools for quantifying reinforcer valuation in both clinical and policy contexts. It also underscores the translational relevance of Jacobs and Bickel's (1999) foundational work by tracing how HPTs have evolved into a standard method for evaluating both consumer behavior and addiction-related decision making. Thus, Roma et al. established general methodological standards for HPT development regardless of clinical applications.

The third epoch of HPT research spans 2016 to present. Following Roma et al.'s (2016) HPT methods review, citations of Jacobs and Bickel (1999) increased from 2016 to mid-2025, with citations per year reaching 18.6 (at the time of this writing). This period is

characterized by applications of the HPT to additional drug categories as well as extensions to consumer decisions (see Roma et al., 2017), public health considerations (see Reed et al., 2025), and experimental public policies (see Reed, Strickland, et al., 2022). The scope of HPT applications has further expanded during this period. The following bibliographic coupling analysis examines the breadth of research citing Jacobs and Bickel's work.

The bibliographic coupling analysis revealed a coherent, multidimensional network of journals citing Jacobs and Bickel (1999), resulting in four principal clusters (Figure 3). Each cluster reflects a distinct disciplinary context in which HPTs have achieved sustained uptake and methodological relevance. The red cluster corresponded to the foundational literature in behavior analysis. Journals in this cluster included *Journal of the Experimental Analysis of Behavior* (the major hub of this cluster), *Journal of Applied Behavior Analysis*, *The Psychological Record*, *Perspectives on Behavior Science*, and *Behavior and Social Issues*. These sources demonstrated dense internal coupling, suggesting a strong intellectual continuity from basic operant research to applied and policy-informed inquiry. The prominence of these outlets underscores the HPT's grounding in behavioral principles and its function as a translational bridge within behavior analytic traditions.

The blue cluster was composed primarily of public health and regulatory science journals. Key nodes included *Nicotine & Tobacco Research*, *Tobacco Regulatory Science*, *Preventive Medicine*, and *Tobacco Control*. The composition of this cluster signals the HPT's expanding role as a decision-support tool in public health, particularly in areas involving tobacco regulation and behavioral policy evaluation. The tight interconnections among journals in this cluster reflect a growing consensus around the utility of behavioral economic demand curves in modeling policy-sensitive health behaviors.

The green cluster represented addiction psychology and clinical behavioral pharmacology. Central journals in this cluster included *Addictive Behaviors*, *Drug and Alcohol Dependence*, *Addiction Biology*, and *Alcohol: Clinical and Experimental Research*. Strong coupling within this domain illustrates the centrality of HPT-derived demand metrics in understanding substance use disorders and evaluating pharmacological and behavioral interventions. This cluster indicates a mature integration of behavioral economic methods into clinical addiction science.

The yellow cluster was characterized by interdisciplinary journals at the nexus of behavioral economics, pharmacology, and health behavior. Notable sources included *Pharmacology, Biochemistry and Behavior*, *Behavioral Economics and Healthy Behaviors*, and related interdisciplinary outlets. The thematic coherence of this cluster suggests that Jacobs and Bickel's (1999) framework has spurred research that transcends disciplinary silos, facilitating dialogue between behavioral science and adjacent fields such as neuroeconomics and experimental pharmacology.

Across clusters, several journals functioned as integrative hubs. *Experimental and Clinical Psychopharmacology* exhibited the highest total link strength, reflecting extensive cross-cluster connectivity. Similarly, *Psychology of Addictive Behaviors* and *Addiction* emerged as central nodes spanning behavioral, clinical, and public health literatures. Together, the

structure of the bibliometric network illustrates that Jacobs and Bickel's (1999) introduction of the HPT seeded a diverse yet interconnected research ecosystem. The clustering pattern affirms the method's conceptual flexibility and enduring influence across foundational, clinical, regulatory, and interdisciplinary contexts.

STUDY 2: SYSTEMATIC REVIEW OF DRUG HPT STUDIES

The purpose of Study 2 was to systematically characterize the empirical literature that has employed HPTs to examine drug demand. This review sought to identify the substances most frequently studied, summarize the modeling practices and metrics used, and evaluate the extent to which studies have leveraged experimental manipulations and advanced statistical methods to test behavioral economic theories of drug consumption. This study should serve as not only a survey of the existing landscape of HPTs but also a guide for future research and development.

Method

Search strategy: A systematic review was conducted to identify peer-reviewed studies employing operant demand analyses in the context of drug use. Literature searches were performed in two major electronic databases: PubMed (n = 1,894) and Web of Science (n = 700), using the following search string:

> ("stimulant" OR "cocaine" OR "cigarette" OR "marijuana" OR "cannabis" OR "alcohol" OR "opioid" OR "caffeine" OR "drug") AND ("demand" OR "economic*") AND ("threshold procedure" OR "purchase task" OR "self-administration")

This search strategy was designed to capture empirical studies that used operant economic frameworks, such as HPTs or self-administration methods, to assess drug demand. An additional hand search was performed on existing review articles (González-Roz et al., 2019; Kaplan et al., 2018; Martínez-Loredo et al., 2021; Reed et al., 2020; Strickland, Campbell, et al., 2020; Zvorsky et al., 2019) to identify any eligible studies that were not captured in the database queries (n = 40).

Study selection and screening: All identified records (N = 2,634) were imported into Covidence (https://www.covidence.org/), a systematic review management platform. Covidence was used to facilitate duplicate removal, screening, and data extraction. A total of 1,207 records were excluded as duplicates, including 10 removed manually and 1,197 identified by Covidence's automated detection system.

After de-duplication, 1,427 articles remained for title and abstract screening. This screening was independently conducted by the first and second authors to exclude irrelevant records. Articles including studies that clearly did not involve empirical data, operant demand analyses, or drug-related outcomes were excluded at this stage (n = 970). The remaining 457 articles were subjected to full-text review.

Eligibility criteria: Full-text review was conducted for all 457 articles. Articles were eligible for the present study if they (1) reported empirical data, (2) used operant demand

methods (e.g., purchase tasks, threshold procedures, or self-administration paradigms), and (3) focused on human drug use. Studies were excluded if they were preprints (n = 1), duplicates missed in earlier steps (n = 9), not empirical (n = 20), not published in English (n = 1), nonhuman studies (n = 130), or human studies that did not include an HPT or analogous demand procedure (n = 16). No articles were excluded due to retrieval failure. In total, 280 articles met the full eligibility criteria and were included in the final review (the full bibliography of these articles is provided in Supplemental Materials 1).

Data extraction and consensus coding: To ensure consistency and reliability of extracted information, a team of eight trained reviewers coded the 280 eligible articles on a prespecified set of variables: drugs studied (open ended with post hoc categorization), independent variable manipulations (“between group”; “within-subject”; “mixed designs”; “no manipulation”), demand curve analysis (observed demand, model used, etc.), demand metrics reported (e.g., α [alpha], observed/derived metrics, breakpoint), and demand metric analyses (as defined in Kaplan, Franck, et al., 2021: “two-stage”; “pooled curve-fitting”; “mixed-effects-modeling”; other). Each study was independently scored by two reviewers. Discrepancies in coding were flagged within Covidence and resolved through consensus review. The first and second authors adjudicated all disagreements, reviewed open-ended comments, and finalized the data set for analysis.

PRISMA flow diagram: The study selection process is summarized in Figure 4, which presents a PRISMA flow diagram detailing the number of articles identified, screened, excluded, and retained throughout each phase of the review process.

Results and discussion

Study Characteristics and temporal trends by drug class: The final sample included 280 studies that employed operant demand analyses to examine drug-related outcomes (see Figure 4; the full database of coded studies is available in Supplemental Materials 2). As shown in Table 1, alcohol (n = 127, 45.36%), cigarettes (n = 95, 33.93%), and cannabis (n = 43, 15.36%) were the most frequently studied substances. A smaller proportion of studies focused on other drugs such as opioids (1.43%), cocaine (3.93%), or e-cigarettes (3.93%), with minimal representation of amphetamines, methamphetamines, or heroin. Finally, 36 articles (12.86% of all articles) studied more than one drug type.

These proportions correspond to longitudinal publication trends in the field. As illustrated in Figure 5, cumulative publications examining alcohol and cigarettes began to accelerate in the late 2000s, whereas cannabis-focused demand studies showed a marked increase starting in the mid-2010s. Key inflection points in publication trajectories coincide with foundational articles that introduced and popularized task variants for different substances (e.g., Jacobs & Bickel, 1999; MacKillop et al., 2008; MPT (Collins et al., 2014). These trends also reflect broader shifts in drug policy, public health priorities, and accessibility of standardized HPTs.

Independent variable manipulations and drug comparisons: Despite the growing number of studies, relatively few conducted experimental manipulations within the demand framework. Across drug categories, only 10.36% of studies employed a between-subjects

design, 23.57% used a within-subjects manipulation, and 13.93% used a mixed approach. The majority (52.14%) reported no manipulation of independent variables (Table 1). Moreover, only 6.43% of studies tested multiple doses of a drug, and just 8.57% compared or correlated demand metrics across different drugs. These patterns suggest a heavy reliance on observational or correlational demand designs, with limited exploration of the causal variables that shape demand.

Demand curve models and trends over time: The Hursh and Silberberg (2008) exponential (41.43%) and Koffarnus et al. (2015) exponentiated (40.36%) models were the most used curve-fitting approaches (Table 2). As shown in Figure 6, cumulative use of both models increased substantially after the publication of Hursh and Silberberg (2008) and Koffarnus et al. (2015), respectively. The exponentiated model appears to now outpace the exponential model, reflecting its growing adoption due to its handling of consumption values equaling 0 (i.e., because the exponential model requires a logarithmic transformation of consumption that is problematic for 0 values due to log 0 being undefined; see discussion in Koffarnus et al., 2022). Note that new emerging models propose alternative methods for handling consumption values of zero, bridging the conceptual approaches of both the exponential and exponentiated models (see Gilroy et al., 2021; Rzeszutek et al., 2025). In contrast, cross-price (2.86%) models remain underused, although they may offer valuable insights in multicommodity or substitution studies (see Weinsztok et al., 2022). Unsurprisingly, the linear elasticity model (Hursh et al., 1988) is relatively absent from HPT studies, given that the exponential model was put forward as a replacement for the linear elasticity approach (Hursh & Silberberg, 2008). Although other models have been proposed in the literature (Gilroy et al., 2021; Newman & Ferrario, 2020; Zhang et al., 2022), they remain largely absent from use in drug HPT studies.

Demand metrics and analytic strategies: Alpha (rate of change in elasticity; α) was the most frequently reported metric, included in 82.86% of studies, followed by observed intensity (73.93%), observed O_{max} (74.64%), and observed breakpoint (71.43%). Derived metrics such as derived O_{max} (10.36%) and derived P_{max} (12.50%) were comparatively rare (Table 2), suggesting limited engagement with the full parametric space offered by demand models. Additionally, most studies (77.14%) employed two-stage analyses (see Kaplan, Franck, et al., 2021), whereas pooled fitting (21.43%) and mixed-effects models (2.14%) were used infrequently. The lack of hierarchical modeling approaches may constrain the field's ability to generalize demand functions across individuals or contexts. Nevertheless, the proposal to use this approach is relatively recent (Kaplan, Franck, et al., 2021; Zhang et al., 2022), so this trend may increase as new studies are published and user-friendly technologies are more widely adopted (Kaplan & Reed, 2025).

The limited use of *derived* P_{max} and O_{max} is notable given advances in demand modeling that permit the derivation of these indices (Gilroy et al., 2019, 2021; Koffarnus et al., 2022). Moreover, freely accessible software solutions have been made available that circumvent any technological or computational barriers to their use (Gilroy et al., 2018, 2019; Kaplan et al., 2019; Kaplan & Reed, 2025). A potential explanation for the limited use of derived indices could be the success of correlating observed indices with clinically relevant outcome

measures (e.g., Zvorsky et al., 2019). Nonetheless, the sensitivity and resolution of derived indices may be superior to those of observed indices; yet this remains an untested empirical question.

Across the articles reviewed, it is evident that HPTs have served as efficient, structured tools for quantifying reinforcer value across a variety of drug types, user populations, and experimental conditions. However, the empirical base is constrained in important ways. Most studies are nonexperimental, documenting that greater drug use severity corresponds to more intense or inelastic demand (e.g., González-Roz et al., 2019; Strickland, Campbell, et al., 2020; Zvorsky et al., 2019) but offering limited insight into causal mechanisms. Nevertheless, an emerging body of research has demonstrated the clinical utility of HPT-derived demand indices for predicting meaningful behavioral outcomes. Longitudinal studies have shown that demand indices predict changes in substance use over 3- to 4-year follow-up periods (Acuff et al., 2024; Bird et al., 2024; Gaume et al., 2022), with these associations remaining significant after controlling for relevant covariates, including baseline consumption levels. Studies employing treatment samples have further established that demand indices predict differential response to alcohol interventions beyond pretreatment drinking levels (Gex et al., 2022; MacKillop & Murphy, 2007; Murphy et al., 2015).

Within the limited number of experimental studies identified, these rarely include manipulations that permit direct inference about the behavioral processes shaping demand (cf., Acuff et al., 2020). Nevertheless, a growing number of experimental investigations have consistently demonstrated environmental factors influencing drug demand. Experimental studies have demonstrated that the availability of substitute reinforcers, including nonalcoholic beverages, produces immediate suppression of alcohol demand (Martinetti et al., 2019), whereas the presence of next-day educational or occupational responsibilities attenuates demand for alcohol consumption (Gilbert et al., 2014; Miller, Murphy, et al., 2023; Skidmore & Murphy, 2011). Moreover, treatment studies have revealed that brief alcohol interventions are associated with reductions in demand and that these reductions mediate subsequent decreases in drinking over time (Gex et al., 2022; Meshesha et al., 2020; Murphy et al., 2015). Experimental research has also identified more modest effects of craving and other visceral states on demand. Complementing these experimental findings, recent correlational investigations have implicated drinking motives, reward deprivation, and socioeconomic disadvantage (Murphy et al., 2025), as well as negative affect, as contributors to elevated demand. These findings suggest that demand indices are sensitive to both momentary contextual influences and broader environmental conditions, supporting their utility as targets for intervention development.

The relatively low proportion of research designs using experimental manipulations in HPT studies stands in contrast to a rich body of preclinical research parametrically manipulating variables within and across drug classes to parse relative abuse potential. Limited research has directly compared HPTs with traditional measures of self-administration in human participants (e.g., drug vs. money choice). However, correspondence has been observed in this limited literature (e.g., Strickland et al., 2023). Future research should work to adapt foundational questions from traditional self-administration literature—such as evaluating the

influence of drug dose, drug type, or experimentally manipulated constraints like economy type—as a framework for advancing HPTs to more mechanistic, comparative models of drug reinforcement. Doing so will help bridge the gap between preclinical nonhuman research and human clinical findings (Strickland & Lacy, 2020).

Summary

Together, these findings provide a comprehensive portrait of how operant demand methods are used in drug HPTs. The literature is dominated by studies on legal substances—particularly alcohol and nicotine—and favors descriptive/associational over experimental designs. Although demand modeling practices are evolving, particularly with increased uptake of the exponentiated model, there remains a need for broader application of comparative designs, multivariate modeling, and advanced statistical techniques. Future research should seek to close these methodological gaps, enabling more nuanced, causal, and scalable demand-based applications in substance use research.

GENERAL DISCUSSION

Across two complementary analyses, we documented the legacy of Jacobs and Bickel's (1999) publication by examining the trajectory of the HPT from a formative laboratory measure to an established translational instrument. Bibliometric evidence delineated three discernible epochs in the HPT's evolution—initial adoption (1999–2006), translational acceleration (2006–2016), and contemporary diversification (2016–present)—each marked by growth in citations, methodological adaptations, and domain-specific uptake. In parallel, a systematic review confirmed empirical diffusion: 280 peer-reviewed studies spanning 11 substance categories, with alcohol, nicotine, and cannabis most frequently represented. Together, these strands of evidence characterize the HPT as a robust, interdisciplinary platform with sustained capacity to integrate operant demand theory, clinical research, and policy modeling.

Functionally, the HPT represents a significant advance to translating operant behavioral economic principles to human research contexts. The HPT operationalizes demand constructs—intensity, elasticity, O_{max}, and P_{max}—within a simulated context that is methodologically rigorous yet ethically tractable (see Reed, Gelino, et al., 2022). By embedding verbal stimuli that delineate economic boundaries (e.g., fixed budgets, closed economies, restricted substitutes), the original design by Jacobs and Bickel effectively retained the structural contingencies of nonhuman demand studies, preserving some ability to conduct cross-species comparisons (see Strickland & Lacy, 2020). This innovation shifted the methodological landscape, enabling quantification of reinforcer value across diverse human samples and hypothetical policy levers (e.g., taxation, dosing limits) without necessitating actual consumption. Thus, the HPT became a generative template through which behavioral principles could inform addiction science, consumer choice, and public health intervention.

Our synthesis reveals notable consistency in analytic practice, with over 80% of studies employing exponential or exponentiated models of demand. Despite this, the preponderance of research remains descriptive, with fewer than one in four studies incorporating

experimental manipulations of contextual variables (e.g., price framing, unit dose). Moreover, while core indices such as intensity and observed O_{max} are routinely reported, derived metrics (e.g., derived P_{max}; Gilroy et al., 2019) and model-based approaches (e.g., mixed-effects modeling; Kaplan, Franck, et al., 2021) remain underused. These omissions underscore a critical opportunity: Future research could benefit from leveraging the experimental malleability of the HPT to enhance causal inference and analytic precision through within-subject manipulations and modeling strategies.

Use of the HPT has diffused unevenly but strategically across disciplinary lines. Behavior analysts have adapted the task to examine theoretical constructs (e.g., reinforcer substitutability; see Weinsztok et al., 2022) and regulatory mechanisms (e.g., "happy-hour" prohibitions; see Roma et al., 2017). Recent translational work in applied behavior analysis has begun leveraging HPTs to inform clinical treatments, such as token system arrangements (e.g., Regnier et al., 2025) and contingency management incentives (e.g., Traxler et al., 2023). Addiction scientists, in contrast, often deploy the HPT to assess clinical outcomes and abuse potential (Aston & Cassidy, 2019; Kaplan, Crill, et al., 2021). These studies—similar to the main findings of our systematic review—typically investigate continuous associations between substance use metrics and demand indices rather than effects of experimental manipulations. Finally, public health researchers model population-level responses to regulatory interventions, often modeling experimental policies' effects on aggregate demand (see Reed, Gelino, et al., 2022; e.g., Gelino et al., 2024). The proliferation of HPT studies in interdisciplinary journals evidences its utility as both a common metric and a customizable framework. This dual function facilitates cross-sector alignment in the empirical study of consumption and regulation.

The trajectory mapped by this review underscores not merely the methodological pervasiveness of HPTs but also the conceptual shift spurred by Jacobs and Bickel (1999). Their original insight—that self-reported consumption under parametric price manipulations could approximate the operant dynamics observed in laboratory-based drug self-administration—served as a pragmatic and theoretical inflection point. In so doing, Jacobs and Bickel offered a rare synthesis: a tool that was at once scalable, ethically tractable, and analytically rigorous. Twenty-five years on, the proliferation of HPTs across diverse populations, settings, and substances suggests potential ecological and translational utility, although continued validation research is warranted. Therefore, the legacy of Jacobs and Bickel (1999) is not only historical but infrastructural: Their contribution forms the epistemic scaffolding upon which contemporary behavioral economic assessments of drug reinforcement are routinely built (see Weinsztok et al., 2025).

The present synthesis, then, can be read as a testament to the enduring relevance of Warren Bickel's work. Indeed, the methodological precision and theoretical coherence introduced in the original Jacobs and Bickel (1999) vignette task persist in modified and expanded forms throughout the empirical literature we reviewed. Far from a methodological curiosity, the Jacobs and Bickel HPT framework has become a conceptual *lingua franca* within applied behavioral economics. As newer adaptations of the HPT continue to be developed—to address emerging substances, sociocultural shifts, and regulatory landscapes—they do so on

the foundation laid a quarter-century ago. Such durability, we contend, reflects not only the utility of the method but the conceptual foresight embedded in its design.

The future of HPT research lies in more deliberate integration of experimental manipulations to analyze moderators of demand (e.g., framing, pharmacological state, access conditions). The adoption of multilevel or Bayesian modeling frameworks would better accommodate nested data structures and enable cross-study generalization (Kaplan, 2025). Methodological innovations—such as ecological momentary assessment and longitudinal task administration (e.g., Aston et al., 2024; Motschman et al., 2022)—could also illuminate the dynamic processes of valuation and behavior change. Open-source analytic tools (e.g., *beezdemand*, *shinybeez*; Kaplan & Reed, 2025) and reporting standards will be essential for sustaining transparency and reproducibility (see Gilroy & Kaplan, 2019). Finally, expanding HPT application to emerging drug classes (e.g., new tobacco products, psychedelics; e.g., Dolan & Johnson, 2020; Heckman et al., 2018) or preventive health care options (e.g., prescription medications, contraceptives; e.g., Jarmolowicz et al., 2020; Strickland, Marks, et al., 2020) will further test the scope and limits of behavioral economic generality.

In parallel, new frontiers in HPT research may be realized by leveraging digital phenotyping technologies to contextualize simulated demand within real-world behavioral patterns, such as geospatial proximity to drug cues or time-linked affective states. Examining demand within the complexity of real-world constraints and choices—that is, amidst competing alternative reinforcers—will further advance the growing consensus that Bickel's reinforcer pathology model (see Bickel et al., 2014) is enhanced with contextualization (e.g., Acuff et al., 2023). This contextualization approach can also be translated to the legal drug market. For example, the adaptation of the HPTs to the complexity of the drug marketplace's concurrent drug choices—such as the Experimental Tobacco Marketplace—has created a more face-valid approach to understanding drug consumer decisions (e.g., Quisenberry et al., 2016). Additionally, neuroeconomic approaches may offer mechanistic insights by linking demand indices to neural markers of valuation and control. And as policy contexts continue to evolve, embedding HPTs within implementation science frameworks could generate rapid, scenario-based forecasts of behavioral response to regulatory shifts (for example, the Illegal Experimental Tobacco Marketplace; Freitas-Lemos et al., 2021). These innovations signal a maturation of the field, one that builds on the foundational logic of Jacobs and Bickel (1999) while embracing new methodological ecosystems.

Another promising trajectory involves using HPTs to probe demand for not only substances but for behavioral health interventions themselves (Gilroy & Kaplan, 2020). Just as drug valuation informs abuse potential and risk assessment, simulated demand for treatment —framed around variables such as cost, inconvenience, stigma, or expected benefit— could illuminate behavioral barriers to care engagement. HPTs could be adapted to model willingness to initiate or persist in treatment under varied programmatic conditions (e.g., telehealth access, medication provision, contingency management availability). This approach would extend the utility of HPTs into the domain of service design and delivery, with potential implications for tailoring interventions, triaging resources, and improving uptake across diverse populations.

HPTs have been proposed as one potential tool within regulatory science contexts, particularly for abuse potential assessment. Koffarnus (2023) has suggested that behavioral economic demand measures, including HPTs, might serve as complementary methods in abuse potential evaluation, although integration into regulatory frameworks would require additional validation and standardization research. Because HPTs can simulate consumption behavior across escalating prices, they offer quantifiable indices of reinforcing value that are sensitive to pharmacological differences among substances, even in the absence of actual administration. This capacity is especially valuable in premarket evaluations of novel psychoactive compounds, where ethical or logistical constraints limit direct self-administration testing. As regulatory science continues to evolve, research examining the potential utility of HPTs within abuse potential assessment frameworks may inform future methodological developments, pending appropriate validation studies.

These findings document the evolution of HPT methodology and its applications across diverse research contexts. While the literature demonstrates methodological flexibility and broad research uptake, continued validation research and methodological refinement will be important for determining optimal applications and limitations. Continued refinement will ensure its relevance as a cornerstone methodology in the evolving science of consumption, valuation, and policy intervention. That the HPT now informs not only substance valuation but also treatment engagement, policy simulation, and mechanistic inquiry is a testament to the enduring foresight of Jacobs and Bickel (1999), whose foundational contribution continues to scaffold contemporary behavioral economic science.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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DATA AVAILABILITY STATEMENT

A spreadsheet of the studies included in the review is available in Supplemental Materials 1. The database of coded variables for all included studies is available in Supplemental Materials 2.

APPENDIX A: HPT VIGNETTE EXAMPLES

A.1 Original Jacobs & Bickel (1999; p. 415) Heroin and Cigarette HPT Vignette

In the questionnaires which follow we would like you to pretend to purchase heroin and cigarettes as you would have before entering treatment. Please answer the questions honestly and thoughtfully. The goods you may buy and their prices are listed on the following sheets. You may buy as much or as little as you'd like, and there are no consequences to your using the heroin. So, assume this is a study that has been approved by the police and all other organizations.

Also, assume that you are NOT in treatment; you are not receiving buprenorphine, naltrexone, or antabuse. In other words, the only drugs you will receive are those you purchase here. Also, assume that you have no other drugs available to you. You cannot purchase more drugs or cigarettes, or any other drugs or tobacco products except those you choose below. Therefore, assume you have no other drugs or cigarettes stashed away, you have no prescriptions for anything, and you cannot get drugs or cigarettes through any other source, other than those you buy here. Also, assume that the heroin and cigarettes you are about to purchase are for your consumption only. In other words, you can't sell them or give them to anyone else. You also can't save up any heroin or cigarettes you buy and use them another day. Everything you buy is, therefore, for your own personal consumption within a 24-hour period.

A.2 Contemporary Cigarette HPT Vignette (from Reed et al., 2020, Supplemental Materials 2)

Imagine a TYPICAL DAY during which you smoke. The following questions ask how many cigarettes you would consume if they cost various amounts of money. Assume that: (1) The available cigarettes are your usual brand. (2) You have the same income/savings that you have now and NO ACCESS to any cigarettes or nicotine/tobacco products other than those offered at these prices. (3) You would smoke the cigarettes that you request within 24 hours; that is, you cannot save, share, sell, or stockpile cigarettes for a later date. (4) You can smoke without any restrictions and without factoring in what might occur in the next 24 hours related to your participation in the study.

There are no "right" or "wrong" responses. Please answer all questions honestly, thoughtfully, and to the best of your understanding as if you were actually in this situation.

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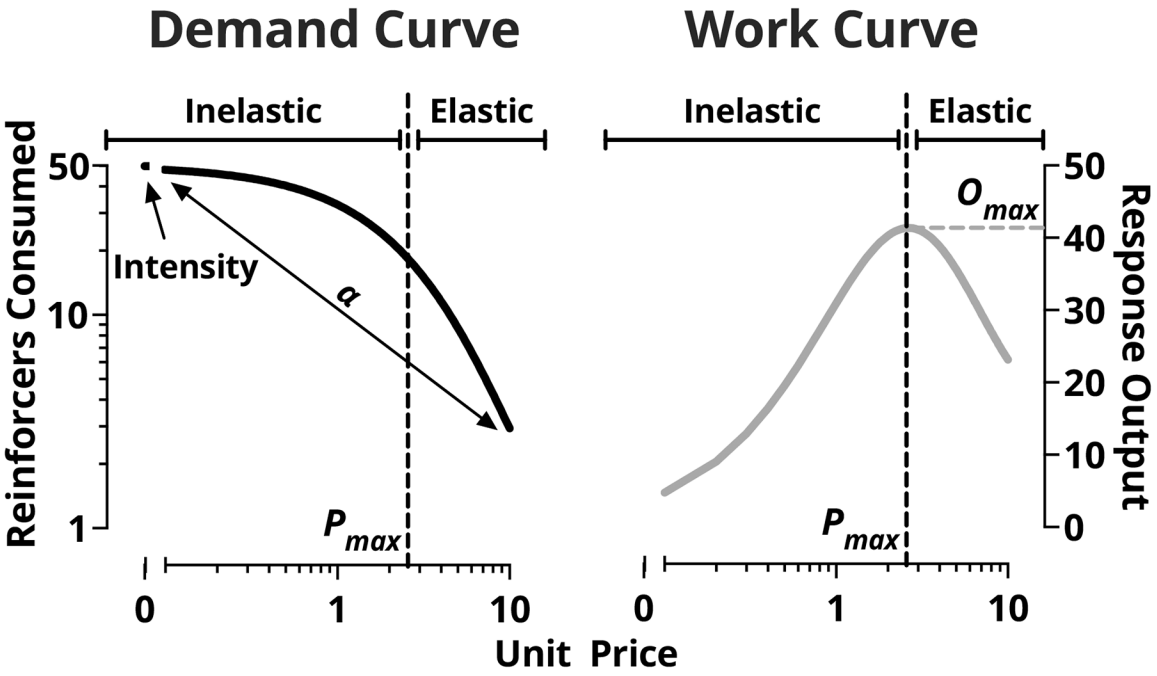

FIGURE 1.
Visual examples of demand (left panel) and work curves (right panel). See text for details.

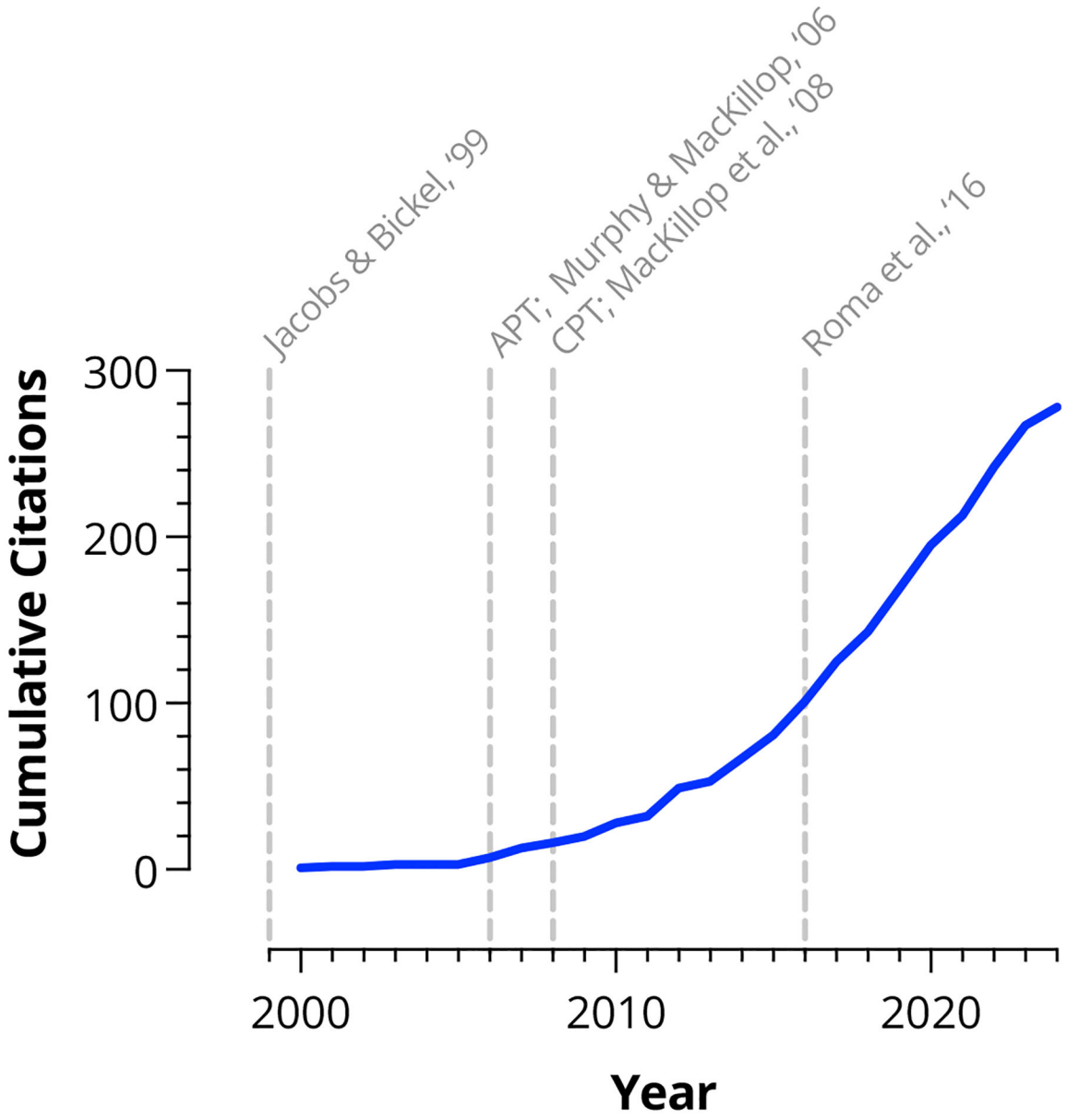

FIGURE 2.
Cumulative citations of Johnson & Bickel (1999). Dashed vertical lines correspond to major HPT publications (see text for details).

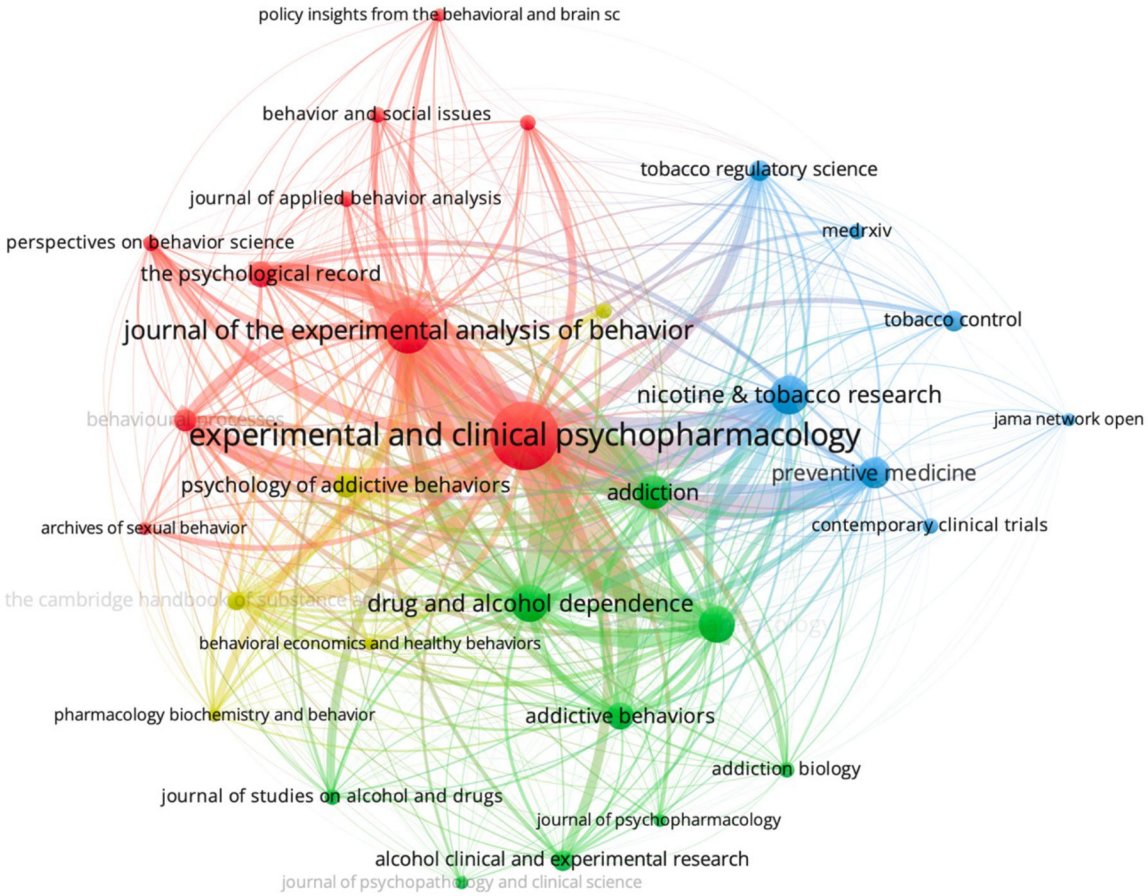

FIGURE 3.

Network visualization of bibliographic coupling among journals citing Jacobs and Bickel (1999), based on shared references. Node size reflects total link strength (i.e., sum of shared citations with other journals). Edges represent bibliographic coupling strength between journals. Colors indicate distinct clusters identified using VOSviewer's modularity optimization algorithm: red = behavior analysis, green = addiction psychology and pharmacology, blue = tobacco and public health, and yellow = neuropharmacology and behavioral economics. Only journals with at least two shared references were included (n = 31). Visualization created using VOSviewer version 1.6.20 (van Eck & Waltman, 2010).

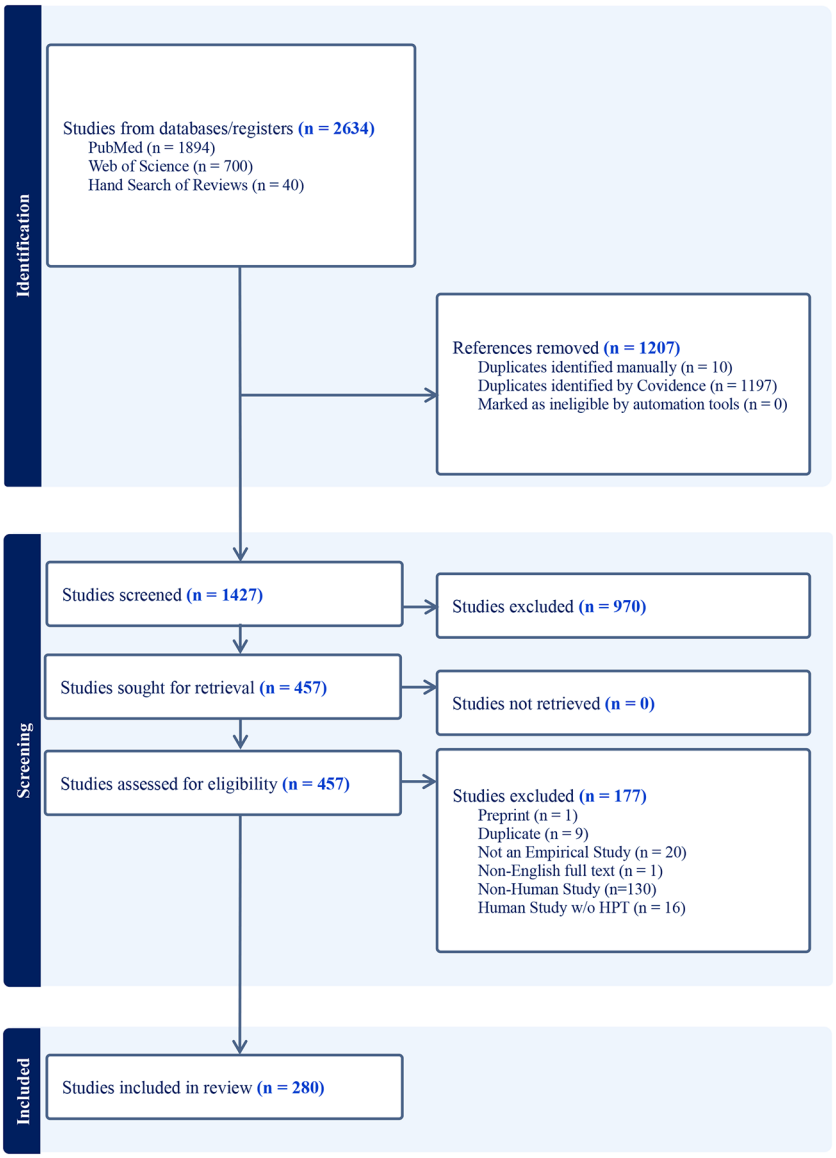

FIGURE 4.
PRISMA 2020 flow diagram illustrating the flow of information through the systematic review process.

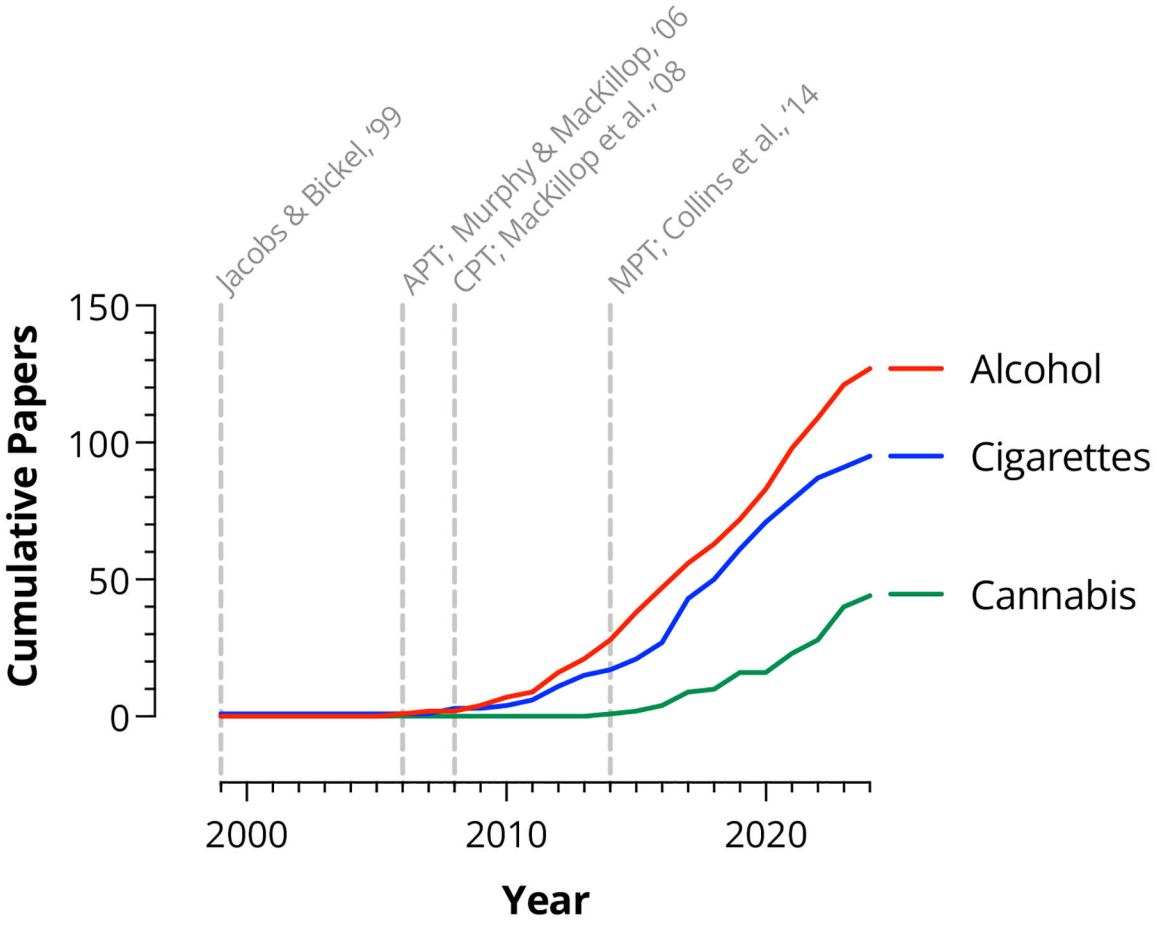

FIGURE 5.
Cumulative alcohol, cigarettes, and cannabis articles identified in the systematic review. Dashed vertical lines correspond to major HPT publications (see text for details).

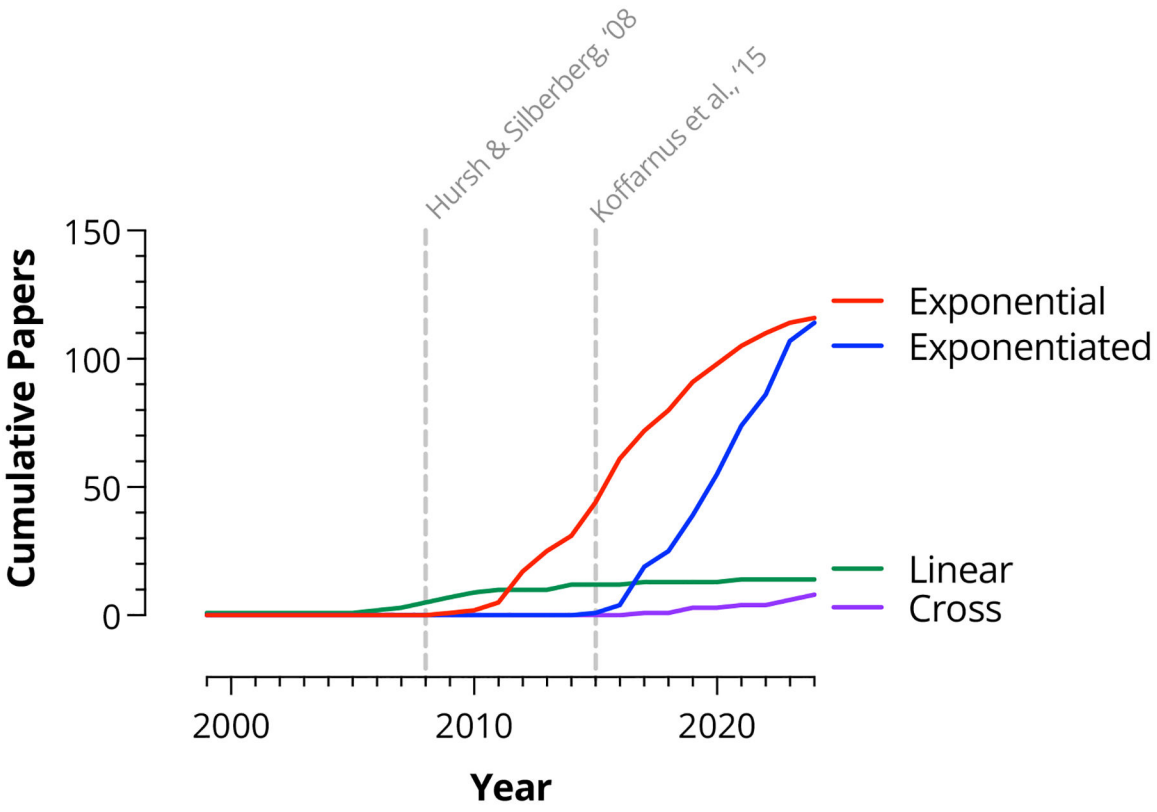

FIGURE 6.
Cumulative articles using the exponential, exponentiated, linear, and cross-price demand models. Dashed vertical lines correspond to major demand modeling publications (see text for details).

TABLE 1

Distribution of drug classes and types of independent variable manipulations in studies using hypothetical purchase tasks.

		Independent variable manipulation *N* (% within drug category)			
Drug	**Drug articles *N* (% of all articles)**	**Between**	**Within**	**Mixed**	**None**
Alcohol	127 (45.36%)	15 (11.81%)	26 (20.47%)	14 (11.02%)	72 (56.69%)
Cigarettes	95 (33.93%)	8 (8.42%)	21 (22.11%)	19 (20.00%)	47 (49.47%)
E-cigarettes	11 (3.93%)	1 (9.09%)	3 (27.27%)	3 (27.27%)	4 (36.36%)
Other nicotine	7 (2.50%)	0 (0.00%)	2 (28.57%)	1 (14.29%)	4 (57.14%)
Cannabis	43 (15.36%)	4 (9.09%)	10 (23.25%)	3 (6.98%)	26 (60.47%)
Cocaine	11 (3.93%)	1 (9.30%)	6 (54.55%)	2 (18.18%)	2 (18.18%)
Amphetamine	1 (0.36%)	0 (0.00%)	1 (100.00%)	0 (0.00%)	0 (0.00%)
Methamphetamine	1 (0.36%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	1 (100.00%)
Opioid	4 (1.43%)	1 (25.00%)	1 (25.00%)	0 (0.00%)	2 (50.00%)
Heroin	3 (1.07%)	0 (0.00%)	1 (33.33%)	0 (0.00%)	2 (66.67%)
Other drugs	6 (2.14%)	2 (33.33%)	1 (16.67%)	0 (0.00%)	3 (50.00%)
Multiple drugs	36 (12.86%)	3 (8.33%)	7 (19.44%)	5 (13.89%)	21 (58.33%)
		N = 29 (10.36%)	N = 66 (23.57%)	N = 39 (13.93%)	N = 146 (52.14%)

Note: Values represent frequency and percentage of articles within each drug category (left) and distribution of experimental manipulation type (right). “None” indicates purely observational HPTs with no experimental manipulation. Column numbers add up to over 100% given that individual drugs are also represented in the “Multiple drugs” category.

TABLE 2

Types of demand-curve models, reported metrics, and analytic approaches in studies using hypothetical purchase tasks.

	N **(% of Articles)**
Demand curve analysis	
Observed demand	238 (85.00%)
Exponential model	116 (41.43%)
Exponentiated model	114 (40.71%)
Linear model	14 (5.00%)
Cross-price model	8 (2.86%)
Brief single-item	12 (4.29%)
Demand metrics reported	
Alpha (elasticity; α)	233 (83.21%)
EV (essential value)	17 (6.07%)
Observed intensity	207 (73.93%)
Derived intensity	23 (8.21%)
Observed O_{max}	210 (75.00%)
Derived O_{max}	29 (10.36%)
Observed P_{max}	161 (57.50%)
Derived P_{max}	35 (12.50%)
Observed breakpoint	200 (71.43%)
Demand metric analyses	
two-stage	216 (77.14%)
Pooled curve fitting	60 (21.43%)
Mixed-effects models	6 (2.14%)
Other	6 (2.14%)

Note: Values represent the number and percentage of articles reporting each model type, demand metric, or analytic method. Percentages are based on the full sample of studies analyzed.