Designing A Web-Based Questionnaire with Incentive Verification and Behavioural Screening Mechanisms to Improve Survey Data Quality

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ABSTRACT

Web-based survey platforms such as Google Forms and SurveyMonkey have become widely adopted in academic and applied research due to their efficiency, accessibility, and low operational cost. However, open online survey environments introduce challenges related to respondent inattentiveness, satisficing behaviours, and data authenticity, which can compromise the reliability and validity of collected data. To address these issues, this study aims to design, develop, and evaluate a web-based questionnaire framework that integrates intervention techniques to enhance response quality. Specifically, the study identifies three practical intervention mechanisms—straightlining detection, consistency or logic checks, and attention check questions—and embeds them within an incentive-based survey system that securely collects respondent banking details for token distribution. The methodology comprises four phases: identification of intervention techniques through literature review; system design and proof of concept; data collection using the developed platform; and usability evaluation conducted with 11 survey instrument developers. Usability was assessed across five dimensions: interface usability, navigation, clarity, satisfaction, and overall experience. Results indicated strong usability performance, with average scores exceeding 80% across all dimensions. Clarity of instructions achieved the highest score (87%), while efficiency scored 80%, suggesting minor areas for optimization. The findings demonstrate that embedded intervention techniques do not detract from user experience while supporting attentive participation. Future work should focus on validating the effectiveness of these intervention techniques in detecting low-quality responses across diverse respondent populations and survey contexts, as well as exploring automation of real-time response filtering to further enhance data integrity.

Keywords: Web-based, interventions, questionnaire, quality responses, survey

INTRODUCTION

The use of web-based survey platforms has expanded rapidly in recent years due to their efficiency, accessibility, and ability to reach large respondent populations (Clement *et al.*, 2023). Free online tools such as Google Forms and Survey Monkey are frequently adopted in academic and applied research because they enable rapid questionnaire deployment with minimal operational cost (Andrade, 2020). Despite these advantages, several methodological challenges remain when collecting data through open online platforms. Researchers often face issues related to uncontrolled survey environments, inattentive responding, and the difficulty of verifying respondent engagement, which can affect the reliability and validity of survey data (Calderon Vriesema & Gehlbach, 2021; Sturgis & Brunton-Smith, 2023).

Another important concern in web-based surveys relates to the cognitive demands imposed on respondents. Many questionnaires require respondents to evaluate statements, recall experiences, or provide reflective judgments, which involve substantial cognitive processing (Clement *et al.*, 2023). When survey questions require sustained attention or complex reasoning, respondents may engage in satisficing behaviours by providing quick or superficial answers rather than carefully processing the items (Calderon Vriesema & Gehlbach, 2021; Sturgis & Brunton-Smith, 2023). Such behaviours may appear in the form of patterned responses, skipped questions, or rapid completion of surveys, thereby compromising the accuracy and consistency of the collected data (Aust *et al.*,2025; Stanley *et al.*, 2020).

In addition, to improve respondent engagement and encourage meaningful participation, researchers frequently provide incentives or tokens for survey completion. Incentives have been shown to increase participation rates and motivate respondents to complete surveys more carefully. However, implementing such incentives requires the collection of respondent identification or payment details, particularly when financial tokens are involved. Consequently, the survey system must ensure that the process of collecting respondent banking or payment details is simple, accurate, and secure while minimizing respondent burden and maintaining data integrity (International Organization for Standardization, 2022).

Beyond incentive mechanisms, modern web-based questionnaires increasingly incorporate embedded response quality control features to ensure that respondents read and understand the questions before answering. Without such controls, respondents may complete surveys too quickly, provide identical responses across multiple items (straightlining), or ignore important instructions embedded in the questionnaire. To address these issues, several intervention techniques can be integrated into survey design, including straightlining detection, consistency/logic checks, and attention check questions. These techniques function as diagnostic indicators that help detect inattentive respondents and improve the overall reliability of collected data in online survey research (Ward & Meade, 2023).

Thus, this study aims to design, develop and evaluate a web-based questionnaire framework that improves response quality in online surveys. Specifically, the study first seeks to identify brief intervention techniques that are suitable for general users to enhance respondent attentiveness and reduce careless responses. Second, the study aims to design and implement a web-based survey model that integrates these intervention mechanisms within the questionnaire system. Finally, the study evaluates the developed system by assessing its usability, focusing on the overall interface design, user experience, and the look-and-feel of the web-based survey platform.

This paper is organized as follows. Section 1 presents the introduction, highlighting the research background, problem statement, and study objectives. Section 2 reviews relevant literature, including the rationale for web-based questionnaires, intervention techniques for improving response quality, and prior related studies. Section 3 presents the conceptual framework, illustrating the relationship between the web-based survey system, embedded interventions, and data quality outcomes. Section 4 describes the research methodology, including the four phases of the study: identification of intervention techniques, system design and implementation, data collection, and usability evaluation. Section 5 presents the results and discussion, analysing the outcome of the system usability evaluation. Finally, Section 6 concludes the paper, summarizing key findings, and recommendations for future research.

REVIEW OF LITERATURE

Web-based questionnaires have become an important instrument for collecting data due to their efficiency, scalability, and ability to reach geographically diverse respondents. Compared with traditional survey methods, web surveys enable faster deployment, lower operational costs, and automated data management. However, the open nature of online surveys also introduces challenges related to respondent authenticity, inattentive participation, and fraudulent responses (Raynes & Marlar, 2024). Recent studies highlight that while online surveys improve accessibility, they are also more vulnerable to careless responding and automated or low-effort participation, which may threaten data reliability and research validity. Consequently, researchers increasingly emphasize the need for more structured and controlled web-based questionnaire systems that incorporate data-quality monitoring mechanisms during the data collection process (Ward & Meade, 2023).

To address these challenges, several intervention techniques have been proposed to detect inattentive or careless respondents in online surveys. Among the commonly used techniques are straightlining detection, consistency/logic checks, and attention check questions. Straightlining detection identifies respondents who repeatedly select identical response options across a series of items, indicating a lack of engagement with the questionnaire. Consistency or logic checks are widely used in survey research to detect inattentive or careless responding. The basic principle is to include paired or reverse-coded questions that measure the same construct in opposite directions. For example, a survey item may state, *"I would recommend bus service"*, while a logically opposite item might read, *"I would avoid bus service"*. If a respondent answers *"5 – Strongly Agree"* to both questions, this indicates a response inconsistency, suggesting that the participant did not read the questions carefully or was responding randomly. By embedding such logic checks, researchers can flag and exclude unreliable responses, improving the overall data quality and validity. This technique is simple to implement in web-based questionnaires and is especially useful when participants are general users who may skim through questions quickly. Consistency checks are often combined with other interventions like response time analysis and attention checks for a more robust quality control system (Goldammer *et al.*, 2020; Muszyński, 2023).

Additionally, attention check questions, also known as instructional manipulation checks, are designed to ensure that respondents carefully read the survey instructions before responding. These techniques are considered practical because they can be easily integrated into web-based questionnaires without increasing respondent burden while providing effective indicators of response quality (Stanley *et al.*, 2020). Several recent studies have implemented similar strategies to improve data quality in online survey research. The following Table 1 summarizes previous study.

Table 1. Summary of Previous Studies

Detection Technique	Supporting Sources	Key Findings / Context
Straightlining Detection	Bloy *et al*. (2025); Clement *et al.* (2023); Johnson *et al.* (2024); Stanley *et al.* (2020); Ward & Meade (2023)	Identifies respondents who select the same response option for a series of questions (e.g., a grid). Considered a key indicator of careless or satisficing behaviours.
Consistency / Logic Checks	Bloy *et al.* (2025); Caven *et al.* (2025); Goldammer *et al.* (2020); Johnson *et al.* (2024); Muszyński (2023); Ward & Meade (2023)	Involves verifying skip patterns, checking for impossible answer combinations, and detecting logical inconsistencies across questions. Often part of broader "high-frequency checks".
Attention Check Questions	Bloy *et al.* (2025); Caven *et al.* (2025); Goldammer *et al.* (2020); Ladini (2022); Muszyński (2023); Silber *et al.* (2022); Ward & Meade (2023)	Also known as Instructional Manipulation Checks (IMCs) or "gotcha" questions; instruct respondents to select a specific answer to verify attentiveness. Noncompliance is a concern, with some respondents failing deliberately.

CONCEPTUAL FRAMEWORK

At the system level, a web-based questionnaire platform serves as the primary data collection environment. The platform incorporates an incentive mechanism, where respondents provide basic banking details to receive

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a participation token upon completion of the survey. The incentive mechanism functions as a motivational factor that encourages respondents to complete the questionnaire while ensuring that respondent identification and payment processes remain simple and accurate. Within this environment, three intervention techniques are embedded to monitor and improve response quality. The first technique, straightlining detection, identifies respondents who repeatedly select identical response patterns across multiple survey items, which may indicate inattentive participation. The second technique, to detect careless or insufficient effort responding, survey designs often incorporate consistency checks. The core principle is the inclusion of item pairs, either as direct repetitions or reverse-coded questions—designed to measure the same concept, with the expectation that an attentive respondent will answer them in a logically consistent manner (Ozaki, 2024). The third technique, attention check questions, also known as instructional manipulation checks, are strategically embedded within the questionnaire to confirm whether respondents carefully read and follow survey instructions. The expected outcome of this framework is the improvement of data reliability, response validity, and overall survey data quality.

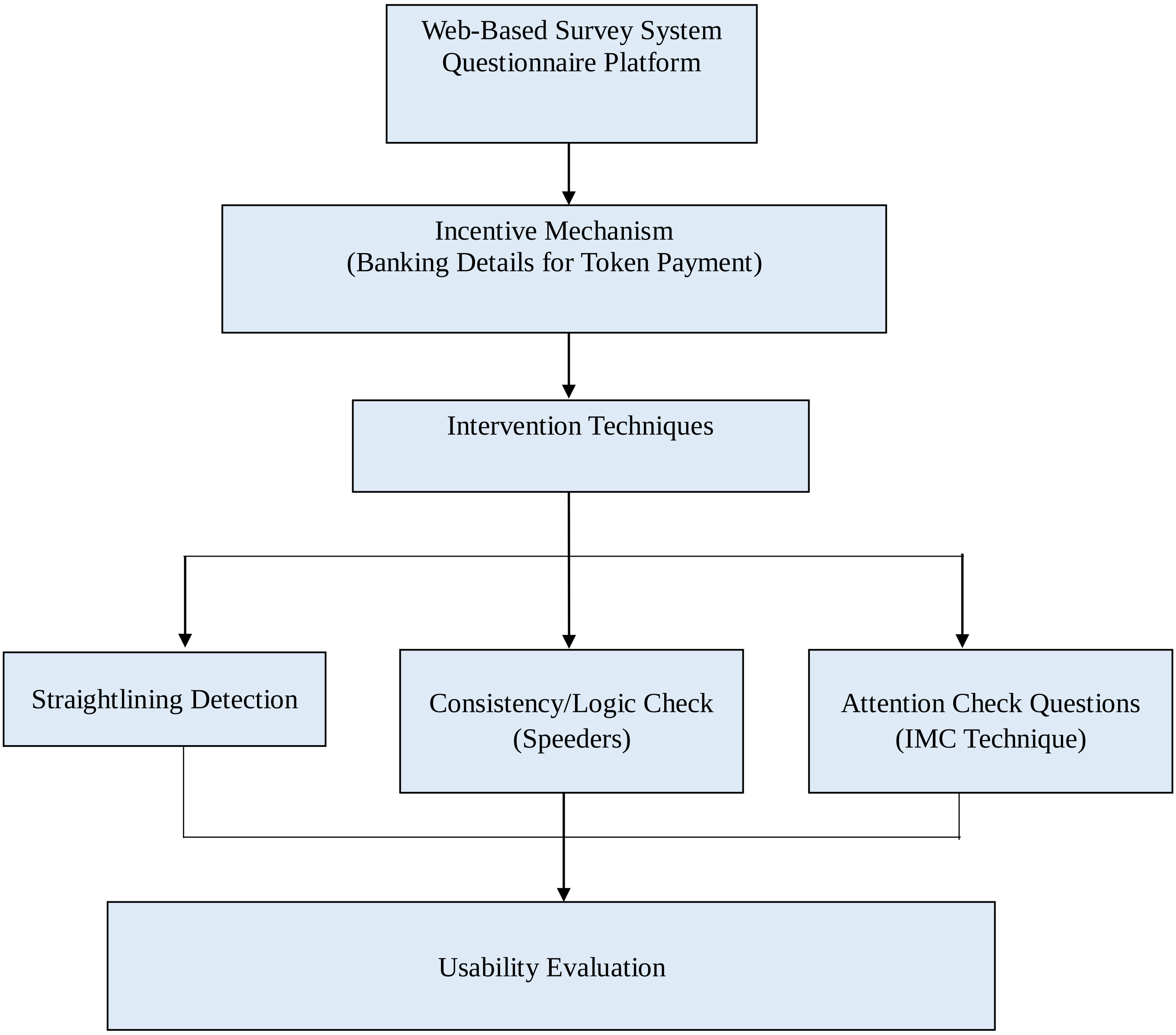

Figure 1. Conceptual Diagram of The Web-Based Survey System

The usability of the questionnaire interface plays a critical role in obtaining high-quality responses from respondents. As illustrated in Figure 1, the proposed framework is grounded in the premise that questionnaire usability constitutes an essential initial step in the validation process. The overall quality of survey data is strongly shaped by the level of respondent engagement and attentiveness maintained throughout questionnaire completion (Höhne *et al.*, 2020; Muszynski & Jabkowski, 2025; Revilla & Höhne, 2020).

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MATERIALS AND METHODS

The methodology of this study is organized into four main phases as shown in Figure 2. Each addressing a critical aspect of the research: identification of intervention techniques, design and implementation of the web-based survey system, data collection, and validation and usability evaluation.

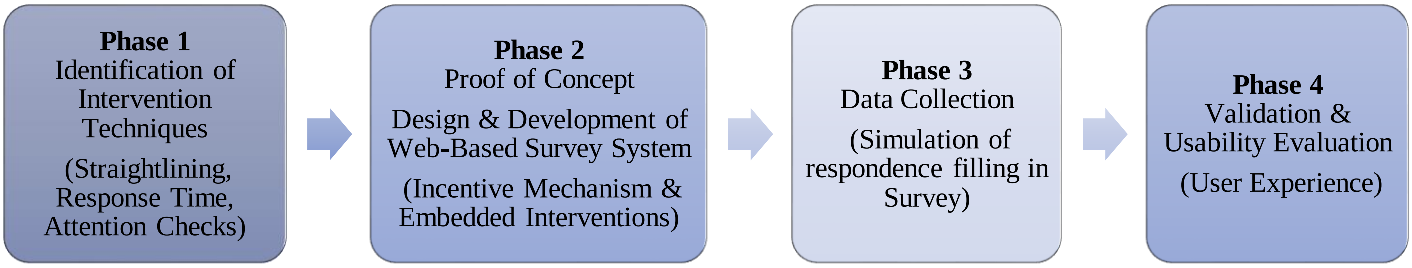

Figure 2. Study Flow Organized into Four Main Phases

Phase 1: Identification of Intervention Techniques

The first phase involves a thorough review of the literature to identify practical intervention techniques suitable for general users. The primary objective is to select techniques that can effectively detect inattentive or low-effort responses without imposing additional cognitive burden on respondents. Based on prior studies, three interventions were chosen: straightlining detection, consistency/logic checks, and attention check questions. This phase ensures that only the most effective and user-friendly techniques are integrated into the survey system.

Phase 2: Proof of Concept

In the second phase, a web-based questionnaire platform was designed as a proof of concept to integrate the selected intervention techniques. The design of the module hierarchy is shown in Figure 3. The system incorporates an incentive mechanism, where respondents provide basic banking or identification details to receive a token upon survey completion. The design process emphasizes simplicity, security, and accuracy in collecting respondent details to ensure seamless token distribution. As a proof of concept, the web survey interface was developed with intuitive navigation, clear instructions, and automated embedding of the three intervention techniques to monitor response quality in real time.

Phase 3: Data Collection Simulation

The third phase employed an iterative simulation of web-based data collection, where successive virtual test cycles refined the survey's design, language, interaction, navigation, and look-and-feel. Each iteration adjusted linguistic clarity, interactive elements, navigational flow, and visual aesthetics based on simulated respondent metrics such as completion rates, response times, and attention check accuracy. The token incentive mechanism was also simulated to optimize engagement. After multiple refinement cycles, the final platform was deployed with real respondents, automatically recording response times, detecting straightlining patterns, and embedding attention checks for real-time monitoring and filtering of low-quality data.

Phase 4: Usability Evaluation

The final phase involves the evaluation of the web-based survey system in terms of usability. The usability evaluation involved 11 respondents who are researchers with experience in developing survey instruments. They assessed the look-and-feel of the platform, including user interface design, navigation ease, and overall user experience. Feedback from respondents is collected using a post-survey questionnaire and analysed to refine the system design. The sample size of 11 respondents limits the statistical generalizability of the findings to a broader population. However, for the purpose of identifying critical design flaws and assessing system interactions, this sample size exceeds the minimum threshold recommended by contemporary usability literature, which affirms that 5 to 10 users are adequate for uncovering most severe usability problems (Lorincz *et al.*, 2026). Additionally, the system is assessed using established usability constructs, as outlined in Appendix 1. While Figure 4 illustrates an example of survey screenshots used for attention check questions. The results are presented in Appendices 2 and 3.

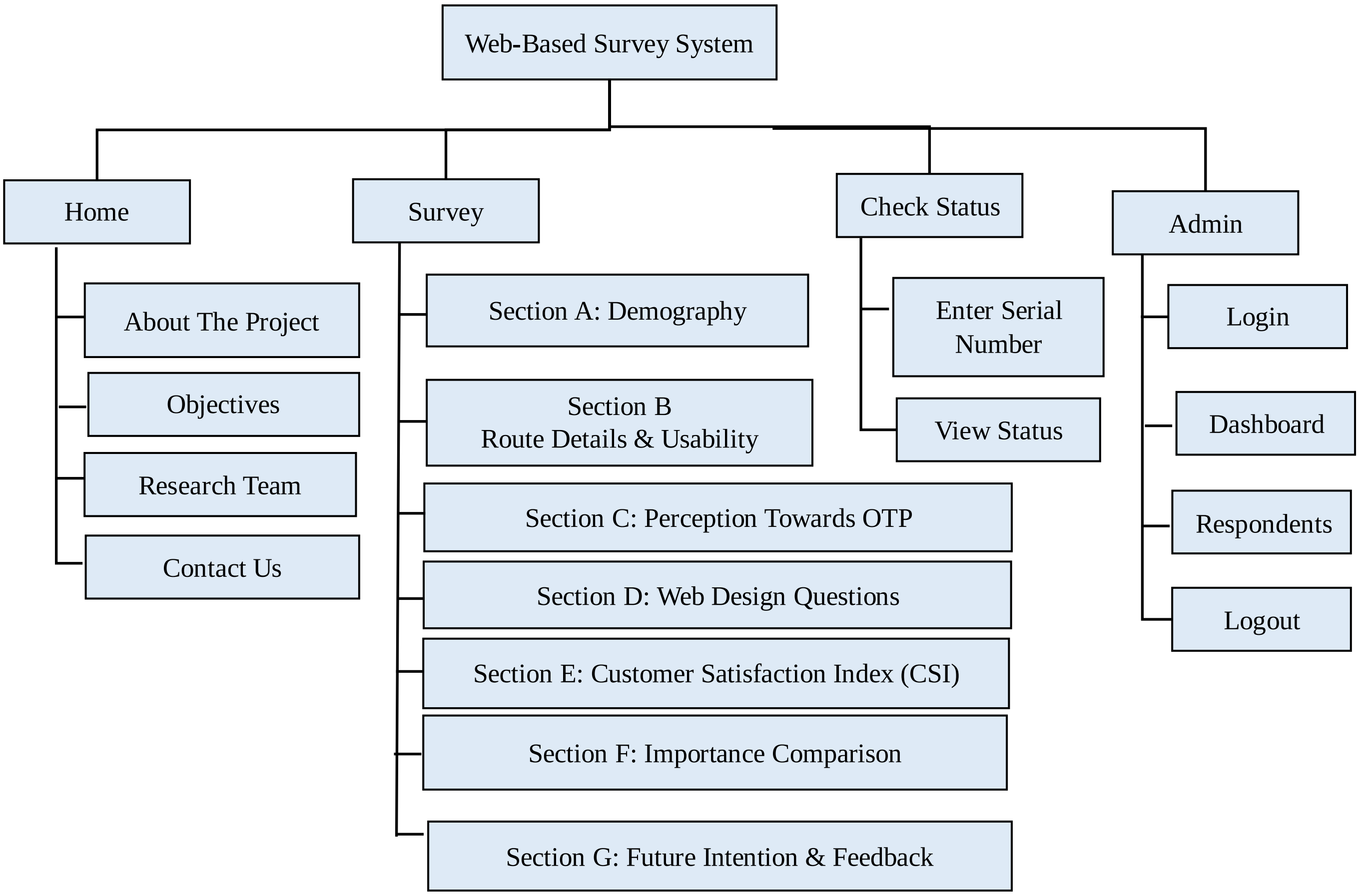

Figure 3. Module Hierarchy

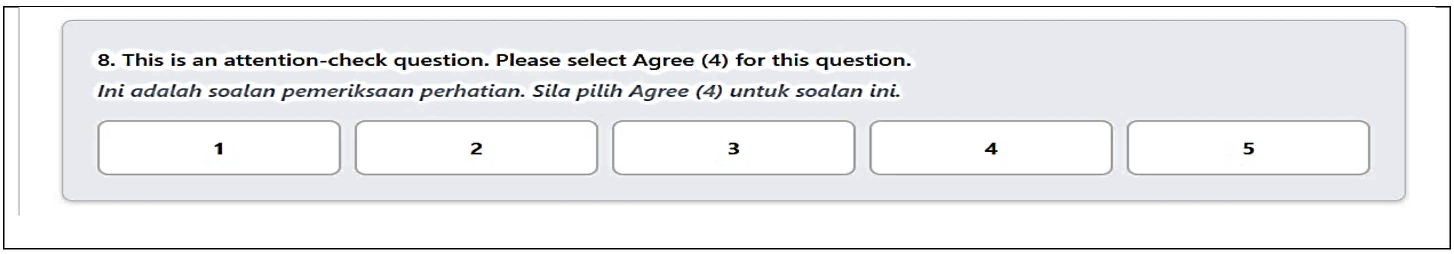

Figure 4. Example of Survey Screenshots for Attention Check

RESULT AND DISCUSSION

The usability evaluation responses were collected using a 5-point Likert scale across five key dimensions: interface usability, navigation, clarity, satisfaction, and overall experience. The results shown in Figure 5 indicate high overall performance, with an average score of 84% across interface usability, navigation, clarity, and overall experience. These findings suggest that the survey platform is intuitive, easy to navigate, and effectively communicates instructions, allowing respondents to complete tasks efficiently. Satisfaction scores were slightly lower (84%), due to the cognitive demands imposed by certain survey items. Some questions

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required extended reading and careful reflection, resulting in a perception of higher effort from respondents. This aligns with prior studies indicating that longer or more cognitively demanding surveys can slightly reduce user satisfaction, even when interface usability is high (Aust *et al.*, 2023).

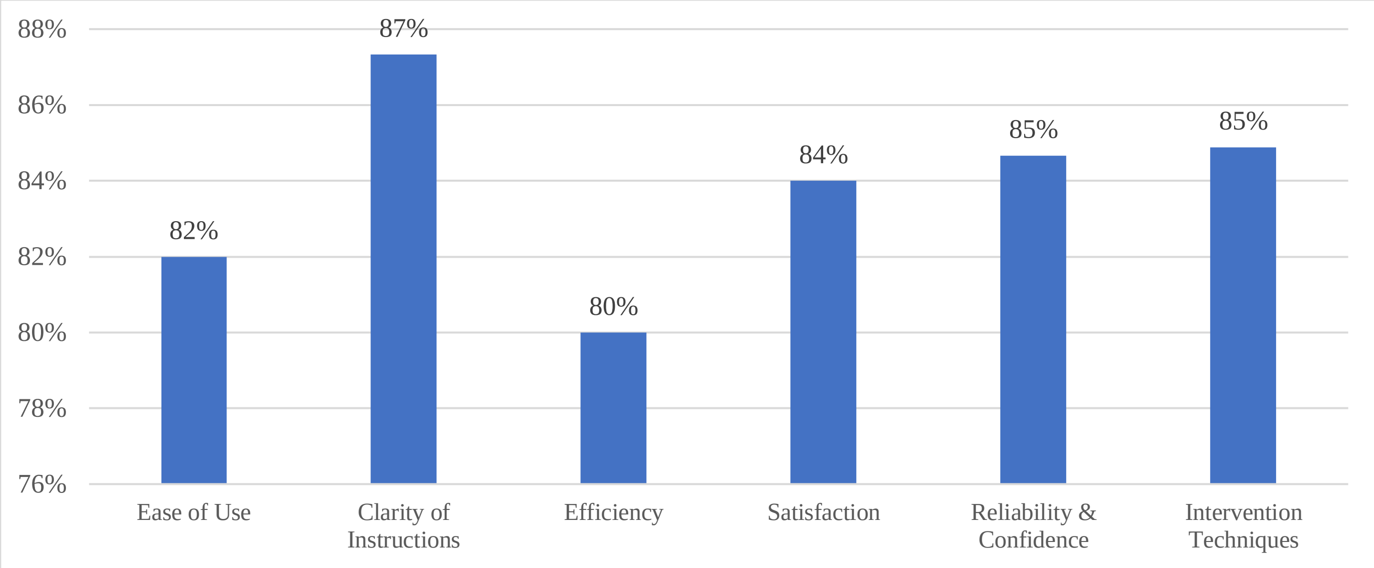

Figure 5. Result of Usability Evaluation by Constructs

The results indicate a strong overall usability performance, with all dimensions scoring 80% and above, reflecting positive user acceptance of the system. Clarity of Instructions recorded the highest score (87%), showing that users found the guidance and system workflow clear and easy to understand. This is followed by Reliability & Confidence and Intervention Techniques, both at 85%, suggesting an elevated level of trust in the system's functionality and decision support capability. Satisfaction scored 84%, indicating that users were pleased with their overall experience. Meanwhile, Ease of Use achieved 82%, demonstrating that the system is perceived as user-friendly and accessible. Although Efficiency recorded the lowest score (80%), it remains within a strong range. The detailed scores for each construct are presented in Figure 6.

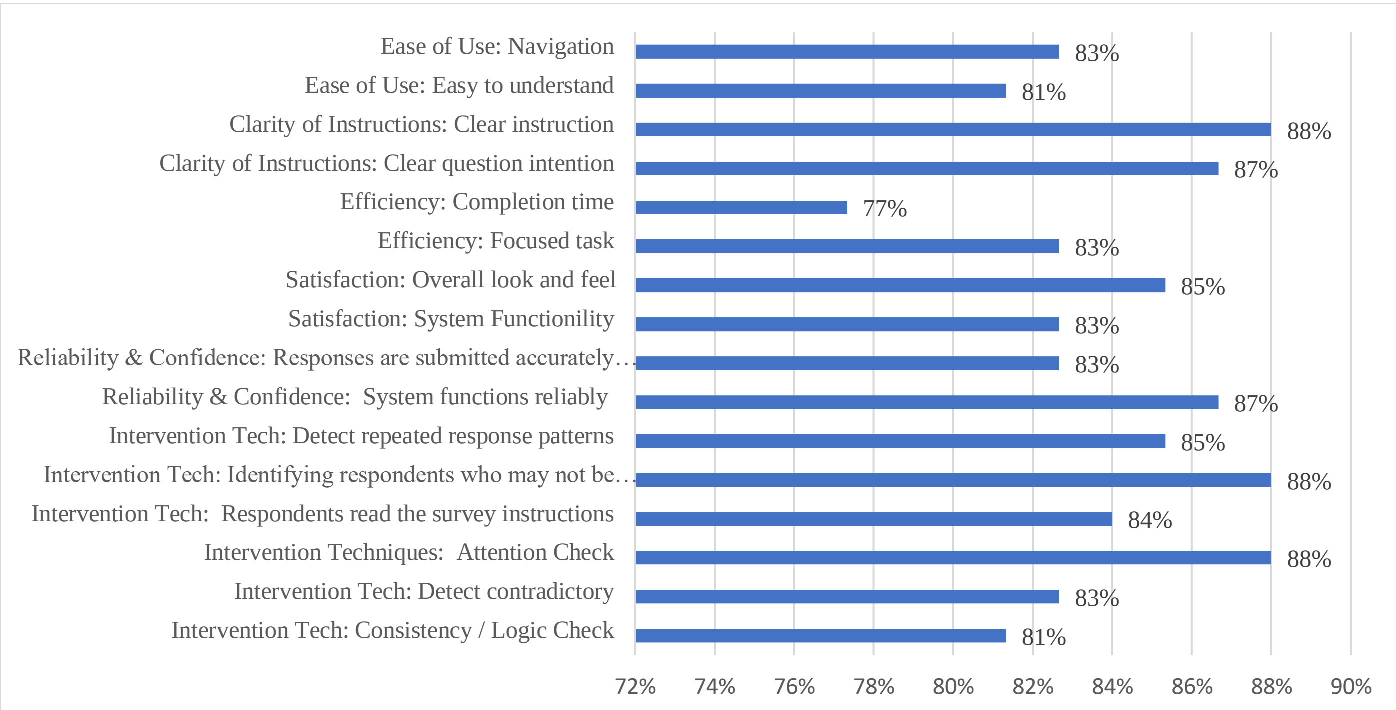

Figure 6. Detail Score of Usability Assessment

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The results demonstrate that the integrated intervention techniques did not negatively affect usability. Respondents were able to engage with the survey effectively while maintaining attentiveness, suggesting that the framework successfully balances data quality monitoring with user experience. These findings demonstrate the feasibility of implementing incentive-based, intervention-enhanced web-based questionnaires for reliable data collection in research contexts.

This study implemented three established behavioural screening mechanisms—straightlining detection, consistency/logic checks, and attention check questions—based on benchmark definitions and methods from the survey methodology literature, as summarised in Table 2 (benchmarking previous studies against the present implementation) and Table 3 (overall benchmark alignment). Straightlining was operationalised as uniform response patterns across multiple items indicating disengagement or satisficing (Reuning & Plutzer, 2020), implemented through long-string variance analysis to flag near-zero variability in consecutive responses. Consistency and logic checks followed benchmark practice using paired and reverse-coded items measuring the same construct in opposite directions, with mismatches in synonym and antonym item responses used to identify inconsistency. Attention checks were embedded as instructed-response items, with accuracy-based detection used to flag inattentive or non-compliant responses. A usability evaluation was conducted prior to distributing the survey questions for the pilot study; this step is essential to ensure that the questionnaire interface is intuitive, reduces cognitive load, minimises respondent burden, and prevents usability-related artefacts that could distort response behaviour and compromise data quality. Empirically, the combined mechanisms demonstrated complementary diagnostic value: straightlining reflected fatigue or satisficing, consistency errors indicated random or careless responding, and attention check failures captured low cognitive engagement, with their removal improving reliability, reducing measurement error, and enhancing inferential accuracy. Collectively, this integrated, benchmark-aligned framework provides a rigorous and scalable approach to identifying and mitigating insufficient effort responding in web-based survey environments.

Usability testing is a key step in instrument validation prior to pilot deployment, ensuring that respondents can correctly interpret items and interact with the survey interface as intended. Evidence shows that usability problems such as unclear layout and high cognitive burden negatively affect data quality and response accuracy, reinforcing the importance of early testing before data collection (Revilla & Ochoa, 2021). Conducting usability testing prior to pilot distribution therefore enables early identification and correction of design flaws, improving clarity, reducing respondent burden, and strengthening the validity and reliability of the instrument.

Table 2. Benchmarking Previous Studies Against the Implementation of the Present Study

Mechanism	Definition / Principle	Detection Method	Benchmark Comparison with the Implementation of the Present Study	Data Quality Implication
Straightlining Detection	Identifies uniform response patterns across multiple items, signalling disengagement or satisficing (Reuning & Plutzer, 2020)	Calculates variance across consecutive items; flags zero or near-zero variance (long-string analysis)	Implements the same definition and detection method as the benchmark identifies uniform response patterns across multiple items by calculating variance and flagging zero or near-zero variance (long-string analysis)	High rates indicate fatigue or speeded answering; removal improves scale reliability
Consistency / Logic Check	Uses paired or reverse-coded	Compares responses on	Implements the benchmark approach of	Inconsistent responses indicate

Mechanism	Definition / Principle	Detection Method	Benchmark Comparison with the Implementation of the Present Study	Data Quality Implication
	items measuring the same construct in opposite directions (Jin & Chiu, 2024)	synonym/antonym pairs; flags mismatched patterns (Goldammer, 2020)	comparing responses on synonym and antonym item pairs, flagging mismatched patterns	random answering; filtering reduces measurement error
Attention Check Questions	Embeds instructed response items (e.g., "Select 'Agree'") to verify attentive reading (Shamon and Berning, 2020)	Analyses accuracy on attention-check items and flagging inattentive respondents. (Kane *et al.*, 2023)	Implements the benchmark method of analysing accuracy on instruction-following items, flagging incorrect responses	Failure correlates with lower overall quality; exclusion improves effect size accuracy

Table 3. Benchmark Alignment

Mechanism	Benchmark Source	Implementation Status	Quality Outcome
Straightlining Detection	Reuning & Plutzer (2020)	Fully aligned	Improved scale reliability
Consistency / Logic Check	Jin & Chiu, (2024)	Fully aligned	Reduced measurement error
Attention Check Questions	Kane et al. (2023)	Fully aligned	Increased effect size accuracy

The present study fully aligns with the benchmark standards for all three behavioural screening mechanisms. Straightlining detection follows the benchmark, resulting in improved scale reliability. Consistency and logic checks adhere to the benchmark, leading to reduced measurement error. Attention check questions conform to the benchmark, yielding increased effect size accuracy. This complete benchmark alignment ensures that the present study's methodological framework is comparable to established best practices in survey data quality research.

CONCLUSION

This study developed and evaluated a web-based questionnaire platform designed to improve response quality through incentive-based participation and embedded behavioural screening mechanisms. By implementing benchmark-aligned methods from the literature, the study operationalised three core techniques: straightlining detection, consistency/logic checks, and attention check questions, forming a multi-layered framework to identify inattentive or insufficient effort responding and ensure comparability with prior research. The findings demonstrate that this integrated approach effectively enhances data quality while maintaining strong system usability across interface design, navigation, clarity, and overall user experience, with only a slight reduction in satisfaction attributed to the cognitive load of certain survey items. Overall, the results indicate that the platform successfully balances rigorous response quality monitoring with a user-friendly design, supporting the validity and reliability of collected data. The study further highlights the feasibility of combining incentive mechanisms with automated quality-control interventions in web-based surveys. For future work, the questionnaire will be distributed for a pilot study to assess its effectiveness in practice. The system can also be extended by incorporating artificial intelligence for bot and automated response detection, scaling to larger populations, integrating adaptive survey logic, and testing across more diverse respondent groups to further strengthen robustness and generalisability.

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Appendix 1: Usability Assessment Constructs

Usability Assessment Constructs	References
1. Ease of Use • The survey interface is easy to navigate. • It is easy to understand how to complete the questionnaire.	Brooke, J. (1996). SUS: A “quick and dirty” usability scale. In P. W. Jordan, B. Thomas, B. A. Weerdmeester, & I. L. McClelland (Eds.), *Usability evaluation in industry* (pp. 189–194). London: Taylor & Francis.
2. Clarity of Instructions • The instructions provided in the survey are clear and easy to follow. • The purpose of each question is easy to understand.	Nielsen, J. (1994). *Usability engineering*. San Francisco: Morgan Kaufmann.
3. Efficiency • Completing the survey does not take longer than expected. • The survey system allows me to complete tasks without unnecessary effort. •	Lewis, J. R. (2018). *The system usability scale: Past, present, and future*. International Journal of Human–Computer Interaction, 34(7), 577–590. https://doi.org/10.1080/10447318.2018.1455307

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4. Satisfaction • I am satisfied with the overall look and feel of the survey. • I feel confident using the survey system.	Sauro, J., & Lewis, J. R. (2016). *Quantifying the user experience: Practical statistics for user research* (2nd ed.). Morgan Kaufmann.
5. Reliability & Confidence • I trust that my responses are submitted accurately by the system. • The system functions reliably without technical issues.	ISO 9241-11:2018. *Ergonomics of human-system interaction — Usability: Definitions and concepts.* International Organization for Standardization.

Appendix 2: Usability Evaluation Results by Construct

Construct	Item	Description	Average Score
Ease of Use	Navigation	Section A: Ease of Use – The survey interface is easy to navigate.	4.13
Ease of Use	Ease of Understanding	Section A: Ease of Use – It is easy to understand how to complete the questionnaire.	4.07
Clarity of Instructions	Clear Instructions	Section B: Clarity of Instructions – The instructions provided in the survey are clear and easy to follow.	4.40
Clarity of Instructions	Clarity of Questions	Section B: Clarity of Instructions – The purpose of each question is easy to understand.	4.33
Efficiency	Completion Time	Section C: Efficiency – Completing the survey does not take longer than expected.	3.87
Efficiency	Task Efficiency	Section C: Efficiency – The survey system allows tasks to be completed without unnecessary effort.	4.13
Satisfaction	Overall Design	Section D: Satisfaction – I am satisfied with the overall look and feel of the survey.	4.27
Satisfaction	System Confidence	Section D: Satisfaction – I feel confident using the survey system.	4.13
Reliability & Confidence	Response Accuracy	Section E: Reliability & Confidence – I trust that my responses are submitted accurately by the system.	4.13
Reliability & Confidence	System Reliability	Section E: Reliability & Confidence – The system functions reliably without technical issues.	4.33
Intervention Techniques	Straightlining Detection (Effectiveness)	Section F: Intervention Techniques – The system's ability to detect repeated response patterns (straightlining) helps ensure thoughtful responses.	4.27

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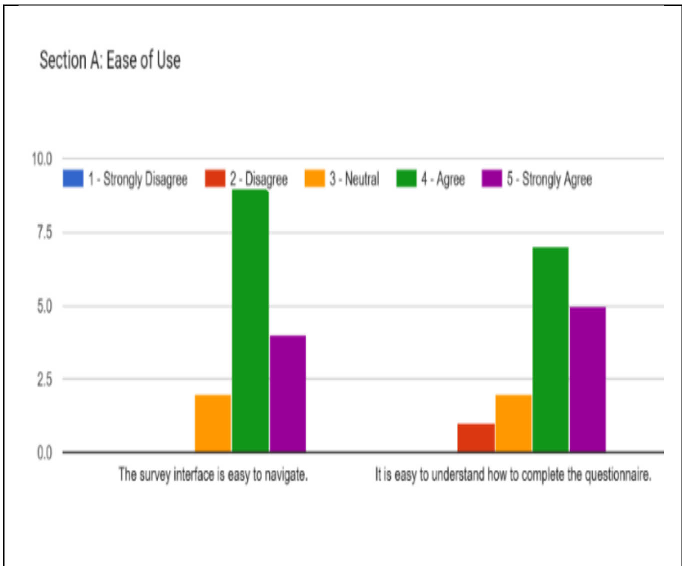
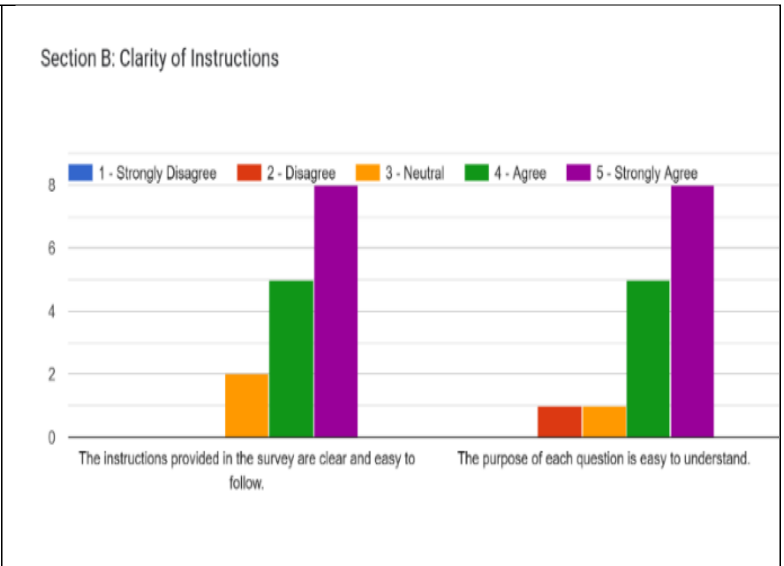
Intervention Techniques	Straightlining Detection (Usefulness)	Section F: Intervention Techniques – The straightlining detection feature is useful for identifying inattentive respondents.	4.40
Intervention Techniques	Attention Check (Instructional Compliance)	Section F: Intervention Techniques – Attention check questions ensure respondents read the survey instructions carefully.	4.20
Intervention Techniques	Attention Check (Data Reliability)	Section F: Intervention Techniques – Including attention check questions improves the reliability of collected responses.	4.40
Intervention Techniques	Consistency Check (Detection)	Section F: Intervention Techniques – Consistency checks help detect contradictory responses.	4.13
Intervention Techniques	Consistency Check (Data Quality)	Section F: Intervention Techniques – Logic and consistency checks improve overall data accuracy and reliability.	4.07
Average			4.20 (84%)

Appendix 3: Usability Evaluation Results by Section (Charts)





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