WHITE PAPER

DATA QUALITY CO-OP

Elevating Data Quality Through Collaboration

How shared signals and cross-industry cooperation improve research outcomes

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Table of Contents

Foreword: Why This Research Matters Now

The market research industry is experiencing mounting pressure to deliver accurate, trusted insights in the face of increasing complexity and market fragmentation. While significant strides have been made in fraud detection and quality assurance, core issues, such as inconsistent sourcing, disengaged respondents, and limited visibility into sampling practices, continue to challenge the foundation of research quality.

What is often lacking is not additional tools, but a more holistic and transparent approach to managing data quality. Many stakeholders still rely solely on isolated, proprietary methods for evaluating quality, resulting in blind spots that compromise research outcomes. Without shared understanding and transparent accountability, quality management remains inconsistent and reactive.

> ***As the industry's first independent clearinghouse for data quality, DQC is building a long-overdue system for measuring and managing data integrity across studies and suppliers.***

This research-on-research initiative was designed to illuminate a path forward. By combining quality signals from various points in the data supply chain (e.g. agencies, sample suppliers, quality "auditors") we were able to explore the transformative power of transparency across buyers, sellers, and other stakeholders. This approach has the potential to reshape how the entire ecosystem manages and perceives data quality. With the growing importance of AI, the need for robust data quality solutions has never been greater. As first-party data is increasingly leveraged to address diverse needs, such as training models, a more unified approach to data quality is essential for the future. These findings reflect the larger goal of Data Quality Co-op (DQC): to provide the infrastructure and shared understanding needed to address quality challenges at scale.

A rising tide lifts all boats. At DQC, we're trying to create that rising tide.

Study Methodology Overview

To conduct this research-on-research study, we purchased sample from two providers without disclosing the purpose of the project, preserving a 'natural' sampling experience. The sample providers were asked to deliver 1,000 parents each, demographically balanced by gender, census region splits, income levels and age of children. Because we wanted to observe the quality of data produced by all participants, we did not terminate survey participation for anyone.

Each sample provider sourced participants through their sub-suppliers, and shared a list of which sub-supplier provided each participant. These included popular sources such as Attapoll, DISQO and Social Loop. In total, the study had 2,006 respondents recruited through marketplace and panel aggregators, 1,290 of which were used in our analysis. We also asked our survey participants what website or app they began our survey from, and identified 112 sources of sample from that data, including sources like Qmee, Five Surveys and BrandBee.

Participants completed a 10-minute survey about food pouches, which included a range of standard research product and package design questions. These included unaided and aided brand awareness, purchase frequency, a MaxDiff task, and a package design test. Additionally, the survey captured attitudinal and behavioral insights, feedback about the respondent experience, and survey participation behavior.

Our Survey: Food Pouches Brand Study

- Brand Trust
- Package Design
- Purchase Behaviors
- Survey Motivations
- Attribute Importance
- Survey Experience
- Attitudes & Perceptions
- Data Quality Signals

To complement the survey data, DQC collected a range of data quality indicators that belong to three broad categories:

- **Technical Signals**, ***typically generated by fraud detection tools.*** These include quality indicators such as IP-geography mismatch, VPN usage and 25 other signals.
- **In-Survey Signals**, ***typically created by research agencies or platforms.*** These included simple indicators like speeding and open-end evaluations; and more sophisticated checks such as the root likelihood score from our Maxdiff exercise. We collected 10 additional in-survey signals.
- **Source Signals**, ***generated by sample suppliers.*** These included a 30-day follow-up flag indicating whether our two sample providers had seen each participant again, and whether that participant had been blacklisted. We collected 11 source signals.

These quality indicators were chosen to be representative of how different participants in the first-party data ecosystem evaluate and manage data quality based on their available views of participant technical and behavioral suitability. Importantly, the quality signals included in this research do not represent the most cutting-edge approaches to fraud- and inattention-detection; but instead represent a set of common signals that are representative of techniques used across the ecosystem. Precision will become more important over time as first-party data is increasingly used to train AI models, not simply to answer a discrete set of predefined questions.

Our Hypotheses

First, due to the hyper-connected and opaque nature of modern sampling, we expect effective data quality management requires breaking silos to combine diverse data quality signals. Second, quality removals matter for the accuracy and precision of the insights we deliver as a profession. **In other words, we are better together.**

Key Findings

Our study found that including or excluding different respondents, based on their data quality characteristics, had a direct impact on the research conclusions. For example, removing participants who displayed inconsistency across the survey shifted the package design winner and product attribute importance rankings. Even when overall conclusions from the data are unchanged, different data removal rules alter the precision of the results.

Additionally, our research shows that:

- Modern respondent sourcing is complex. Understanding this is key to understanding data quality.
- Even when providers draw from the same sample sources, your choice of sample provider still matters for data quality.
- Survey design, more than ever, matters for collecting quality responses.
- Every survey requires thoughtful data cleaning
- Multiple types of data quality signals are required for effective data quality management.

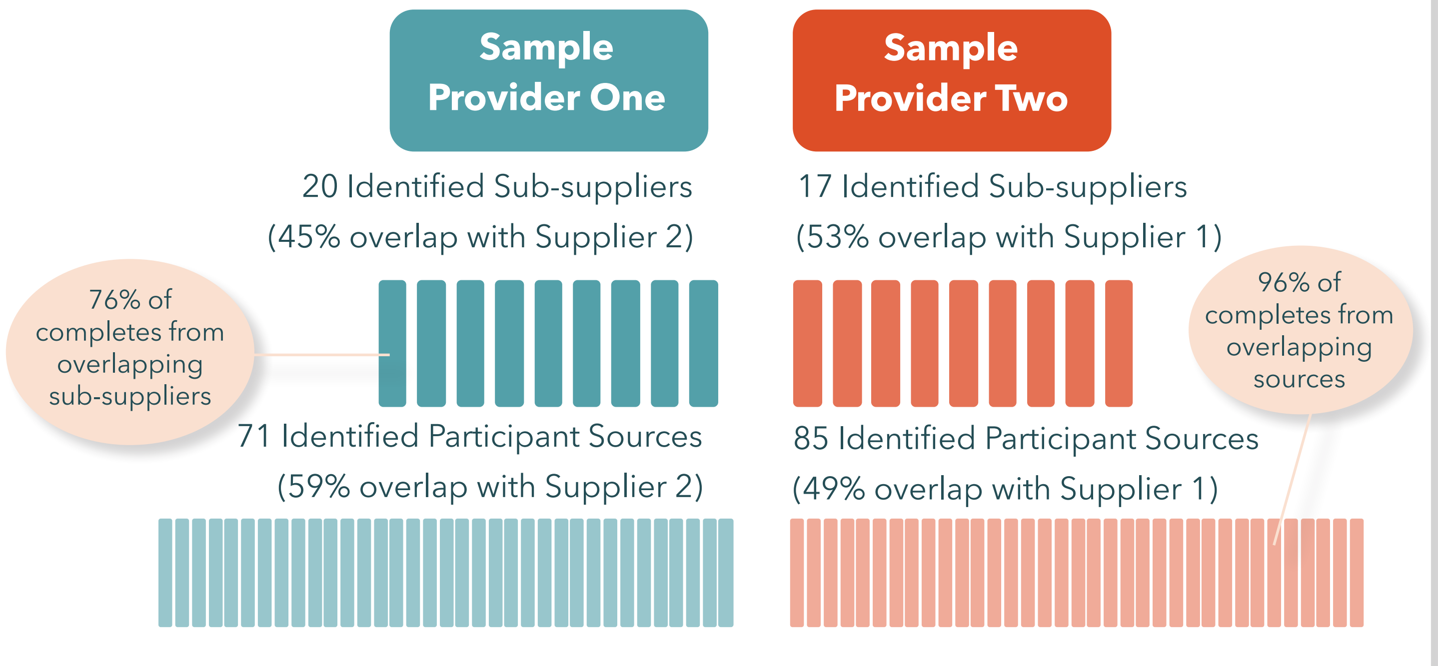
Key Finding 1

Understanding Respondent Sourcing: It's More Complex Than Most of Us Think

The composition of our sample reinforces a growing reality in modern research: managing data quality today requires coordination across a complex and often opaque sampling ecosystem. For this study, we engaged two sample providers, who collectively disclosed 28 sub-suppliers. We also asked participants directly, "Which website or app did you use to start this survey?" and were able to identify and visit 112 distinct sources for a single project.

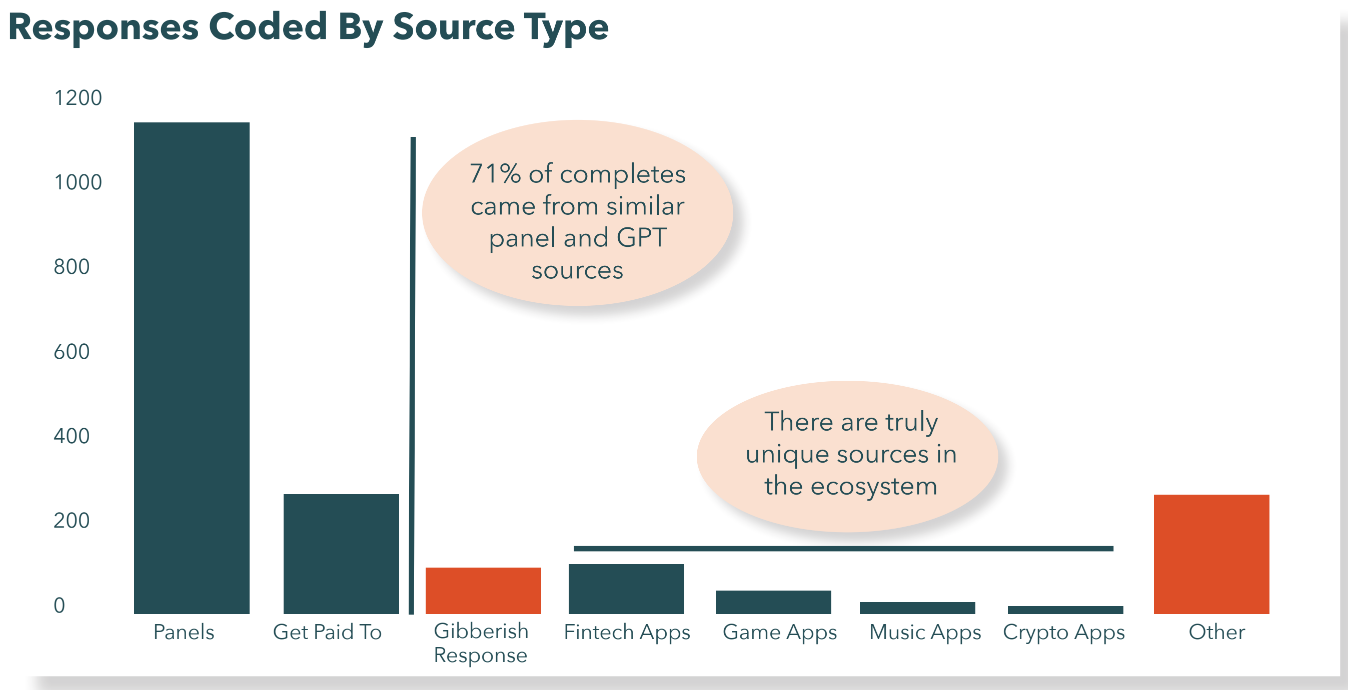
Seventy-eight percent of completes came from overlapping sub-suppliers named by both providers. An even larger proportion—96% of completes—came from overlapping sources based on participant-reported origins.

Rethinking quality for real world sampling



By coding our participant-reported sample sources, we found that:

- 60% of completes came from panels
- 15% came from get-paid-to (GPT) sites; and
- 25% from a long tail of other sources. These included fintech tools (like EBT management apps), mobile games, music apps, and even crypto platforms.



Today's ecosystem is an interconnected, multi-channel web that is nearly impossible for any one buyer or supplier to fully track on their own. This reality is underscored by work led by the Market Research Society in its latest paper for the Global Data Quality Project, "Online Participant Sourcing Ecosystem", which clearly outlines this significant fragmentation across the research process. This paper, and our study findings, underscore how modern sampling differs from legacy assumptions, specifically the idea of a one-to-one relationship between a participant and a panel. Collecting participant-reported data alongside supplier-reported sources offers a more complete, and more actionable, view of sampling complexity.

Key Finding 2

Regardless of Underlying Sample Sources, The Provider You Choose Matters

Even though most participants came from overlapping sources (96%), we still observed meaningful differences between the two providers in both targeting accuracy and quality outcomes.

For example, Fieldwork results showed that Provider 1 had a 74% targeting accuracy, meaning 26% of their respondents were not actually parents, while Provider 2 had stronger targeting accuracy at 86%, with 14% outside the intended audience.

Quality metrics varied as well. Provider 1 contributed 63.7% of the “Bad Open End” segment: participants who generally passed fraud checks but provided low quality responses. Provider 2, by contrast, accounted for 61% of the “Fingerprint Flagged” group, or participants whose in-survey behavior was fine but who raised technical red flags (e.g., VPN usage or IP mismatches). We dive deeper into participant segments in Key Finding 5 on page 13.

These differences were both expected and meaningful. They may reflect variations in internal processes, bundling practices, and how quality tools are deployed. Seeing these signals in the context of each provider’s competitive set is essential for understanding which partner aligns best with a buyer’s specific needs. In a crowded landscape of overlapping supply, how a provider works still matters.

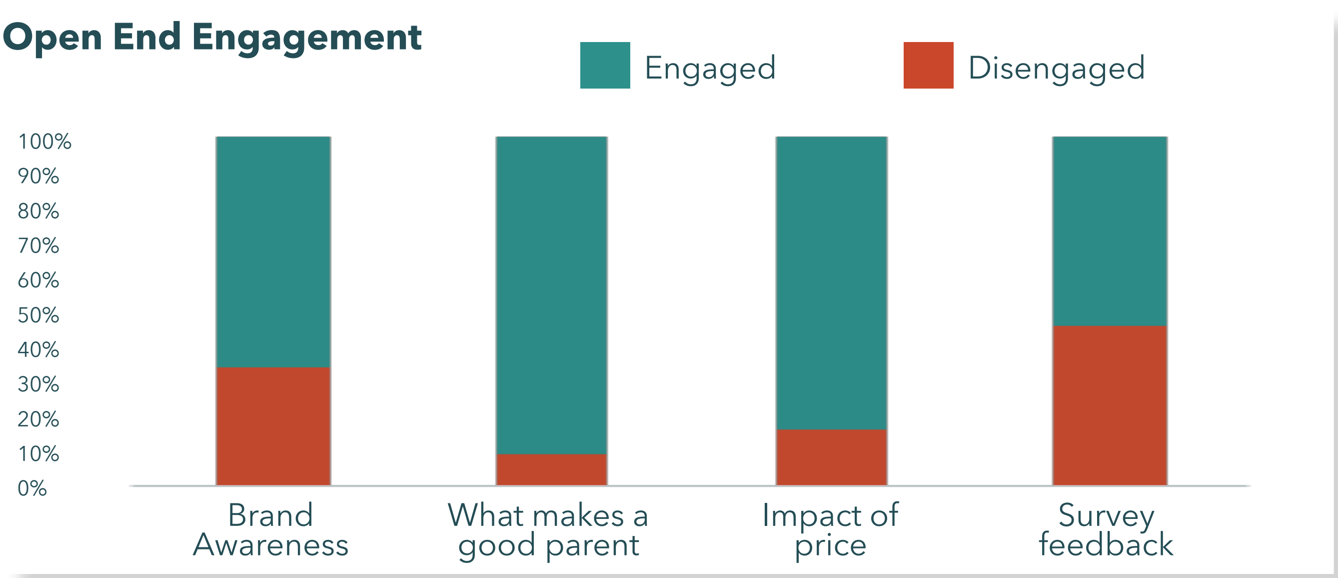
Key Finding 3

Regardless of Sample, Survey Design Matters

Independent of sample provider selection, we observed two interesting indicators that survey design matters for common data quality measures. Groves, Singer and Corning proposed (2000) two forces driving participation in surveys: leverage (e.g. incentives) and salience (e.g. relevant topics). Based on sample sources used, we expect each survey participant in our survey was incentivized and still observed a strong salience effect in our open ended response patterns.

We asked four open-ended questions, starting with an unaided brand awareness question.

- *When you think of food pouches, which brands come to mind?*
- *In a few words, tell us what you think makes a good parent.*
- *Thinking about the preferences you just shared with us, how does price influence these preferences and your decision when choosing to purchase a food pouch?*
- *Do you have any other thoughts you'd like to share about what makes for a good survey experience?*



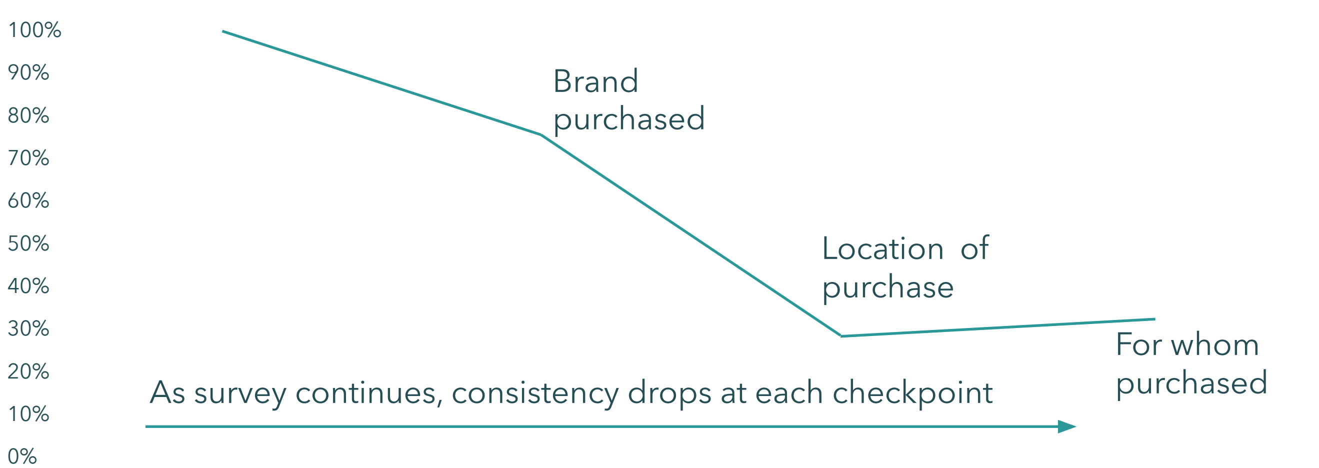
Participant engagement varied widely across these four questions. Many participants, who clearly satisficed on brand awareness and price topics provided thoughtful, rich perspectives on parenting. Almost half our participants declined to provide useful feedback on the survey-taking process. We posit this is an indication that participants do not believe their feedback will improve the ecosystem.

Because we wanted to collect as many quality signals as possible, we chose not to terminate any participant from the survey. This provided an interesting view into how survey design affects data quality, particularly how creating paths through a survey that are less relevant will reduce the quality of the data a participant provides. This is a common experience for a frequent survey taker; answering a qualifying question with an honest, but tepid, response which yields many detailed follow-up questions on topics for which they do not hold strong opinions.

In our survey, for example, we asked questions about category engagement. If the participant indicated that they had not made a purchase in the category (i.e., were out of category), they were still shown follow-up questions about which brands they had purchased, where they had made those purchases, and for whom.

We found that participants whose data otherwise appeared high quality will, over time, acquiesce and do their best to answer when presented with irrelevant questions. This behavior illustrates an important insight: the temptation to collect incremental data from lightly qualified participants should be tempered by the knowledge that this tendency for acquiescence introduces a clear quality versus quantity tradeoff.

Category Purchase Behavior Consistency Across Survey



Key Finding 4

Every Survey Requires Thoughtful Data Cleaning

At first review, roughly one-third of our survey data did not meet simple criteria for quality. For example, 34% of participants were not able to share a single in-category brand in the unaided brand awareness question. Additionally, 36% of participants were familiar with our nonexistent 'Pouchables' brand of food pouches. This proportion carried through a number of high level quality checks, including the open-ended response engagement reported above.

In reporting on Wave 0 of its industry data quality benchmarking* efforts, the Insights Association has shared that sample providers are removing 25.4% of participants pre-survey, and research agencies are removing an incremental 49.4% of participants during- and post-fieldwork. This is a shockingly high percentage of survey participants that are removed from our datasets: what other industry accepts a ~75% failure rate in its supply chain? It also confirms our observation that all surveys require thoughtful data cleaning.

Lastly, the delta between our initial data quality observations (suggesting roughly one-third of the survey data is not fit for purpose) and the Insights Association's data cleaning benchmarks, suggest there's more to do beyond looking at 'obvious' quality indicators in survey data, which is why we chose to dive deeper into the data quality indicators collected as a part of this project.

**www.insightsassociation.org/Resources/Data-Quality-Standards/Data-Quality-Benchmarking*

Key Finding 5

We Need To Consider Different Types of Participants and Their Impact on Data Quality

One of the clearest takeaways from this study is that not all poor-quality data stems from outright fraud. Given the large number of quality signals we collected, spanning technical flags, survey behaviors, and source-reported metrics, it became evident that different types of participants contribute to data quality issues in different ways.

Following the footsteps of Deb Ploskonka and Kenneth Fairchild (2022), our research segmented respondents into four categories based only on their in-survey behavior and other quality indicators.

Out of our total set of data quality signals, our segmentation made use of 13 quality signals to produce four distinct segments of survey participants. The quality signals that defined these groups spanned all three categories: *technical, in-survey* and *source signals* as seen below.

Technical Signals	In-Survey Signals	Sources Signals
Fraud score	Root likelihood score*	Survey taking frequency
Geo-IP match	Speeding	30-day activity check
VPN usage	Open end quality	Source / sub-supplier match
Geo-timezone match	Answer consistency	Sample source type
	Fake brand awareness	

**sawtoothsoftware.com/resources/blog/posts/Improve-Survey-Data-Quality-With-Root-Likelihood*

Our four participant segments were:

1. **Fingerprint Flagged (11% of participants):** These participants are characterized by fraudulent technical quality indicators. For example, they tend to have low fraud scores assigned by quality tools. Although their survey behavior was not problematic, these respondents raised flags due to suspicious technical footprints.

2. **Bad Open-Enders (26% of participants):** Despite not being defined by any technical I fraud flags, these respondents provided low-quality data, such as meaningless open-ended answers and inconsistent responses to preference questions.

3. **Professional Panelists (29% of participants):** These respondents tend to originate from panel sources, are seen frequently and provide thoughtful, consistent responses, making them the most reliable and valuable data source for research. They are professional in every positive sense of the word: they know the process, show up and produce reliable data.

4. Survey Newbies (34% of participants): This segment of participants is more complicated. They exhibit inconsistent behavior, such as missing answers or incorrect responses. They are also regularly flagged for simple technical issues like mismatched IP addresses and geolocation. Lastly, they tend to be 'one and done' more than repeat survey takers. Therefore, we believe that Survey Newbies is, at least partially, made up of participants who begin but do not persist in our survey-for-rewards ecosystem.

1. Survey Newbies	2. Professional Panelist	3. Bad Open Ends	4. Fingerprint Flagged
34%	**29%**	**26%**	**11%**
Inconsistent stated behaviors	High RLH (consistent attribute importance)	No unaided brand identification	Use a VPN
Fake brand trap	App source match	Low RLH (inconsistent attribute importance)	Slow survey takers
Mismatch IP geo	Panelist returns	Speeding	App source mismatch
Panelist not seen again in platform	Panel sourced	Gibberish open ends	Low trust score
			Mismatched IP geo and time zone

Most importantly, this segmentation reinforces the idea that no single indicator can fully capture respondent quality. Some participants may pass traditional checks yet still degrade the integrity of the dataset in subtler ways. A more nuanced understanding of participant types and their varied impact on insights is essential for evolving industry standards and quality frameworks. It also underscores the need for multi-signal approaches to quality evaluation, beyond binary fraud flags.

Key Finding 6

Data Removal Rules Matter:
Survey Responses Differ Across Quality Segments

The biggest question, building on the five previous key findings is how do research conclusions change based on the inclusion or exclusion of various quality participant segments?

We provide three answers to that question below:

1. The 'headline' research answers vary somewhat across each segment. For example, our Professional Panelist segment rates 'no added sugar or preservatives' as the most important attribute for food pouches, while the other three segments chose 'good source of protein.' You can see differences outlined in the table below:

Each Segment Responds Differently

	1. Survey Newbies	2. Professional Panelist	3. Bad Open Ends	4. Fingerprint Flagged
Package winner:	**Package C** 	**Package C** 	**Package B** 	**Package B** 
Most important product attribute:	Good source of protein	No added sugar or preservatives	Good source of protein	Good source of protein
Least important product attribute:	Transparency window	Transparency window	Eco-friendly packaging	Carbon neutral
Competitor perception:	Has a good reputation	Provides good value for the money	Visually appealing packaging	Has a good reputation

2. Our Maxdiff methodology did a good job of creating a consistent recommendation from the data as sample composition changed. However, all methodologies involve tradeoffs. Our Maxdiff, for example, requires more time than single response questions and will increase the cost and complexity of fieldwork. Given the robust, stable results produced we felt this was a good tradeoff.

   Each combination of 3 segments created largely consistent recommendations for package design and product attributes as outlined in the table below:

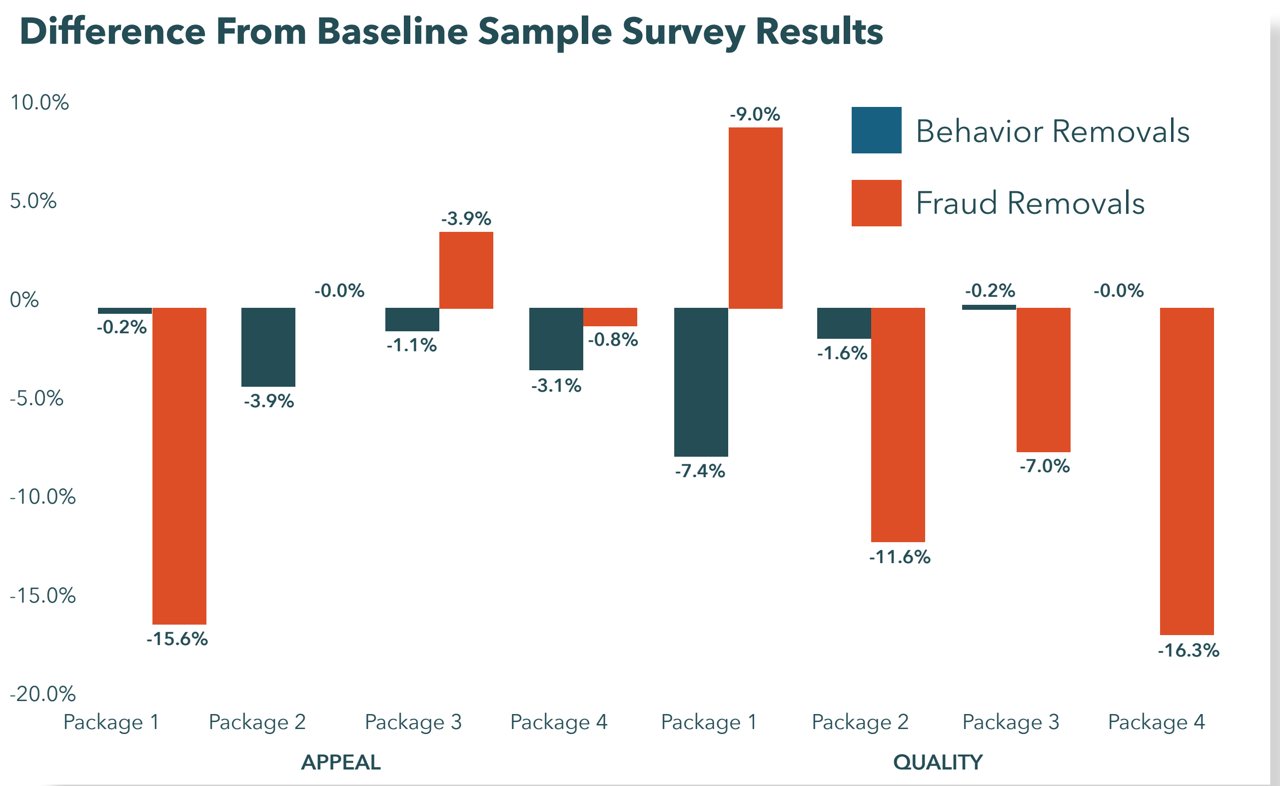
	Package Design Winner		Product Attributes		
Segment Combinations	Appeal	Quality	Most Important	Second Most Important	Least Important
Total Sample	Package 2	Package 2	Protein	No Added Sugar	Transparency Window
1+2+3	Package 3	Package 2	Protein	No Added Sugar	Transparency Window
2+3+4	Package 2	Package 2	Protein	No Added Sugar	Transparency Window
3+4+1	Package 3	Package 2	Protein	No Added Sugar	Transparency Window
4+1+2	Package 2	Package 2	Protein	No Added Sugar	Transparency Window

The package winner based on overall appeal switched from Package 2 to Package 3 depending on sample. That said, the difference in ranking in these cases was decided by less than a single percentage point.

Good news for researchers: choosing reliable methodologies and modeling techniques yields more reliable data!

3. The precision of recommendations depends on data quality removal rules. After analyzing the data, we built a simulator that allowed us to observe changes in package design and product attribute rankings based on which of the four segments are included in the sample. And, while the maxdiff produced consistent 'winners' and 'losers,' the intensity of preference changed significantly across our four package types and 10 product attributes.

   As one example, we created two simple removal strategies: 1. remove fraud (fingerprint flagged segment); and 2. remove suspect in-survey behavior (remove the survey newbies and bad open ends segments) measured against the baseline of including all survey responses. Each removal strategy created meaningful differences in the intensity of feelings about package appeal and package quality as outlined in the chart below.



The Role of Collaboration in Enhancing Data Quality

This research demonstrates that relying solely on traditional quality checks that are easy for a sample provider, sample buyer or fraud tool provider alone is not sufficient in today's complex research environment. In fact, aggregating simple signals from all levels of the supply chain—sample providers, buyers, and auditors—ensures better data quality and more reliable insights. Collaboration between these groups is vital for creating a seamless, efficient, and transparent data ecosystem. By working together and sharing quality signals, we can eliminate inefficiencies and reduce the risks associated with low-quality data.

More importantly, in a world where data is used to train models in addition to answering distinct one-time business questions, the precision of 1st-party data is becoming more important. The only way for us, as a profession, to elevate our data quality game is to observe quality signals outside our own silos.

Moving Toward a Collaborative Future

This study provides a clear takeaway: data quality cannot be addressed in isolation. Sourcing, fielding, and analysis are deeply interconnected, and every player in the research supply chain has a role to play in improving outcomes.

By aggregating signals across sub-suppliers, survey platforms, and buyers, we gain a more complete and accurate picture of respondent behavior. This integrated approach not only improves the clarity of the data, but also reveals inefficiencies, inconsistencies, and opportunities for more proactive decision-making.

As DQC continues to expand its capabilities, we encourage more organizations to contribute to and benefit from a shared ecosystem of data quality signals. Doing so will reduce noise, elevate industry standards, and support smarter, faster, and more credible research.

Building The Infrastructure For Trusted Data

Traditional methods of managing data quality—focused on project-by-project checks—are no longer enough. The industry needs a scalable, transparent, and persistent framework for evaluating quality across all data sources.

Data Quality Co-op was created to meet that need. As the first independent clearinghouse for first-party data quality, DQC aggregates signals from across the industry to create a single, objective source of truth. Our platform brings together in-survey diagnostics, external fraud detection, supplier-level metadata, and other key indicators to benchmark quality and support decision-making at every level.

Much like clearinghouses in finance or digital advertising, DQC enables both buyers and suppliers to operate with greater confidence and accountability. Procurement teams can rely on real-time vendor scorecards. Researchers gain access to filtering tools that support cleaner, more focused analysis. Suppliers can validate their performance and improve their standing over time.

Our platform is designed to become smarter with each contribution. The more participants in the ecosystem, the stronger and more predictive the model becomes. By joining DQC, organizations take a concrete step toward better research, better outcomes, and a more trusted industry.

Learn how the Data Quality Co-op is building the infrastructure to support scalable, multi-source quality evaluation, and why it matters now more than ever.

Reach out or visit dataqualityco-op.com

About the Authors

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Bob Fawson is Co-Founder and CEO of the Data Quality Co-op, promoting transparency and data quality for consumer insights. An experienced executive, strategic advisor and consumer insights expert, Bob has contributed to the evolution and improvement of consumer data through a number of Strategy, Operational and Product roles at Numerator, Dynata, SSI and Opinionology. As Board Chairman at Samplecon, and a strategic advisor to innovative market research companies, Bob enjoys contributing to the next wave of insights innovation. Bob lives in Salt Lake City with his family, and is an avid mountain biker and skier.

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Paul graduated from BYU with a M.S. in Statistics. He spent 15 years working in market research with a wide variety of experience including phone surveys, online surveys, and passively collected data. He loves finding innovative ways to combine behavioral and survey data with a specialty in discrete choice models. He has volunteered and served on committees in AAPOR at both the local and regional level. His research efforts have been featured at AAPOR, ESOMAR, ARF, Insights Association, and Sawtooth conferences. He is most proud of his wife and two sons and loves playing games with them.

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Kelsey is a research strategist with deep expertise in both qualitative and quantitative methods, applied across a wide range of industries. She has led studies spanning healthcare, public policy, technology, and consumer behavior for global brands, nonprofits, and mission-driven organizations. Previously, Kelsey built and led a cross-functional research and analytics team focused on data storytelling. Today, through her independent consulting practice, she helps clients turn complex questions into clear, actionable insights.