Discrete Choice Experiments and Their Application and Prospects in Mental Health Management

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Abstract

Discrete choice experiment is a preference measurement method based on random utility maximization theory. It quantifies how individuals trade off between different attributes in health decisions by simulating multi-attribute decision-making contexts. This paper systematically reviews the application of this method in mental health management research, where results can be analyzed from four aspects: relative importance, willingness to pay, heterogeneity analysis, and scenario prediction, providing practical guidance for the optimization and stratified delivery of intervention programs. Future efforts should promote the deep integration of this method with psychological theories to reveal the psychological mechanisms underlying preferences, and incorporate it into the curriculum teaching system of psychological methods to expand empirical research tools.

Full Text

Abstract

Discrete choice experiments (DCEs) are preference elicitation methods grounded in the theory of random utility maximization. By simulating multi-attribute decision-making scenarios, DCEs quantify how individuals make trade-offs between different attributes in health-related choices. This paper systematically reviews applications of DCEs in mental health management.

Research outputs are synthesized across four lenses: relative importance, willingness to pay, heterogeneity analysis, and scenario forecasting. The findings offer practical insights for tailoring intervention programs and implementing stratified strategies. Future research should aim to integrate DCEs with psychological theories to better understand the underlying cognitive and affective

mechanisms driving preferences. Additionally, incorporating DCEs methodology into psychology curricula could enrich the methodological repertoire available for empirical research in the field.

Keywords: discrete choice experiments, mental health management, preferences, decision-making

Introduction

Global mental health challenges have become increasingly severe. According to the World Health Organization (2022), the global incidence of anxiety and depression rose by over 25% in 2021. The *Report on National Mental Health Development in China (2021-2022)*, published by the Institute of Psychology of the Chinese Academy of Sciences, reveals that 10.6% of adults are at risk for depression, 15.8% at risk for anxiety, and 14.8% of adolescents face depression risk (Fu & Zhang, 2023). In response to this critical situation, developing evidence-based management and intervention strategies to promote public mental health is urgently needed. In mental health management practice, accurately identifying and quantifying individuals' intrinsic preferences for mental health services and interventions is essential for effectively predicting and guiding mental health behaviors.

However, traditional psychological methods exhibit notable limitations in capturing the "multi-attribute trade-off" process inherent in real-world decision-making. First, experimental methods often oversimplify reality in pursuit of strict variable control, manipulating only a few factors and failing to reproduce the complexity of multiple interacting elements. This approach cannot adequately explain non-linear decision patterns exhibited by individuals. For instance, while most studies on attitudes toward mental health management programs focus on single or limited factors affecting patient attitudes (Lee et al., 2024), actual attitudes are typically shaped by multiple combined factors such as safety, efficacy, waiting time, cost, and service format (Lattie et al., 2022). Second, widely used scale measurement methods decompose complex decisions into self-report items. Although convenient for construct measurement and structural modeling, these scales fail to capture how individuals weigh multiple factors in specific contexts. For example, the Attitudes Toward Psychological Online Interventions (APOI) scale demonstrates good reliability and validity in assessing overall attitudes and acceptability (Ellis & Anderson, 2023), but primarily reflects relatively stable attitudes or knowledge rather than the trade-off process between different options. Such "trade-off" mechanisms involving multi-factor comparisons and compromises cannot be directly revealed through traditional self-report items.

Discrete choice experiments (DCEs) offer a novel approach to address these methodological limitations. By constructing realistic multi-attribute choice scenarios that require participants to make a series of selections among different option combinations, DCEs quantitatively estimate the relative contribution of each attribute to decision-making and reveal trade-off mechanisms and population heterogeneity (Louviere et al., 2000). It is important to clarify that DCEs are fundamentally a choice-based preference measurement method, not a randomized controlled experimental method for assessing causal effects. Grounded in random utility maximization theory and systematically developed by Louviere and colleagues in the 1980s and 1990s, DCEs have achieved significant advances in experimental design (e.g., D-efficiency design) and modeling approaches (e.g., mixed logit and latent class logit models) (Louviere et al., 2000). Since the 1990s, DCEs have been widely applied in health economics and health services research, with the International Society for Pharmacoeconomics and Outcomes Research (ISPOR) publishing comprehensive guidelines that standardize processes for attribute development, experimental design, and results reporting (Hensher et al., 2015).

Notably, current DCEs research in mental health management demonstrates a strong pragmatic orientation, first evident in researchers' selection of attributes that closely mirror real-world decision contexts. Unlike traditional psychological research that often focuses on subjective variables such as attitudes, motivations, and beliefs, DCEs researchers tend to select objective, operational structural variables. For example, in studies of depression treatment preferences, researchers include attributes such as treatment duration, side effect types, and costs, while rarely addressing treatment attitudes or subjective efficacy (Ng-Mak et al., 2017). Similarly, in studies of urban residents' preferences for mental health services, practical factors such as provider type, privacy protection, and insurance coverage are frequently set as key attributes (Yuan et al., 2025). This design approach significantly enhances the operationalizability and policy applicability of research findings, providing direct references for health service optimization and resource allocation.

Although DCEs are well-established in health economics and health services research, their application in psychological research remains in its infancy and has not received sufficient attention. Moreover, no systematic review has applied DCEs to mental health management research. This situation has limited psychology researchers' awareness and application of this method's potential advantages. This article aims to systematically introduce the methodological principles and implementation procedures of DCEs, with a focus on reviewing representative applications in mental health management preference research. We seek to promote the dissemination and practice of this method within psychology, providing methodological support for constructing psychological theories that more closely reflect real decision-making processes and developing more precise personalized intervention strategies.

2.1 Theoretical Foundations of DCEs

Discrete choice experiments are structured choice-task-based preference measurement methods built upon Lancaster's characteristics theory of demand and random utility maximization (RUM) theory. Characteristics theory posits that individuals do not derive utility directly from "goods or services" themselves, but from combinations of their attributes and levels (Lancaster, 1966). Therefore, in DCEs, researchers characterize alternatives using attribute-level combinations, and individual preferences can be understood as the sum of marginal utilities for these attributes (and their levels). This theory establishes the foundational modeling logic of "program → attribute-based representation → measurability."

Random utility maximization theory assumes that individuals will choose the option with the highest total utility from a set of available alternatives. Total utility comprises a fixed component (the observable characteristics of the choice alternative that the model can explain and observe) and a random component (unobservable random factors that influence individual choice) (Boeri & Longo, 2017; Lancsar & Louviere, 2008). This framework connects "attribute differences → utility differences → choice probability," enabling identification of attribute marginal utilities and relative importance. Utility here refers to the degree to which an individual's desires are satisfied or goals are achieved when selecting a service, depending on subjective psychological evaluation. The utility function can be expressed as:

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

where the first term represents fixed utility (the observable component based on attributes and levels), and the second term represents random utility (the unobservable component including unobserved utility and error terms).

2.2 DCEs Design Steps

DCEs design involves several key steps: attribute and level development, choice set construction, data collection, and estimation model selection (Louviere & Timmermans, 1990; Hensher et al., 2015).

2.2.1 Attribute and Level Development

The first step involves identifying key features that may influence choice behavior—attributes—and their divisions into levels (Mangham et al., 2009). Selected attributes and levels need not encompass all factors affecting preferences but must accurately reflect participants' perspectives and experiences while remaining manipulable within the study (Trapero-Bertran et al., 2019). For example, when studying cancer patients' preferences for anxiety and depression screening programs, researchers might establish an attribute such as "screening method" with four levels: online format, paper-and-pencil, telephone, and face-to-face interview (Yim et al., 2021).

Currently, no unified standard exists for attribute and level development, but common approaches include literature review, qualitative interviews, priority setting, expert consultation, and pilot surveys (Wang et al., 2020; Lü et al., 2024). To obtain appropriate attributes and levels, researchers typically recommend combining two or more methods based on study objectives. Too many attributes and levels create excessive cognitive load, while too few fail to capture key preference factors. Settumba et al. (2019) suggest that controlling attributes to 5–8 and levels per attribute to 2–4 represents a reasonable configuration. Such settings effectively balance study complexity and participant burden, thereby more accurately capturing preferences.

2.2.2 Choice Set Construction

After determining attributes and levels, the next step involves constructing choice sets comprising different attribute-level combinations. Each choice set typically contains two or more alternatives. Using the cancer patient screening preference study as an example (Yim et al., 2021), each choice set presents two screening programs (Program 1 and Program 2) and asks participants to select their preferred option (see Table 1).

Although full factorial design (presenting all possible attribute-level combinations) could theoretically exhaust all choice possibilities, the number of choice tasks increases dramatically when many attributes have more than three levels, increasing cognitive burden and compromising data quality (Lancsar & Louviere, 2008). Consequently, most studies employ fractional factorial design, which selects a representative subset of all possible combinations to generate more manageable choice sets, balancing statistical efficiency and participant experience (Johnson et al., 2019).

Optimal DCE designs should generally satisfy four principles: orthogonality, utility balance, level balance, and minimal overlap (Zwerina et al., 1996). Orthogonality means each attribute's levels vary independently; utility balance means each alternative in a choice set has equal utility; level balance means each attribute level appears with equal frequency; and minimal overlap means alternatives within a choice set share few identical levels. While designs satisfying all principles minimize error, this is practically difficult to achieve. Therefore, the most widely used fractional factorial designs in health psychology are orthogonal design and D-efficiency design (Rose & Bliemer, 2014). Orthogonal design satisfies orthogonality, level balance, and minimal overlap, whereas D-efficiency design sacrifices some orthogonality to achieve utility balance, offering greater flexibility and applicability in balancing experimental complexity and data precision (Rose & Bliemer, 2014). Common software for generating choice sets includes Stata (https://www.stata.com/), R (https://www.r-project.org/), and Ngene (https://www.ngene.co/).

Several design considerations can enhance data reliability and validity. First, including opt-out options helps avoid overestimating attribute effects but may reduce valid data if participants avoid making choices (Watson et al., 2017). Second, repeating a choice set can test internal consistency and identify invalid responses, though whether to include repeated data in analysis remains debated

(Johnson et al., 2019). Additionally, using visual aids such as different colors or formats to distinguish attribute levels can reduce cognitive burden without interfering with choice outcomes (Mulhern et al., 2018). Finally, when many choice sets exist, they can be divided into multiple versions, with each participant completing only one version—for example, dividing 64 choice sets into four versions of 16 choices each (Yim et al., 2021)—to reduce participant burden and improve completion quality.

Table 1 Example DCE Choice Set

Screening Program 1	Screening Program 2
Frequency: Once per month	Format: Online questionnaire
Provider: Oncology psychology group at cancer service center	Cost: $300
Cost: $300	
Which would you prefer?	

Note: Adapted from Yim et al. (2021).

2.2.3 Data Collection and Estimation Models

Before data collection, researchers should determine the minimum sample size to ensure cost-effectiveness. de Bekker-Grob et al. (2015) proposed the Orme equation for calculating minimum DCE sample size:

$$N = \frac{500 \times c}{t \times a}$$

where N represents sample size, 500 is a constant, c is the maximum number of levels in the study design, t is the number of choice tasks per questionnaire version, and a is the number of alternatives per choice task (excluding the opt-out option). Note that N represents the minimum sample size *per questionnaire version*, so the total study sample size equals N multiplied by the number of versions. Generally, higher statistical precision requires larger sample sizes. In practice, to ensure adequate estimation precision for both overall and subgroup analyses, researchers should maximize sample size whenever possible.

After questionnaire design, researchers survey target populations to ensure data quality and validity. Following data collection, data should be cleaned and appropriate models fitted for analysis. Early commonly used discrete choice models included standard logit models (binary, multinomial, and conditional logit) and generalized extreme value models (e.g., nested logit). With methodological advances, models capable of handling preference heterogeneity have emerged, such as multinomial probit, mixed logit, and latent class logit models. Mixed logit and latent class logit models are most frequently used. Common analysis software includes NLOGIT, Stata, Biogeme, SAS, MATLAB, Python, and R.

3 Applications of DCEs in Mental Health Management

DCEs have been used to identify individual preferences for anxiety and depression screening and treatment, as well as preferences for broader mental health service systems (Yim et al., 2021; Sonik et al., 2020). Designing programs and delivering services based on understood preferences can better meet patients' diverse needs, thereby improving adherence and treatment outcomes (Lokkerbol et al., 2019; Losi et al., 2021; Muntingh et al., 2019; Tünneßen et al., 2020). Study results can typically be interpreted through three dimensions: (1) relative importance and willingness to pay, which assess how attributes and levels influence health preferences and to what degree; (2) heterogeneity analysis, which examines differences in health preferences across subpopulations; and (3) scenario forecasting, which simulates the probability of individuals choosing a particular program under specific attribute-level combinations. The following sections elaborate on these three dimensions with specific examples from mental health management research.

3.1 Relative Importance

Relative Importance (RI) refers to an attribute's independent contribution to preferences while other attributes remain constant—essentially, its determining influence on overall preferences. RI is typically calculated by computing the range of utility coefficients across an attribute's levels (maximum utility minus minimum utility), then expressing this difference as a percentage of the sum of all attributes' ranges (Lancsar et al., 2007). The formula is:

$$RI_k = \frac{\max(\beta_k) - \min(\beta_k)}{\sum_{k=1}^{K}[\max(\beta_k) - \min(\beta_k)]} \times 100\%$$

where max and min represent the highest and lowest utility values for attribute k, respectively. The sum of all attributes' RI equals 100%; a larger RI percentage indicates greater influence on participants' choices (Lancsar et al., 2007).

In mental health management, RI varies across populations and contexts. Kumar et al. (2023) found that among young pregnant women in Kenya, information delivery method was the most important attribute for depression treatment and perinatal services, followed by treatment duration and provider type—suggesting that "how services are delivered, by whom, and for how long" are key considerations for this vulnerable group. In digital health, Simblett et al. (2023) demonstrated that among adults with depression using mobile health technology, symptom monitoring accuracy carried the highest weight, followed by privacy protection, clinical support level, and user benefits. For youth populations, Ho et al. (2025) showed that Australian young adults aged 18–25 preferred low- or zero-cost online mental health interventions with therapist guidance and moderate total duration (5 hours), reflecting that "affordability plus professional support" is most attractive. Chinese university students prioritized VR games for stress and depression treatment with no adverse events, lowest cost, and moderate treatment duration (Jin et al., 2023). At the German general public level, Phillips et al. (2021) found preferences for evidence-based, low-cost mental health services combining online and offline formats.

These differences reflect how context and population characteristics critically shape preferences. For instance, in resource-limited settings with vulnerable patients (Kenyan pregnant adolescents), individuals emphasize supportive and reliable care processes; in digital health, technical accuracy and privacy become focal concerns; while for younger users, affordability must be balanced with professional guidance. Nevertheless, commonalities emerge across studies: patients universally value intervention effectiveness and appropriate support. Therefore, mental health service design should optimize attribute configurations based on specific population preferences to enhance acceptance and effectiveness.

3.2 Marginal Willingness to Pay

Marginal Willingness to Pay (mWTP) refers to the additional amount individuals are willing to pay to improve a specific attribute level while holding other attributes constant, reflecting their trade-off tolerance for that improvement. The formula for attribute k's mWTP is (Lancsar et al., 2007):

$$mWTP_k = -\frac{\beta_k}{\beta_{cost}}$$

where β_k and β_{cost} represent the marginal utilities of attribute k and cost, respectively. When the utility function is specified as linear in parameters, an attribute's marginal utility equals its regression coefficient, making mWTP the negative ratio of the attribute's coefficient to the cost coefficient. Positive values indicate willingness to pay for a service at that attribute level, while negative values indicate required compensation.

By including a monetary cost attribute in DCEs, researchers can convert participants' preferences for attribute levels into monetary amounts, quantifying the economic value of different levels. For example, Yim et al. (2021) used DCEs to measure cancer patients' preferences for anxiety and depression screening. The study revealed that when oncology nurses administered screening, patients were willing to wait approximately 45 extra days (WTW 44.92 days) and pay about $156.29 more for the service. If screening was conducted by specialized psycho-oncology teams within cancer services, patients' willingness to wait extended to about two months (WTW 61.08 days), with willingness to pay increasing to approximately $214.43. Incorporating cost attributes and calculating mWTP in mental health DCEs helps policymakers understand patients' economic valuations of different service elements, enabling resource allocation and pricing decisions that better align with patient needs.

3.3 Heterogeneity Analysis

Heterogeneity Analysis aims to identify differences in choice preferences among participant subgroups and how these differences affect decision-making. Two primary analytical approaches exist: (1) using mixed logit models to analyze whether preferences for attributes and levels differ significantly across groups with different characteristics (e.g., age, gender, income level); and (2) using latent class logit models to automatically classify participants into latent classes based on preference patterns, exploring within-class homogeneity and between-class differences (Lancsar et al., 2007).

These methods have revealed substantial heterogeneity in mental health management preferences. Sonik et al. (2020) used DCEs to compare depression treatment preferences across racial and gender groups in the United States. Mixed logit analysis found that non-Hispanic White individuals and men preferred medication over talk therapy, while non-Hispanic Black, Hispanic, and female participants showed no clear preference. The study also found that individuals' depression treatment preferences may be influenced by experiences of healthcare discrimination, particularly among non-Hispanic Black individuals and women, who were more likely to prefer medication over talk therapy if they had experienced discrimination. In Australia, Yim et al. (2021) used latent class logit analysis to identify two classes: Class I (73% of participants) preferred regular screening accompanied by cancer nurses, while Class II (27%) favored one-time screening by psychologists, particularly among highly educated women in this class.

In summary, whether in depression treatment modality selection or cancer patient psychological screening service design, "one-size-fits-all" approaches rarely meet all groups' needs. Heterogeneity also exists in broader mental health service system preferences. Yuan et al. (2025) found that Chinese youth tend to prefer low-cost, non-private, and alternative treatment services, but urban differences are significant: Shenzhen youth favor private services, while Beijing youth prefer public services. Customizing service schemes for different regions and population characteristics can better meet diverse needs and improve service utilization and effectiveness.

3.4 Scenario Forecasting

Scenario forecasting uses parameters estimated from discrete choice models to simulate and predict participant choice behavior under specific hypothetical situations. Scenarios refer to particular combinations of attribute levels, and forecasting calculates the probability or market share of an option being selected under these hypothetical conditions. Technically, this involves establishing choice probability equations based on model parameters, then inputting the attribute levels of interest to solve for the resulting choice probabilities (Lancsar et al., 2007). This process helps researchers and decision-makers prospectively understand decision-making trends under different hypothetical conditions.

For example, Cunningham et al. (2022) conducted a DCE on Canadian university students' preferences for mental health services. Scenario forecasting results showed that if students were provided access to psychological support via text message or phone, most would be willing to replace their originally preferred one-on-one individual therapy with more cost-effective group therapy. This finding indicates that service improvements such as adding digital contact channels can significantly alter preference patterns within target populations, making previously less popular intervention formats more acceptable. Through scenario forecasting, researchers can more comprehensively capture potential future changes in choice behavior and identify key drivers of mental health management preferences. This is particularly valuable for decision-makers, as it provides a virtual "testing ground" to pre-evaluate the impact of policy or service changes before actual implementation.

Future Directions

Compared to traditional questionnaire measurement and experimental paradigms in psychology, discrete choice experiments offer advantages in revealing individuals' real choice behaviors, preference weights, and trade-off logic under multivariate conditions, making them especially suitable for exploring complex dynamics in real-world mental health management decisions. However, DCEs have not yet been systematically integrated into psychology research methods curricula, and their awareness and usage remain limited among psychology researchers (McGrady et al., 2020). To further advance theoretical development and application expansion of this method in psychology, future research should pursue three key directions.

First, strengthen integration between DCEs and psychological theories to transform the method from an "applied tool" to a "theory-driven paradigm." Most current studies focus on ranking preference attributes and identifying heterogeneity, lacking systematic analysis of the psychological mechanisms underlying choice behavior. For example, while research on adolescent depression interventions reveals preferences for cost, time, and format attributes, systematic explanations of individuals' cognitive appraisals, emotional responses, and motivational structures are lacking (Ho et al., 2025). Moreover, attributes and levels often rely on qualitative methods like expert interviews or focus groups, without systematic connection to classical psychological theories, resulting in high variability in variable selection and structural design across studies, fragmented findings, and limited comparability and cumulative potential (Powell & Rowen, 2022; Rahmani et al., 2023; Ride et al., 2022). Future research could incorporate classical psychological theories such as the Health Belief Model, Theory of Planned Behavior, and Expectancy-Value Theory into attribute setting and results interpretation to enhance theoretical depth and causal inference capability. Theoretical integration would not only help reveal psychological motivations behind preference formation but also improve the foundation for dialogue and cumulative potential across studies, laying groundwork for systematic health behavior explanation models.

Second, the application scope of DCEs in psychology urgently needs expansion. Current research primarily concentrates on mental health service preferences and intervention strategy selection, without fully covering more complex cognitive and social behavioral processes in health psychology. In contemporary health communication environments characterized by information overload, misinformation spread, and conflicting risk perceptions, DCEs could simulate decision-making scenarios with conflicting information sources to systematically examine how information source, credibility, emotional appeal, and risk framing affect individual cognition and behavioral intentions. Introducing DCEs into these areas could provide more detailed preference structure analysis and intervention pathway recommendations for health misinformation governance, false information identification, and risk communication strategies.

Finally, we recommend systematically incorporating discrete choice experiments into psychology research methods curricula. As a structured method for behavioral prediction and preference modeling, DCEs are applicable not only to mental health management research but also to social, developmental, educational psychology, and other subfields that face complex decision-making behaviors. Course integration would broaden students' understanding of research design dimensions and enhance their capabilities in variable operation, data modeling, and policy translation. Particularly in the current academic environment that advocates data-driven and evidence-oriented approaches, systematic training in DCEs methodology would help psychology researchers more effectively engage in interdisciplinary collaboration and expand the social impact of research topics.

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Note: Figure translations are in progress. See original paper for figures.