FROM THE RESEARCH BENCH

Conjoint analysis estimates preference, not demand

A conjoint study can reveal trade-offs in a designed choice, but demand also depends on awareness, availability, timing, capacity, and competition.

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MANAGEMENT SUMMARY

A conjoint response is evidence about a designed choice situation, not automatically a forecast of realized demand. The bridge to a launch decision must account for awareness, availability, timing, production, sales coverage, adoption, competition, and purchasing delay. Research on premarket forecasting shows why several methods can be reconciled against a defined product concept, while work on market dynamics and fuzzy demand scenarios keeps uncertainty visible. This article offers a preference-to-demand audit: declare the estimand, alternatives, attributes, price, outside option, sample, scenario, next validation signal, and decision use before a choice result becomes a launch forecast. It is not a software tutorial, share estimate, or universal accuracy claim.

Keywords: Conjoint analysis · Consumer preference · Demand forecasting · Premarket research · Market validation

The slide says that the market will buy the winning concept. The underlying evidence says that respondents selected one alternative in a designed situation. Those statements may be connected, but they are not the same observation.

Conjoint analysis estimates preference inside the choice design you gave respondents. It can show which attributes and levels create trade-offs, how a stated alternative compares with another, and how a price or feature change alters modelled choice under the scenario. Realized demand adds conditions the task may not observe: awareness, availability, timing, production, sales coverage, competition, adoption, and purchasing delay.

That boundary is not an argument against conjoint analysis. It is an argument for naming the inference step. A choice study can be excellent evidence for a preference question and still be insufficient evidence for a launch commitment. The decision should state what the study estimates, what it assumes, and which next observation could support, narrow, or falsify the interpretation.

Why must conjoint analysis specify the exact preference estimand before testing?

Before reading a utility score or a simulated share, write the object the analysis is supposed to estimate. Possible objects include:

- relative preference for attributes inside a defined product concept;
- stated choice among alternatives shown in the task;
- modelled choice under a specified price, assortment, and outside option;
- scenario demand under assumptions about awareness, availability, and timing;
- realized orders, adoption, usage, or revenue after the product can actually be bought.

These are not five names for the same number. The first three can be generated inside a designed choice environment. The last two require assumptions or observations outside that environment.

Goodman draws a related boundary between market potential and a sales forecast. Market potential describes an opportunity or market state, while a forecast is conditional on marketing decisions (Goodman, 1972). A conjoint output may inform the opportunity or the conditional scenario. It does not become a sales forecast by being multiplied by a market total.

The word “demand” is especially dangerous because it can mean willingness to choose, willingness to pay, orders placed, units delivered, or a quantity function under a price and availability condition. Select one. If the study cannot observe it, describe the output more narrowly.

What structural variables does a discrete choice task control experimentally?

A conjoint task is valuable because it controls parts of the comparison. The researcher chooses the attributes, levels, alternatives, price representation, task design, sample, and scenario. Those choices make trade-offs visible that a broad question about whether someone would buy the product often leaves ambiguous.

The control also creates the task’s boundary. A respondent may compare two products that the firm has not yet produced, through a route that does not yet exist, with information that a real buyer would not receive in the

same sequence. The model can estimate a preference pattern under that design. It cannot observe the unbuilt supply chain merely because the task mentions it.

Record the design before interpreting the result:

1. Concept. What product or service did the respondent evaluate, and what was left unspecified?
2. Attributes and levels. Which differences could the task show, and which material conditions were absent?
3. Price and unit. Was the price one-time, recurring, per use, per seat, or another basis?
4. Alternatives. Which competitors, substitutes, status quo, or outside option could be chosen?
5. Sample. Who answered, under what recruitment and screening conditions, and who is absent?
6. Scenario. What awareness, availability, timing, purchase authority, and use context was assumed?
7. Estimand. Is the result a relative utility, stated choice, scenario probability, or a forecast conditional on extra inputs?

The list is not a sample-size prescription. It is a provenance record for the interpretation. Leaving the outside option blank is particularly costly. If every respondent must choose between the concepts shown, the result may describe substitution inside the task rather than a decision to buy the category.

Why are external purchase constraints structural conditions rather than model noise?

Oren and Rothkopf model the path from preference to sales through awareness, availability, production, sales-force size, purchasing delay, and other changing market states (Oren & Rothkopf, 1984). Their model concerns a new industrial product and its application, not a universal launch equation. Its use here is to show that adoption is a path with conditions rather than a switch from preference to revenue.

A choice result can therefore be directionally right and commercially early. Buyers may prefer the concept but not know it exists. They may know it exists but not find it through the buying route. They may find it but face a delivery date that does not match the decision window. They may have authority to recommend but not to purchase. The product may be available to one segment while capacity is reserved for another.

Name the link that is doing the work:

- Awareness: who knows the product exists?
- Availability: where and when can it be evaluated, ordered, and delivered?
- Adoption: what learning, switching, installation, or internal approval is required?
- Competition: what alternative changes the real choice set?
- Capacity: what limits production, implementation, support, or sales coverage?
- Timing: what is the purchasing window and what happens if it is missed?
- Delay: how long can a buyer wait before a preference becomes an order?

These conditions can be model inputs, validation questions, or observed fields. They should not be silently treated as one generic “conversion rate.”

Why does combining research methods fail to automatically eliminate preference uncertainty?

Thomas describes premarket forecasting as a process that can define a product concept, obtain independent operationalisations, and reconcile the outputs against the concept with explicit judgemental weights (Thomas, 1987). The value is not the promise that a larger method count produces a better forecast. The value is the requirement to say what each method sees and why its output deserves a particular role.

Thomas's 1987 study states the method plainly: "Multiple methods help to ensure that what is measured is due to the phenomenon under study and not the method" (Thomas, 1987). That is a recommendation to compare evidence, not a claim that more methods automatically create a more accurate demand estimate.

Urban, Weinberg, and Hauser combine Information Acceleration, qualitative research, engineering information, and managerial judgement in a General Motors electric-vehicle application (Urban et al., 1996). That case illustrates a response to novelty: give respondents more concrete information about a future product and combine it with other evidence. It is not a modern accuracy benchmark or a transferable launch parameter.

The practical rule is to add a method only when it covers a blind spot that matters to the decision. Conjoint may reveal attribute trade-offs. Interviews may expose language, objections, or unseen use conditions. Engineering may test whether the promised performance is feasible. Distribution research may test availability. A pilot may observe adoption or delay. None should be added merely to make a slide look triangulated.

The reconciliation record should contain the reason for the weight, the condition that would change it, and the decision use. If two methods disagree, preserve the disagreement until the object, population, unit, and time horizon have been aligned. An average can hide a definition conflict.

How should commercial teams represent preference uncertainty in product pricing models?

Aydin, Kwong, Ji, and Law combine fuzzy modelling, discrete-choice analysis, and market-potential estimation in a tablet-PC application (Aydin et al., 2014). Their case keeps alternative demand scenarios and uncertain inputs visible. It does not prove that fuzzy modelling improves forecast accuracy in every setting, and it does not supply current tablet demand.

The transferable discipline is to let the scenario carry its assumptions. A high scenario may require broader availability, faster production, or lower purchasing delay. A low scenario may reflect a credible constraint rather than a pessimistic mood. The model should show which input changed and what evidence would move the decision from one scenario to another.

Precision is not the same as validation. A simulated share with two decimal places can still depend on an unobserved outside option, an optimistic awareness assumption, or a price basis that does not match the future invoice. The extra decimal describes the model's arithmetic, not the market's certainty.

What empirical criteria must a preference-to-demand translation audit satisfy?

Use the following ladder before a choice result is placed in a launch plan. Each stage defines the observation, the required assumption bridge, and the permitted decision scope.

Table 1 The preference-to-demand inference ladder

Inference stage	What the task observes	Required assumptions	Permitted decision use
1. Designed choice	Stated choices among task concepts and levels	Respondent understands attributes; task has internal validity	Feature trade-offs & relative preferences
2. Preference estimate	Modelled relative utilities and simulated trade-offs	Representative sample; valid outside option (no-choice)	Concept refinement & packaging direction
3. Scenario demand	Simulated choice probability under specified scenario	Defined awareness, route availability, timing, and capacity	Conditional scenario comparison
4. Realized outcome	Actual orders, repeat adoption, and realized revenue	Sales execution, pricing realization, and purchasing delay	Commercial launch commitment & capacity investment

Author's synthesis grounded in Goodman (1972), Thomas (1987), Urban, Weinberg and Hauser (1996), Oren and Rothkopf (1984), and Aydin et al. (2014). The rows represent discrete inference tiers and required validation bridges.

For each step, record five fields:

1. Observation. What was directly measured or shown to a respondent?
2. Estimand. What quantity does the analysis claim to describe?
3. Assumption. What must be true for the result to travel to the next step?
4. Validation signal. What next observable outcome could support, narrow, or falsify it?
5. Decision use. What decision is permitted now, and what decision must wait?

The missing bridge is not simply a sample-size problem. Each step changes the object being described. A respondent may be able to compare two concepts without having access to either one; a buyer may value an attribute without being able to authorize a purchase; an interested account may still face a budget cycle or installation constraint. These are not residual details to be filled in after the forecast is announced. They determine whether the estimand has travelled from preference to demand. Make each bridge explicit, assign it an evidence source, and record whether it is observed, assumed, or simulated. If a bridge is simulated, vary it across a plausible range and show what decision changes. If it is unknown, keep the output at the prior rung. That discipline preserves the usefulness of conjoint analysis by making its scope visible rather than asking the method to answer a question its design did not observe.

At the designed-choice step, the study may support task-level trade-offs. At the preference estimate step, it may support a relative interpretation of attributes under the model. At the scenario-demand step, it can inform a conditional forecast if awareness, availability, competition, timing, capacity, and delay are stated. At the realized-outcome step, the product has generated an observation in the market, but attribution and comparability still require their own design.

Which three distinct commercial use cases demand escalating burdens of conjoint proof?

Feature trade-off. The lightest use asks which attributes matter relative to one another inside the designed concept. Keep the result close to the task. It can guide concept refinement or the next research question without pretending to estimate units.

Scenario comparison. The middle use compares specified offers, prices, or availability conditions. It requires a visible outside option, a declared sample, a time frame, and a scenario model. Report the result as conditional. Explain which change drove the comparison.

Launch forecast. The heaviest use connects the preference result to a forecast of orders, adoption, revenue, or capacity. It needs external inputs and a validation plan. The next evidence may be awareness, route availability, production readiness, a pilot order, sales coverage, or observed delay. A choice study can be one component of that forecast. It cannot replace the missing conditions.

This hierarchy prevents the common slide transition from preferred to will buy. The words may be adjacent in a presentation and several decisions apart in evidence.

Which boundary conditions restrict the operational interpretation of conjoint utility scores?

Treat disconfirmation as part of the design. The interpretation should be narrowed if:

- the outside option was absent or unrealistic;
- the price unit in the task does not match the future transaction;
- the sample does not contain the buyer or decision-maker who can act;
- the concept omitted the condition that drives availability, capacity, or adoption;
- the simulated result changes materially under plausible awareness or delay assumptions;
- the first realized observation is not comparable with the task's population or scenario;
- a method disagreement is averaged without resolving the object or time horizon.

A narrower claim is often more useful than a larger forecast. Respondents traded feature A against price under this scenario can guide the next test. The market will buy cannot guide a capacity decision until its bridges are visible.

Where are the empirical boundaries of conjoint choice modeling?

Conjoint analysis can be strong evidence about preference and designed choice. The cited premarket, market-dynamics, and scenario sources explain why demand and realized sales require additional conditions. The audit ladder is an author synthesis. It does not claim that conjoint analysis predicts market share, price realization, or launch accuracy by itself, and it supplies no current product or market estimate.

The adjacent premarket method matrix asks how different methods should be reconciled before a new-product forecast is committed. The market allocation ledger keeps opportunity, firm reach, resources, and return separ-

ate. This article sits between them: it protects the preference result from carrying a demand claim it has not observed.

Aydin, R., Kwong, C. K., Ji, P., & Law, H. M. C. (2014). Market demand estimation for new product development by using fuzzy modeling and discrete choice analysis. Neurocomputing, 142, 136–146. https://doi.org/10.1016/j.neucom.2014.01.051

Goodman, C. S. (1972). Measuring industrial markets: Uses and limitations of available data for market measurement. Industrial Marketing Management, 3, 279–293. https://doi.org/10.1016/0019-8501(72)90020-X

Oren, S. S., & Rothkopf, M. H. (1984). A market dynamics model for new industrial products and its application. Marketing Science, 3(3), 247–265. https://doi.org/10.1287/mksc.3.3.247

Thomas, R. J. (1987). Forecasting new product market potential: Combining multiple methods. Journal of Product Innovation Management, 4(2), 109–119. https://doi.org/10.1111/1540-5885.420109

Urban, G. L., Weinberg, B. D., & Hauser, J. R. (1996). Premarket forecasting of really-new products. Journal of Marketing, 60(1), 47–60. https://doi.org/10.1177/002224299606000105

END OF ESSAY

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