



CRIC and MRS GDQ Guidance

SURVEY DATA QUALITY

Controls, Detection,
Validation, and Removal



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Introduction

The quality of any analysis depends on the integrity of the data being analysed. Even well-designed surveys can be compromised by disengaged participants, inconsistent responses, or increasingly, fraudulent and AI-generated inputs. Poor-quality data not only distorts findings but can lead to misinformed decisions, wasted resources, and reduced confidence in research outcomes. Maintaining high data quality requires a structured, end-to-end approach.

Data quality is established long before fieldwork begins. Decisions around sample sources, recruitment strategies, research design and questionnaire design shape who participates and how they respond, directly impacting representativeness and reliability. Factors such as survey length, question design, and device compatibility all influence engagement, while effective screening—particularly in B2B research—helps prevent ineligible participants from entering the dataset.

Within this broader framework, in-survey controls (e.g., attention checks, logic validations, and fraud detection signals), combined with external indicators such as participant source, enable the identification and removal of low-quality or fraudulent responses while preserving valid data. Depending on the strength and timing of these signals, removal may occur in real time or post-fieldwork.

This guide builds on previous Global Data Quality efforts (all available via the GDQ and MRS portals) but particularly [Improving Data Quality & Integrity – Some Practical Approaches](#) (available via the GDQ and MRS portals), helping practitioners and buyers alike connect upstream design choices with downstream removal of records. There are also numerous existing resources covering participant experience and data degradation related to poor design, survey length, and related factors (see: www.globaldataquality.org/GDQ-resources).

In a landscape of evolving panel quality, shorter attention spans, and emergent AI-generated responses, a comprehensive strategy that pairs thoughtful planning with robust record removal is no longer optional - it's essential to deliver reliable, actionable insight.

Key components in the quality process

There are three key area in the quality process that if done well will mitigate against problematic data



Pre-survey

This covers topic areas before the participant begins the actual survey



In-survey

This covers topic areas during which response data is being collected



Post-survey

This covers topic areas post the collection of the response data and when the response data is being processed.

Pre-survey quality process

Taking measures to prevent quality challenges prior to a participant entering a survey can remove a significant proportion of fraudulent and low-quality participants.

Sample

Sample providers and their overall offerings play a critical role in the data quality process. For further detail, refer to:

[MRS/GDQ Data Quality Transparency Checklist](#)

[MRS/GDQ Online Participant Sourcing Ecosystem](#)

Survey Design

Whilst this guidance does not explore survey design in detail, key areas to consider are:

- **Transparency:** Inform participants about the importance of thoughtful responses to set expectations and encourage engagement.
- **Pilot testing:** Test quality controls before full launch to ensure they function as intended and do not exclude valid participants.
- **Review and iterate:** Use learnings from previous surveys to refine quality control mechanisms.

Technical Implementation

Technical checks can reveal problematic response sources or fraudulent participation. The use of specialised software (e.g., digital fingerprinting) can be particularly effective in identifying suspicious patterns.

Some sample providers implement technical checks upstream on sample; practitioners could consider adding technical checks themselves even if their provider is doing so, but especially if they are not. There is more information on technical checks that could be considered in the [Improving Data Quality & Integrity](#) document such as [IP location check](#). Whilst these checks may block the more blatant out-of-country fraud, many fraudsters – individuals or groups – have access to technical solutions which circumvent such checks.

A range of internal techniques can also be applied:

- Use [honeypots](#) for bot detection without impacting user experience. These are hidden questions visible only to bots.

Use **CAPTCHA-style checks** to confirm human participation, although these do not validate anything beyond that. For more details click [CAPTCHA](#).

Recognise that technical checks can block obvious fraud but may be circumvented.

Flag and remove cases with:

- Multiple responses from identical IP addresses
- Geographic inconsistencies between reported and detected location
- Suspicious device or browser signatures
- Unusual survey access patterns

Important consideration:

Given the increasing sophistication of fraud, particularly with the rise of AI, it is strongly recommended that robust, purpose-built fraud detection platforms (either bespoke or third party) be used. These solutions are typically more advanced than standalone techniques and are better equipped to detect emerging fraud behaviours.

In-Survey Checking points and Initial Quality Assessment

In-survey checks refer to a suite of methods embedded into questionnaires to assess and assure response quality. These checks complement pre-survey validation steps carried out by sample providers or agencies before participants enter the survey, creating a layered defence against poor-quality or fraudulent data.

Embedding quality measures within surveys is critical because it enables early detection of poor-quality data, preventing contamination of the overall dataset and enabling the inclusion of high-quality participants during data collection. These checks allow for immediate corrective action, such as removing problematic participants or switching suppliers, while data collection is still in progress, helping maintain timelines, and target sample sizes and reduce likelihood of additional fieldwork costs. By reducing the need for extensive post-survey removal, in-survey checking points improve efficiency and conserve resources. Most importantly, they ensure high-quality data that enhances the credibility of results and builds trust among stakeholders.

While no single indicator can definitively identify all low-quality responses, combining multiple detection methods provides a robust framework for assessment. Multiple software tools are available to assist with detection and assessment, but the principles remain the same: use a combination of indicators and methodologies to flag suspicious patterns early and preserve the integrity of legitimate responses. Depending on the strength and confidence of these checks, review and removal may occur during live data collection or after survey completion.

Before commencing any post-survey removal, personal information should be removed or masked from the dataset unless required for field validation.

The Subjectivity of Data Checks

Defining a “problematic” participant with 100% accuracy is challenging. There are no universal standards, and judgements often vary between practitioners and even automated systems. A study sponsored by MRS in the UK and US illustrates this point. The survey included multiple in-survey checks across closed and open-ended questions, and five reviewers (three manual, two automated using AI/ML) assessed open-end responses to flag participants for attention.

Percentage of Records Flagged by Reviewer

Type of check	Reviewer	% Flagged	
		UK	US
Manual	1	4%	5%
	2	11%	14%
	3	10%	11%
Auto	4	8%	8%
	5	6%	6%

Agreement across reviewers was low: only **13% of flagged participants** were flagged by all five reviewers, while **47% (UK)** and **42% (US)** of flagged participants were flagged by just one reviewer.

This highlights the inherent subjectivity, even automated systems differed due to varying models and thresholds. However, overall agreement was higher for “OK” responses: **82% were deemed acceptable by all reviewers**, and **2% were unanimously flagged as problematic**, giving total agreement of **84% (UK)** and **85% (US)**. This still leaves approximately 15% disagreement between reviewers.

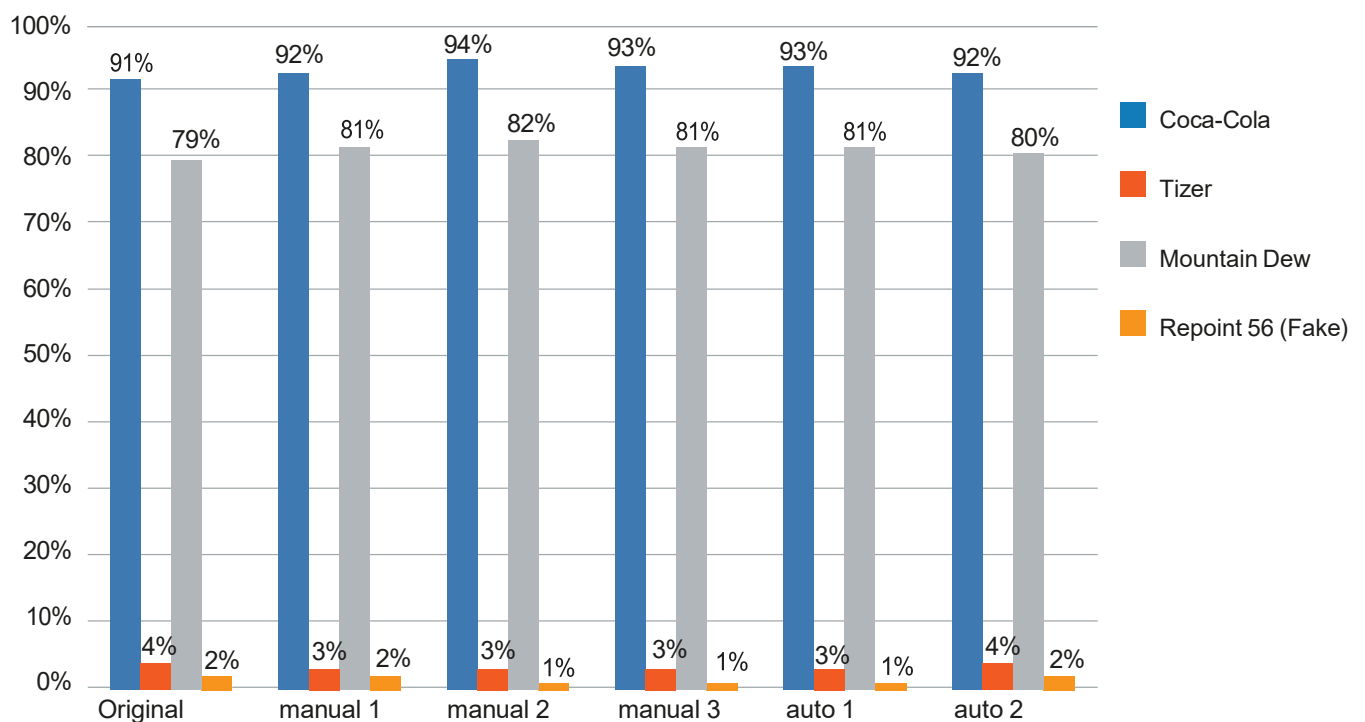
	Base: total completes		Base: flag count breakdown	
	US	UK	US	UK
All reviewer match levels				
All agreed – participant ok	82%	82%		
1 Reviewer – flagged	8%	8%	47%	42%
2 Reviewers agreed to flag	3%	3%	18%	15%
3 Reviewers agree to flag	2%	3%	13%	14%
4 Reviewers agree to flag	2%	3%	9%	15%
All agreed to flag	2%	2%	13%	13%
All matched	85%	84%		

The key takeaway: data checks, especially open-end evaluations, are subjective, and even widely used checks like “speeding” vary by context. Practitioners must understand their dataset and apply multiple indicators to make informed decisions. Care should be taken to address any potential reviewer bias when removing participants. A standard approach to this should be applied and

documented and potentially be auditable as needed. Interestingly, removing flagged records often had minimal impact on key measures (e.g., brand awareness), underscoring that while striving for high-quality data is essential, the practical effect of exclusions can be limited.

US - awareness of brands

Adjusted by removal of those flagged as part of the open end review by each reviewer



Real time or Post field ?

Assessment and record removal

There are pros and cons to the assessment and potential removal of records based on how and when these are done. Some considerations below:

Real Time Pros

If records are flagged and removed in real time, then they should not count towards the completes or quotas. This makes the fieldwork process efficient from a resource and time perspective.

Where clear guidelines to define “poor” and “good” participants have been established then real-time checks provide some consistency to the approach and is less subjective than having different people manually assessing each data set each time.

Cons

If the reasons for the removals are subsequently not justified on further review, and the level of removals is significant, then the representativeness of the non-removals may be questioned.

Depending on the types of flags used (e.g., red herrings, attention checks, patterned responses, etc), some participants may accidentally fail due to the difficulty of the survey design, even when answering honestly, or abort the survey from frustration due to the seemingly unnecessary questions.

Post Field Pros

Allows time to make observations and layer in additional information about participants, (e.g., data from suppliers to see if they recognise anything odd about the queried participants).

Data quality can be a very subjective topic, and it is not always easy to immediately make a judgement on each single participant. Sometimes assessing the quality of a single participant’s responses compared to all other participants is required, which can most successfully be done once all data is gathered.

Cons

If there are significant removals post fieldwork, data collection may need to be re- opened, which causes additional resources, time and cost to the project.

Types of In-survey Checking points

1. Identify and Remove Duplicates

The first step in the data removal process is to identify and remove duplicate responses. Duplicate responses can occur because of technical issues/errors, deliberate intent from a participant (for incentives or to influence results) or from the same individual participating in multiple panels used for the same survey.

Duplicates can be identified pre-survey using several technical identifiers (e.g., digital IP address, cookie tracking, email address, shared identifiers between panels, etc.).

In-survey review of response pattern and timing of response can also identify a likely duplicate. For example, a high similarity in responses on key questions, including demographics, can be an indication of a possible duplicate participant, as can responses that occur in succession.

Implementation

- Remove clear duplicates based on technical identifiers
- Score likely duplicates based on response pattern analysis and timing of responses and flag for potential removal.
- Ideally this should be done in real time based on the information available

2. Speeding Checks

(Survey Completion Time)

Monitoring how quickly participants complete a survey, or specific sections, can help identify inattentive participants or bots. Those finishing significantly faster than the norm may not be giving questions due consideration. However, this check is highly subjective: there is no industry standard for what constitutes “too fast.”

Completion time can vary based on device type, routing, typing speed, question complexity, and participant familiarity with the topic. Speeding should be treated as a potential indicator, not an automatic exclusion criterion. Combine timing analysis with other checks (e.g., response patterns, open-end quality) before making decisions.

Why Speed Matters

- Extremely fast completions often correlate with lower-quality data.
- Speeding can occur across the entire survey or selectively within grids or multi-question pages.

Challenges

- Thresholds are subjective—should you use total time, median time, page-level timing, or section-level timing?
- Natural variation means some fast participants may still provide valid answers.

Implementation Tips

- Calculate **median completion time** for your sample.

- Flag participants who complete the survey in an agreed unrealistic time e.g., 20% of the median.
 - If >10% of participants are flagged at this level, then a review should be undertaken to understand if there is a potential issue with the check. If using multiple sources, then see if patterns exist across the sources or is more limited. If more limited this suggests an issue with that source, and if spread across sources then indicates that might be more likely to be a set up error.
- Participants who complete the survey above the agreed unrealistic time but still faster than the norm, for that particular survey, should still be reviewed by comparing against data points and flags of the other participants.
- For longer surveys, consider reviewing **section-by-section timing** to detect selective speeding.
- Consider using timers at the **individual question level**, especially for grids or multi-item pages.

3. Open-Ended Response Quality

Open-ended questions add richness and context to survey data, providing insights beyond closed-ended responses. While some practitioners have reduced their use due to participant effort especially on mobile devices. Typing responses has become more common with the rise of messaging platforms, making open ends still valuable for quality checks.

Why Include Open Ends?

- They help identify inattentive or fraudulent behaviour through content analysis.
- They provide an opportunity to detect patterns such as copy-paste responses, AI-generated text, or irrelevant answers.
- They can reveal language mismatches (e.g., responses in a language different from the survey language or market).

Recommendation: Include at least two full open-ended questions in a survey, even if they are not part of client deliverables, to support quality assessment.

Indicators of Poor Quality

- Gibberish or nonsensical text (e.g., keyboard slaps).
- Extremely short or irrelevant responses.
- Profanity or inappropriate language.
- Duplicate responses across questions or records.

-
- Responses in the wrong language.
 - Overly long, technical or detailed answers that are error free may indicate AI or bot involvement.

Important: Gibberish alone does not necessarily mean a participant is fraudulent. In the MRS study, 11 participants provided gibberish in all open ends, but five of these had no or minimal additional flags. Removing such cases without supporting evidence risks excluding valid participants. Points to consider:

- Vulnerable participants
- Neurodiverse participants
- Language proficiency
- Participant preference

To enable the above offering prompts to open-end questions, such as ‘Please ensure responses are clear and understandable’, could assist with identifying attentive participants from those who are attentive but dislike open-ends.

Implementation Tips

- Review all open-ended responses where possible.
- Flag responses based on multiple indicators (length, relevance, duplication, coherence).
- Use bot detection tools.

- Remove responses with offensive and aggressive language and manually review others before exclusion. This does not necessarily mean all bad language, such as swearing, which in some contexts such as customer satisfaction surveys may make sense.

- Consider cultural differences, some markets provide shorter or more minimal responses.

Key Insight: Open-ended checks are powerful but should be used alongside other indicators (e.g., speeding, consistency, honesty checks). If removal is considered, practitioners should assess representativeness and consult suppliers to confirm patterns of fraud and/or data quality concerns.

Sometimes practitioners may decide to collect open-end response via speech or video-recording. The same principle would apply when using alternative modes, with adjustments for quality checks e.g., listening to response, etc.

4. Response Pattern Indicators

Detecting response patterns can help identify potential disengagement or fraudulent behaviour, but interpretation requires caution. Patterns such as **straight-lining** (selecting the same option across multiple items) or **zigzagging** (alternating extremes or creating diagonal patterns) may indicate inattentiveness or automation. However, these behaviours can also occur for legitimate reasons, such as consistent attitudes or question design, so they should never be used as sole grounds for exclusion.

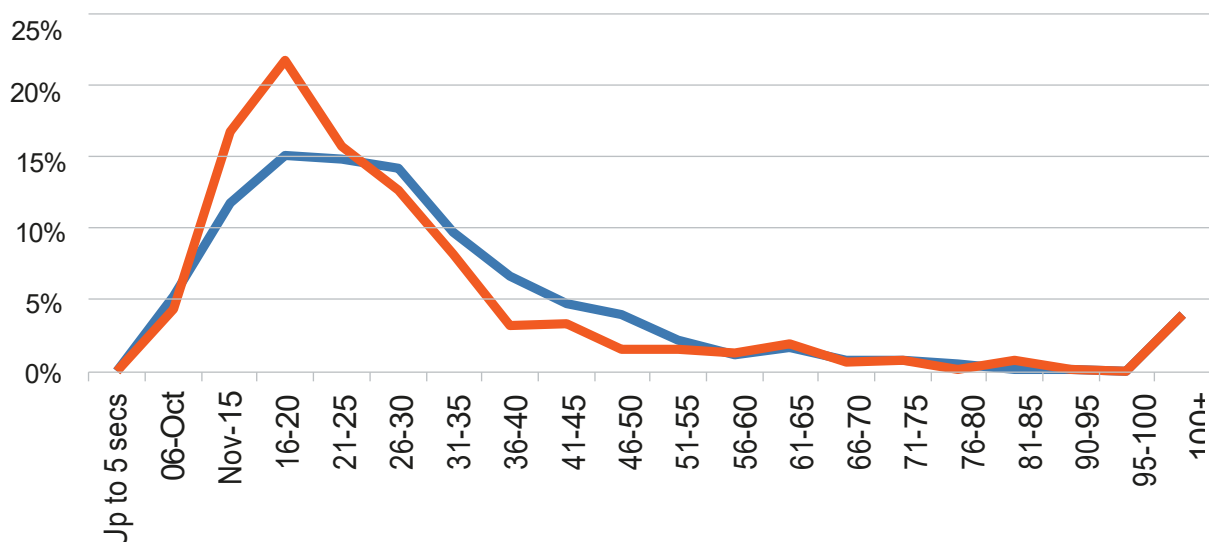
5. Straight Lining Detection

Straight lining is common in grid or matrix questions and easy to spot in data. Yet, rejecting participants based solely on this behaviour risks removing valid responses.

For example, in the MRS study, 30% of participants gave identical answers to a series of environmental responsibility statements, a reasonable outcome given the similarity of items.

The time taken to complete the list was reviewed and it was noted that the five quickest participants who completed the grid did not “Straight Line” which is another illustration of why removing a participant based solely on [Straight lined](#) is not good research practice.

if straight line v. time taken (sec)



— No — Yes

There is no clear-cut evidence that the “straight liners” have provided less thoughtful answers than those who did not provide the same response.

Similarly, in a second grid on washing machine purchase priorities, 9% straight-lined, and most rated all attributes as “Very important,” which is plausible.

It is not expected that practitioners who have thought through either of these questions would flag participants who provided the same response. However, anecdotal responses from practitioners suggest that there are instances when participants could be flagged solely based on the fact they have “straight lined” rather than considering the question set.

Key Considerations:

- Straight-lining alone is not a definitive indicator of poor quality.
- Review question design before flagging—similar items often elicit similar responses.
- Combine straight-lining checks with other metrics, such as **time spent on the question**, to assess engagement.

Implementation Tips:

- Include positively and negatively worded statements within grids to encourage variation.
- Calculate **standard deviation** for each participant’s answers within matrix questions. As part of the review, the likelihood that the same response could be provided across a grid needs to be factored in. Based on time taking through the grids, the likelihood of the same response being made across the grid, then calculate a threshold. If more than 5% of participants are above the threshold then review the data and other information e.g., sources and other checking points. Then as required, adjust the threshold.
- Manually review flagged cases where consistent responses may be valid (e.g., brand loyalty).

Zigzag and Pattern Responses

Some disengaged participants or bots create detectable patterns, such as alternating extremes or diagonal sequences. These are harder to spot when question order is randomised but can be identified using pattern recognition techniques.

Implementation Tips:

- Apply algorithms to detect non-linear patterns in matrix responses.
- Use visualisation tools to display response patterns for manual review.
- Combine pattern checks with timing and other behavioural indicators for robust assessment.
- Make sure there are at least two options where it is expected that answers would differ e.g., “*I love to keep up with new fashions*” & “*I don’t follow fashion*”. Though you can allow for the same response for the mid-point, then for all other points, the same response is more unlikely, and a potential indicator of a poor participant.

It should be noted that excessive grid / statement blocks are not favoured by panellists and that a poor set of responses might be the result of poor design.

6. Honesty and Attention Checks

Honesty and attention checks are designed to identify inattentive or fraudulent participants by testing engagement and plausibility of responses. These checks can take several forms, but their effectiveness and appropriateness vary by context.

Instructional Manipulation Checks (IMCs), Trap Questions, and Red Herrings

These involve embedding explicit instructions (e.g., “*Please select ‘Somewhat Agree’ for this question*”) or asking impossible questions (“*Have you visited Mars?*”, “*Please answer $5 + 2$* ”) to catch inattentive participants. In the MRS research survey, a trap question was asked “*What is the colour of “go” on a traffic light?*” and the possible responses were - Green, Blue, Purple or Black. Only 20 (1%) responded differently to Green and this was the only flag among five of those 20 participants.

While they can detect some inattentiveness, they have limitations:

- **Fraudulent participants often avoid detection** as these checks are widely known. They do not present a significant challenge.
- **Risk of disengagement:** Out-of- context or humorous traps may confuse legitimate participants, leading them to give a wrong answer.

- **Length of interview:** Unnecessary questions add to survey length and given that these questions are considered a low indicator, these should not be considered as a standard, isolated approach.
- **Best practice:** If used, tie them closely to survey content, vary requested responses, and limit their number to avoid fatigue.

Behavioural Validation and Plausibility Checks

Beyond traps, behavioural checks assess the plausibility of responses:

- **Extreme or improbable claims:** Include a mix of high-incidence (e.g., *Used a mobile phone in the past 48 hours*) and low-incidence behaviours (e.g., *Been to the opera in the past week*) to identify unlikely patterns.
- **Fake brand awareness:** Adding fictitious brands to a list can flag inattentive participants but beware of halo effects— up to 10% may claim awareness if the fake brand sounds real. Stronger indicators include claiming frequent use of fake brands, and more weight should be given to participants who respond that they most often / regularly buy or use the fake brands rather than just being aware of brands.
- **Unexpected answers:** For example, selecting *Do not take online surveys* when asked about devices used for surveys is a strong anomaly.

Practitioners should build in considerations for participants who are neurodivergent which may affect response patterns, language use, etc.

See [MRS guidance: Essential Safeguards Series No 7: Conducting data activities with neurodiverse individuals](#).

Implementation Tips

- Apply behavioural checks thoughtfully, considering context and plausibility.
- Limit trap questions and integrate them naturally into the survey flow. Note that it might not be appropriate to include these in all research types, such as healthcare research or research on sensitive topics.
- When trap questions are used, vary the requested response option to prevent learning effects, place checks strategically in sections where attention may wane, and minimize the number of trap questions used to avoid participant disengagement.
- Combine honesty checks with other indicators (e.g., timing, response patterns) for robust decisions.
- For B2B studies, tailor checks to expected knowledge and monitor response time— long delays may indicate external research.

7. Answer Consistency Checks

Consistency checks/contradictory answers

involve strategically repeating questions or comparing logically related answers to identify discrepancies that may signal inattentiveness, misunderstanding, or dishonesty. For example, if a participant claims never to shop online but later reports frequent online purchases, this inconsistency should raise a flag.

How It Works

- Repeat key questions at different points in the survey or phrase them differently to test alignment.
- Use internal logic validation to identify contradictions across related questions.
- Program automated flags for inconsistencies and weight them based on severity (minor vs. major contradictions).

Practical Insights from MRS Research

In the MRS study, two repeated questions were tested:

- **Number of children under 18 in the household** (asked at start and end): 4% of participants gave different answers.
- **Dog ownership** (asked in two formats): 5% gave conflicting responses.

However, most inconsistencies were isolated:

- Of those with different answers on children, **31% had no other flags**, and **29% had only one additional flag**.
- Across both questions, only **17 participants (<1%)** were inconsistent on both measures.

Key Insight:

These checks are low-level indicators and should not be used alone for exclusion. Mis-clicks or misunderstandings happen, and legitimate participants can make mistakes. Consistency checks are most valuable when combined with other signals (e.g., speeding, response patterns, honesty checks).

Implementation Tips

- Create **consistency matrices** for question pairs that should logically align.
- Automate flags for contradictions and review manually where needed.
- Use revalidation prompts to allow participants to correct mistakes before submission.

8. Creating a Composite Quality Score

Rather than relying on single indicators, develop a weighted quality score that incorporates multiple dimensions of response quality.

Sample Scoring System:

- Assign points for each quality issue detected.
- Weight issues based on severity and reliability as quality indicators.
- Establish threshold scores for flagging and potential exclusion.
- Document scoring methodology clearly for transparency.

By systematically applying these detection methods, practitioners can identify potentially problematic responses that warrant further investigation or exclusion from analysis. The next section will explore appropriate decision frameworks for determining which responses to remove from your dataset.

What to do Once Poor-Quality Responses are Identified

Identifying potential data quality issues is only the first step - deciding how to act requires a balanced, evidence-based approach. Overly aggressive removing can distort representativeness, while lenient standards risk contaminating insights. The goal is to apply consistent, defensible decisions that maintain data integrity without alienating participants or introducing bias.

Key Principles

- **Use Multiple Indicators:** Avoid decisions based on a single check. Combine evidence from multiple sources (e.g., speeding, open-end quality, response patterns) before excluding a participant.
- **Consider Non-Survey Data:** Supplement survey checks with additional information such as:
 - **Device behaviour:** Compare patterns across devices (e.g., mobile vs. desktop), accounting for demographic differences.
 - **Sample source/sub-source:** Identify whether issues cluster by supplier; collaborate with suppliers to verify fraud patterns.
 - **Panel tenure:** New participants often pose higher fraud risk; review registration history.
- **Balance Rigour with Respect:** Excessive checks or denying incentives post-field can frustrate genuine participants and harm panel engagement.
- **Transparency:** Inform participants about the importance of thoughtful responses to set expectations and encourage engagement.
- **Pilot Testing:** Test quality controls before full launch to ensure they work as intended and do not exclude valid participants.
- **Adapt to Context:** Tailor checks to survey length, complexity, audience type (e.g., B2B vs. general population), and incentive structure.
- **Review and Iterate:** Use learnings from previous surveys to refine quality control mechanisms.

Decision Framework

Implement a **classification system**:

1. **Clear Excludes:** Responses with unambiguous issues (e.g., failed multiple attention checks, impossible completion times, confirmed fraud).
2. **Clear Includes:** Responses with no significant concerns.

Multi-Factor Validation:

Require evidence from multiple indicators before exclusion. For example:

Exclude participants who fail at least three independent checks (e.g., speeding, open-end gibberish, and straight-lining).

Severity Weighting:

Assign weights to indicators based on reliability:

- High: Failed attention checks, extreme speeding
- Medium: Straight-lining (context-dependent)
- Low: Minor inconsistencies

Documentation and Reporting

Maintain detailed records of:

- Pre-specified quality criteria and thresholds
- Number and percentage of participants failing each criterion - see the [GDQ/MRS/SampleCon Feedback Loop](#) resources.
- Final disposition of flagged cases
- Impact on key metrics and representativeness

Transparency in Reporting:

When projects result in high levels of challenges with data quality, it can be useful to include original and final sample sizes, exclusion criteria, and sensitivity analyses showing whether findings change under different removal levels. This information may be gathered for internal purposes in addition to transparency in reporting. The new [ISO 20252:2026](#) standard has introduced new transparency requirements to improve sample user transparency.

Representativeness and Sensitivity

If there is a high level of removals that cannot be replaced, consider the following:

- Compare demographic profiles before and after removals.
- Apply weighting adjustments if exclusions create imbalances.
- Conduct sensitivity analysis to test robustness of findings under varying removal stringency.

Key Insight:

Data removal decisions should be systematic, documented, and context aware. The optimal approach combines multiple indicators, supplier collaboration, and transparent reporting.

The Risks of Over-Removal: When Quality Control Becomes Counterproductive

While considered data removal is essential for research integrity, overly aggressive removal can introduce significant risks that compromise validity, representativeness, and efficiency. The goal should always be **optimal—not maximal—removals**, removing responses that genuinely compromise data quality while preserving legitimate diversity.

What Is Over-Removal

Over-removal occurs when researchers apply excessively strict criteria or remove participants based on questionable indicators, excluding valid responses that could provide valuable insights. This often stems from well-intentioned efforts to maximize quality but can undermine research objectives.

Key Risks

1. Bias Introduction

- **Demographic Bias:** Certain groups may naturally exhibit patterns that trigger flags (e.g., older participants take longer; younger participants complete more quickly).
- **Cultural and Linguistic Bias:** Cultural norms influence response styles; non-native speakers may show inconsistencies or longer times due to language challenges.

2. Loss of Representativeness

- Removing legitimate responses can distort demographic balance and reduce diversity of perspectives.
- Over-removal from datasets may appear more consistent than reality, leading to overconfident conclusions.

3. Reduced Statistical Power

- Each exclusion reduces sample size, widening confidence intervals and limiting subgroup analysis.
- Removing more than 15–20% of responses can significantly impact analytical precision.

4. Variance Distortion

- Excluding participants with unusual but valid patterns reduces natural variability, masking niche segments or minority viewpoints.

5. Economic and Efficiency Costs

- High removal rates waste recruitment and incentive costs.
- Larger initial samples and extended fieldwork may be needed to compensate for exclusions.

Best Practices to Avoid Over-Removal

- **Evidence-Based Thresholds:** Base removal criteria on empirical analysis, not arbitrary standards. In some situations, it might be worth testing whether flagged responses materially affect key outcomes.
- **Graduated Strategies:** Instead of outright removal, consider:
 - Flagging for sensitivity analysis
 - Weighting questionable cases to reduce influence
 - Parallel analyses with and without flagged responses
- **Multi-Factor Validation:** Require multiple indicators before exclusion (e.g., speeding + gibberish + failed attention checks).
- **Severity Weighting:** Assign higher weight to strong indicators (e.g., failed attention checks) and lower weight to weaker ones (e.g., minor inconsistencies).
- **Transparency and Documentation:** Record decisions, thresholds, and impacts on representativeness. Share methodology with stakeholders.
- **Regular Review:** Update data removal standards as survey environments and participant behaviours evolve.

Key Insight

In some cases, removal decisions may need to consider the question:

“Is this really making a difference to the outcome?”

Removing responses for minor issues (e.g., straight-lining alone) can harm representativeness without improving data quality. Strive for balance, protect integrity while preserving diversity.

Special Considerations for Different Research Types

Tracking Studies

For longitudinal research, consistency in data removal methodology is crucial.

Best Practices:

- Document removal procedures in detail.
- Apply consistent criteria across waves.
- When methodology must evolve, implement parallel analysis for trend validation.

Low-Incidence Populations

For rare participant types, consider modified approaches.

Adapted Techniques:

- More reliance on manual review of flagged cases.
- Adjusted thresholds based on population-specific response patterns.
- Greater emphasis on cross-validation of quality indicators.

By implementing these structured decision frameworks, research teams can make defensible, consistent data removal decisions that optimize data quality while maintaining sample integrity.

