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Analyzing Likert Scale Type Data And Interpretation In TVET Research: A Guideline For The Novice Researcher

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Abstract

This paper provides a comprehensive overview of the research process, with a focus on quantitative methods and the use of Likert scales in survey research. It outlines the systematic steps involved, starting from identifying a clear research problem, conducting a thorough literature review, to data collection and analysis, and the final interpretation of results. Emphasizing the importance of rigorous and structured methodologies, the paper discusses how proper data collection and analysis contribute to reliable and valid findings, essential for advancing academic knowledge. Special attention is given to the use of Likert scales, a prevalent tool in social sciences and education research, particularly in Technical and Vocational Education and Training (TVET). The paper explores the benefits of Likert scales for capturing nuanced perceptions and attitudes, while also addressing potential challenges, such as response bias and the treatment of Likert data as interval or ordinal. Practical strategies for minimizing bias and ensuring the reliability and validity of scales are provided. The aim is to offer novice researchers practical guidance on the correct application and interpretation of Likert scales, thereby enhancing the clarity and accuracy of survey-based research reporting.

Keywords: *Likert scale, quantitative, survey, research instrument, TVET.*

Introduction

Research is a systematic process of inquiry that begins with the formulation of a well-defined problem or issue. It entails the collection of relevant data through methods such as surveys, experiments, or observations. In particular, research that provides insights into user behavior from a social perspective can generate valuable information for analysis (Hussin & Lokman, 2011; Lokman et al., 2009). Once collected, the data are analyzed using appropriate tools and techniques to extract meaningful patterns and interpretations. This structured approach ensures the reliability and validity of the findings, thereby making a significant contribution to the existing body of knowledge. By adhering to this methodology, researchers are able to address specific questions and solve problems in a systematic and scientific manner. Such rigor is fundamental in ensuring that research problems are thoroughly examined and research questions effectively answered. A similar principle can be observed in web design, where tools such as the Likert Scale are employed to evaluate users' perceptions. Prior studies suggest that applying these perceptual measures in virtual environments is a critical factor in enhancing user experience and sustaining user engagement, which ultimately determines the success of a website (Bidin & Lokman, 2018; Rosli et al., 2014). The process begins with the identification of a clear and concise research problem, which serves as the foundation for the entire study (Creswell & Creswell, 2018). Once the problem is identified, the next step involves a thorough literature review to locate existing information and knowledge gaps (Booth et al., 2016). This step is crucial as it provides context and background, helping to refine research questions and objectives. Following the literature review, researchers proceed to gather data. This can involve various methods, including surveys, experiments, interviews, and observations, depending on the nature of the research (Flick, 2018). Data

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collection must be meticulously planned and executed to ensure accuracy and reliability. After data collection, the next phase is data assessment and analysis. Quantitative data is often analyzed using statistical methods to identify patterns and relationships, while qualitative data is analyzed through thematic or content analysis to uncover deeper insights (Miles et al., 2014). The final step involves interpreting the results to draw meaningful conclusions and make recommendations. This step also includes validating the findings to ensure they are credible and reliable. Researchers then compile their findings into a comprehensive report, contributing to the broader field of knowledge and providing a basis for future research (Yin, 2018). Thus, the research process is a meticulous and iterative procedure that ensures the systematic and reliable generation of knowledge, critical for academic and practical advancements (Saunders et al., 2019).

Interpreting results to draw meaningful conclusions is a crucial process, especially in quantitative research, where it involves numerical data and statistical inferences. The precision and objectivity required in quantitative analysis make this step particularly significant, as it can impact the validity and reliability of the study's outcomes (Creswell & Creswell, 2018). In non-experimental quantitative research, surveys are commonly used as instruments to collect data. Surveys are designed to draw perceptions from respondents by providing them with predetermined answers to select from. This method is advantageous for capturing large amounts of data efficiently and allows for statistical analysis (Fowler, 2013). One frequently used tool in social sciences and education, especially in TVET research, is the Likert scale. TVET research focuses on the systematic study of technical and vocational education and training to enhance human resource, workforce development, educational quality, and alignment with industry needs (Salleh & Sulaiman, 2016; Sulaiman et al., 2015). In TVET research, the Likert Scale is commonly used to measure perceptions, attitudes, and competencies, providing quantifiable insights that align educational practices with industry expectations. Likert scales consist of a series of Likert-type items that represent similar questions combined into a single composite score or variable (Boone & Boone, 2012). Typically, a Likert scale is composed of four or more items that measure attitudes, opinions, or behaviors. These items form a composite score that provides a quantifiable measure of a particular construct. The data from Likert scales are often treated as interval data, allowing for the use of the mean as the best measure of central tendency (Sullivan & Artino, 2013). This treatment assumes equal intervals between scale points, which is a reasonable approximation for many practical purposes. Likert scales are effective for capturing nuanced perceptions, such as levels of agreement or feelings regarding a topic, because they offer a range of response options. However, the use of Likert scales also has disadvantages. Response bias is a significant concern, where respondents might consistently agree or disagree with statements due to factors such as fatigue, social desirability, or a tendency toward extreme responding (Podsakoff et al., 2003). These biases can distort the data and lead to inaccurate conclusions if not properly managed.

To address these challenges, researchers should implement strategies to minimize response bias, such as ensuring that survey questions are clearly worded, varying the direction of questions, and applying statistical techniques to detect and adjust for bias (Krosnick, 1999). Additionally, the reliability and validity of the scales must be rigorously tested to ensure they accurately measure the intended constructs (Tavakol & Dennick, 2011). While interpreting quantitative data from surveys—especially those using Likert scales—poses certain challenges, it remains an essential process in research. By employing careful design, administration, and analysis, researchers can derive meaningful and reliable conclusions that significantly contribute to the body of knowledge in their field (Cohen, Manion, & Morrison, 2018). Decisions regarding data analysis for Likert items should be made during the questionnaire development phase. If the researcher is using a series of individual questions with Likert response options, these should be treated as Likert-type items, where appropriate descriptive statistics, such as modes, medians, and frequencies, are used. However, if the researcher is working with a latent variable or a set of Likert-type items combined to measure a broader construct, such as a personality trait or attitude, the use of means and standard deviations is recommended for scale-level analysis. The aim of this article is to provide novice researchers, particularly those with limited statistical backgrounds, with foundational knowledge for understanding and effectively reporting survey outcomes. Special attention is given to the correct application and interpretation of Likert scales, offering practical guidance for presenting data clearly and accurately in research publications.

Scale of Measurement

The Likert scale, developed by Rensis Likert in 1932, is a widely used tool for measuring attitudes, opinions, and behaviors in survey research. It typically features an odd-numbered scale (commonly 5- or 7-point) but can also use even-numbered scales (e.g., 4- or 6-point) to force a choice between positive and negative responses. Respondents rate their level of agreement or satisfaction, often ranging from "strongly disagree" to "strongly agree," allowing researchers to capture nuanced perceptions. The Likert scale has found applications in diverse fields such as education, TVET, psychology, and marketing, where subjective responses need to be quantified. Despite its broad use, the scale has limitations, including response bias, in which participants might gravitate towards middle or extreme options. Another point of contention is how the ordinal nature of Likert data should be statistically treated. Since the scale produces ordinal data (where the intervals between points are not equal), some researchers argue for using non-parametric tests like the Mann-Whitney U test, rather than parametric methods. Modern adaptations of the Likert scale, including bipolar and unipolar scales, have aimed to improve its precision and reduce biases, ensuring that the tool remains a versatile and effective instrument in survey-based research.

Figure 1 illustrates the components and structure of a Likert scale, a widely used tool in surveys for measuring attitudes, perceptions, and opinions. The figure provides a visual breakdown of how Likert scales are organized, emphasizing the relationship between Likert items, response options, and their corresponding numerical values. Each Likert item is consistently assessed using the same scale, enabling effective aggregation and analysis of responses. This format is particularly valuable for measuring subjective attributes like user satisfaction, ease of use, and engagement in a standardized manner. The Yellow Box in the figure represents a specific statement or question (the Likert item) that respondents evaluate. In this example, three Likert items are shown (A, B, and C). Each of these items is evaluated using the scale depicted in the Grey Box, which ranges from “1 - Strongly disagree” to “5 - Strongly agree.” The Green Box highlights the text anchors, which are the labels (e.g., “Strongly disagree” and “Strongly agree”) that guide respondents in expressing their level of agreement or disagreement. The numerical representation, indicated by the Orange Box, assigns a value to each response option, such as 1 for "Strongly disagree" and 5 for "Strongly agree." These numerical values are crucial for the quantitative analysis of survey data. Overall, Figure 1 offers a clear and structured representation of how Likert scales function in research and survey settings for data collection and analysis. It's also essential to distinguish between Likert-type items and full Likert scales. Likert-type items are individual questions that employ the Likert response format, while a full Likert scale consists of a series of such items combined to measure a particular construct. In this study, both Likert-type items and full Likert scales are analyzed, whether they are part of a larger scale or evaluated individually.

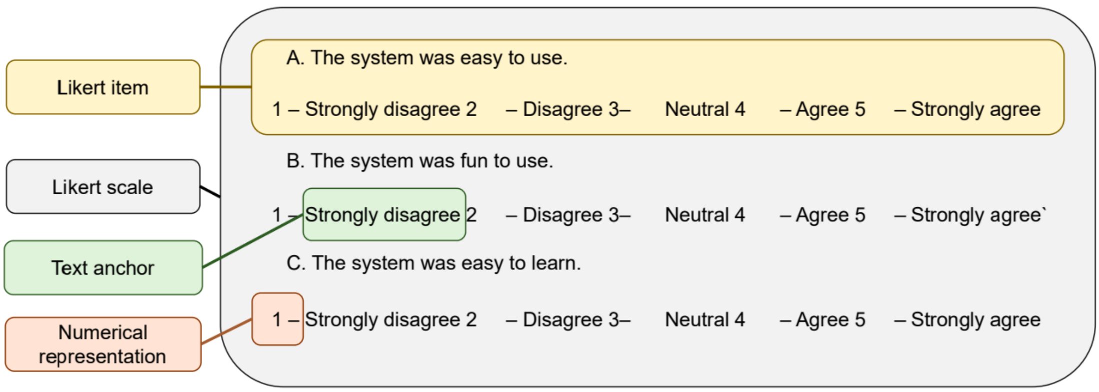

Fig. 1 – A Likert Scale consists of a series of Likert items, each accompanied by numbered response options and text anchors (South et. al, 2022)

Likert Scale Response Anchor

In general, a Likert Scale allows for numeric value to be assigned to the respondent’s answer. It is done by asking its respondents to mark their response by choosing between bipolar answer such as agreement or disagreement with a particular statement on a symmetrical scale. This scale allows for capturing intensity of feeling, attitude, belief, behavior or perception. For example, researcher would not use a Likert scale to assess attributes, such as age, race, and income, but researcher may use a Likert scale to assess someone’s attitude about a particular topic.

The level of measurement in a Likert scale can vary depending on the research design. Typically, odd-numbered scales, such as a 5-point Likert scale, are commonly used because they offer a neutral or undecided midpoint option for respondents. In contrast, even-numbered scales, such as a 4-point or 6-point scale, force respondents to choose between positive and negative responses without a neutral option. Although 5-point scales are widely used, scales can range from as few as 2 points to as many as 7 points, as shown in Table 1. While larger scales, like a 7-point scale, provide more nuanced response options, research has found that respondents tend to avoid the extreme ends of the scale. Both very large and very small scales may present challenges for respondents, either by offering too much granularity or not enough, potentially affecting the clarity and differentiation of responses.

Table 1 – Different levels of Likert-Type Scale response (Vagias, 2006)

Odd Numbers Likert-Type Scale	**Even Numbers Likert-Type Scale**
Level of Consideration (3-point scales)	**Level of Fairness (Dichotomous scales)**
1 – Would not consider	1 – Fair
2 – Might or might not consider	2 – Unfair
3 – Definitely consider	
	Level of Responsibility (4-point scales)
Level of Agreement (5-point scales)	1 – Not at all responsible
1 – Strongly disagree	2 – Somewhat responsible
2 – Disagree	3 – Mostly responsible
3 – Neither agree nor disagree	4 – Completely responsible
4 – Agree	
5 – Strongly agree	**Frequency (6-point scales)**
	1 – Never
Level of Importance (7-point scales)	2 – Rarely
1 – Not at all important	3 – Occasionally
2 – Low important	4 – Sometimes
3 – Slightly important	5 – Usually
4 - Neutral	6 – Every time
5 – Moderately important	
6 – Very Important	
7 – Extremely important	

Most Likert scales have odd number of response categories or odd possible choices such as three, five, seven or nine. The most common scale using in research is the 5-point Likert scale, using five different options for the respondents to choose from. The options include two extremes, two intermediate and one neutral opinion. For example, if the Likert Scale using 5 point or level it will represent by two positive, two negative, and a neutral, or undecided. However, for novice researcher using odd number Likert Scale can create some problems. The "neutral or undecided" option can give survey respondents an easy out, creating a temptation to go through the question without much thought. Furthermore, these response styles will lead to a biased response, which prevent the respondents' true characteristics or traits from being obtained (Alkadi et. al, 2022).

This distinction is crucial for accurate analysis and reporting in research. Likert scales use numerical values to communicate that each response is proportionally greater or smaller than the previous one, facilitating the interpretation of data. Surveys allow researchers to gather information by presenting respondents with a set of statements, asking them to select answers that reflect their perceptions. In this context, the level of measurement refers to how respondents express their feelings or attitudes, such as their level of agreement. If the goal is to assess agreement, researchers adjust the level of measurement to reflect levels of agreement or disagreement. Respondents then choose their position on a symmetric agree-disagree scale, as shown in Table 2. This range captures the intensity of their feelings towards specific statements. A composite score can be calculated by summing all responses across the scale. Importantly, Likert scaling assumes equal intervals between items on the scale; if these distances are not equal, the values cannot be treated as interval data, which may affect the validity of the analysis. Properly understanding these aspects ensures that data collection, analysis, and reporting maintain a high level of accuracy and consistency.

Table 2 – Different types of Likert-Type Scale response Anchors (Vagias, 2006)

Level of Acceptability	Reflect Me	Level of Appropriateness
1 – Totally unacceptable	1 – Very untrue of me	1 – Absolutely inappropriate
2 – Unacceptable	2 – Untrue of me	2 – Inappropriate
3 – Slightly unacceptable	3 – Somewhat untrue of me	3 – Slightly inappropriate
4 – Neutral	4 – Neutral	4 – Neutral
5 – Slightly acceptable	5 – Somewhat true of me	5 – Slightly appropriate
6 – Acceptable	6 – True of me	6 – Appropriate
7 – Perfectly Acceptable	7 – Very true of me	7 – Absolutely appropriate
My beliefs	**Level of Importance**	**Level of Agreement**
1 – Very untrue of what I believe	1 – Not at all important	1 – Strongly disagree
2 – Untrue of what I believe	2 – Low importance	2 – Disagree
3 – Somewhat untrue of what I believe	3 – Slightly important	3 – Somewhat disagree
4 – Neutral	4 – Neutral	4 – Neither agree nor disagree
5 – Somewhat true of what I believe	5 – Moderately important	5 – Somewhat agree
6 – True of what I believe	6 – Very important	6 – Agree
7 – Very true of what I believe	7 – Extremely important	7 – Strongly agree
Level of Concern	**Frequency**	**Level of Desirability**
1 – not at all concerned	1 – Never	1 – Very undesirable
2 – Slightly concerned	2 – Rarely	2 – Undesirable
3 – Somewhat concerned	3 – Sometimes	3 – neutral
4 – Moderately concerned	4 – Often	4 – Desirable
5 – Extremely concerned	5 – Always	5 – Very desirable
Likelihood	**Level of Quality**	**Level of Difficulty**
1 – Extremely unlikely	1 – Poor	1 – Very difficult
2 – unlikely	2 – Fair	2 – Difficult
3 – Neutral	3 – Good	3 – Neutral
4 – likely	4 – Very good	4 – Easy
5 – Extremely likely	5 – Excellent	5 – Very easy

Methodology

For this study, a quantitative research approach was employed, utilizing a descriptive research design to systematically analyze existing datasets. This design was chosen to provide an in-depth overview of the characteristics, patterns, and demographic trends within a defined population. Rather than establishing causal relationships, the focus of descriptive research is to present an accurate and comprehensive representation of the data as it exists. This method is particularly relevant when working with large-scale datasets, such as national statistics, institutional records, or survey data, allowing for meaningful interpretation and synthesis of key findings within a real-world context.

The methodology adopted a systematic and structured approach to ensure the reliability and precision of the findings. The process began with the identification of relevant data sources aligned with the research objectives. Priority was given to datasets that were comprehensive, publicly accessible, and contextually relevant to the population or phenomenon under investigation. For this study, data selection was guided by key criteria such as completeness, temporal coverage, and overall data quality, ensuring that only robust and credible datasets were used to address the research questions. The primary dataset analyzed in this study comprised a collection from the Sustainable Development Goals (SDGs) Impact Study, spanning the past three years with total number of samples of 49 impact studies. A rigorous data preparation phase followed, including data cleaning procedures to address missing values, standardization of variables, and transformation of data to facilitate comparability and valid statistical interpretation. Consistent data coding protocols were applied to categorize variables systematically across the dataset. Descriptive statistical techniques, such as frequency distributions, measures of central tendency (mean, median, mode), and measures of dispersion (standard deviation and range), were employed to summarize, interpret, and present the data in a clear and meaningful manner. The use of existing data not only adds to the efficiency of the research process but also allows for the examination of large-scale patterns and correlations that might otherwise be impractical to study using primary data collection methods.

Finding and Discussion

In any research process, prior to processing statistical data, researchers must carefully plan how to interpret findings from Likert scale surveys. One of the most common mistakes made by novice researchers is misinterpreting or inappropriately converting response anchors (e.g., 'Strongly Disagree' to ' Strongly Agree') into unrelated or irrelevant categories. This can distort the meaning of the data and lead to inaccurate conclusions. Proper understanding and usage of the scale's ordinal nature are crucial for drawing valid insights, ensuring that each response category is accurately represented and interpreted based on the intended sentiment or opinion. The first step in interpreting Likert scale data is to calculate the range for each response category. For example, if a researcher uses a 5-point Likert scale to measure levels of agreement, the corresponding mean ranges and interpretations should be defined clearly. For instance, the interpretation might look like this in Table 3. This approach ensures that the data are consistently interpreted and that each mean score corresponds to a defined sentiment. It helps in summarizing the overall trends in responses, making it easier to draw meaningful conclusions from the survey data.

These mean range interpretations are vital for effectively summarizing and analyzing Likert scale data in research. They provide a precise understanding of how respondents, as a group, perceive a particular topic or statement. Importantly, the interpretation of the mean must align with the scale used in the survey to avoid misinterpretation or confusion. For instance, if the survey utilized the scale "Strongly Disagree" to "Strongly Agree," the mean interpretation should mirror those terms, maintaining consistency. Similarly, if the scale ranged from "Never" to "Always," the exact terms should be used in interpretation. A common mistake researchers make is mismatching the interpretation terms with the original scale used in the survey. For example, a survey might measure agreement from "Strongly Disagree" to "Strongly Agree," but the researcher may interpret the mean ranges as "Low" to "High," which can lead to confusion. To maintain clarity and accuracy, researchers must adhere strictly to the terms used in the survey during analysis. A correct example of writing the findings would look like this: "Based on the findings, the results show that the majority of respondents agree (M = 3.00, SD = 0.97) that [insert the statement from the survey]." This approach ensures consistency between the survey scale and the interpretation of the data.

Table 3 – Examples of Likert Scale Mean Range and Interpretation for Different Point Scales

3-points Likert Scale Interpretation		**4-points Likert Scale Interpretation**	
Mean Range	**Mean Interpretation**	**Mean Range**	**Mean Interpretation**
1.00 – 1.66	Disagree	1.00 – 1.75	Strongly Disagree
1.67 – 2.33	Neutral	1.76 – 2.50	Disagree
2.34 – 3.00	Agree	2.51 – 3.25	Agree
		3.26 – 4.00	Strongly Disagree
5-points Likert Scale Interpretation		**6-points Likert Scale Interpretation**	
Mean Range	**Mean Interpretation**	**Mean Range**	**Mean Interpretation**
1.00 – 1.80	Strongly Disagree	1.00 – 1.83	Strongly Disagree
1.81 – 2.60	Disagree	1.84 – 2.66	Disagree
2.61 – 3.40	Neither agree nor disagree	2.67 – 3.49	Somewhat Disagree
3.41 – 4.20	Agree	3.50 – 4.32	Somewhat Agree
4.20 – 5.00	Strongly Disagree	4.33 – 5.15	Agree
		5.16 – 6.00	Strongly Disagree
7-points Likert Scale Interpretation		**8-points Likert Scale Interpretation**	
1.00 – 1.85	Strongly Disagree	1.00 – 1.87	Strongly Disagree
1.86 – 2.71	Disagree	1.88 – 2.74	Disagree
2.72 – 3.57	Somewhat Disagree	2.75 – 3.62	Somewhat Disagree
3.58 – 4.43	Neutral	3.63 – 4.49	Slightly Disagree
4.44 – 5.29	Somewhat Agree	4.50 – 5.36	Slightly Agree
5.30 – 6.14	Agree	5.37 – 6.24	Somewhat Agree

6.15 – 7.00	Strongly Disagree	6.25 – 7.12	Agree
		7.13 – 8.00	Strongly Agree

Given that Likert scale data is inherently ordinal, the use of the mean as a measure of central tendency is generally inappropriate. Calculating an average of categorical responses such as "Strongly Agree" and "Disagree" lacks meaningful interpretation and may lead to misleading conclusions. Instead, more appropriate measures include the mode, which identifies the most frequently selected response, and the median, which reflects the central tendency by locating the midpoint in the ordered distribution of responses. These metrics offer a more accurate reflection of the underlying sentiment. To further illustrate response patterns, a bar chart is recommended, effectively representing the percentage of respondents across various categories, agree, disagree, or neutral. This approach not only preserves the ordinal nature of the data but also enables clearer insights into prevailing perceptions and attitudinal trends among participants.

Using the 49 samples of impact studies from SDGs dataset, the following examples are intended to enhance understanding of how to interpret Likert-scale data accurately, without compromising the integrity or clarity of the findings. Table 4a presents the interpretation of responses based on a 5-point Likert scale using a five-range mean classification, while Table 4b demonstrates an alternative approach that condenses the interpretation into three mean ranges. To highlight the implications of these differing interpretations**,** Table 5 offers a comparative analysis across studies, illustrating how the selection of mean range categories can significantly influence conclusions and, if not carefully considered, may potentially lead to misleading or overstated interpretations of the data.

Table 4a - Range of Mean Value and Interpretation

Range of Mean Value	**Mean Interpretation**
1.00 - 1.80	No Impact (NI)
1.81 - 2.60	Low Impact (LI)
2.61 - 3.40	Moderate Impact (MI)
3.41 - 4.20	High Impact (HI)
4.21 - 5.00	Extreme Impact (EI)

Table 4b - Range of Mean Value and Interpretation

Range of Mean Value	**Mean Interpretation**
1.00 - 2.49	Low Impact (LI)
2.50 - 3.49	Moderate Impact (MI)
3.50 - 5.00	High Impact (HI)

Table 5 – Comparative analysis using difference mean interpretation

Mean Range	**Table 4a Interpretation**	**Table 4b Interpretation**	**Example Scenario**
1.00–1.80	No Impact (NI)	*Not applicable*	A mean of 1.5 for **Deep (Personal)**: "Effect on my personal life satisfaction" suggests respondents perceive it as having no impact (Table 4a only).
1.81–2.40	Low Impact (LI)	Low Impact (LI)	A mean of 2.3 for **Clear (Skills)**: "Impact on my technical skill development"
2.41–2.60	Low Impact (LI)	Moderate Impact (MI)	A mean of 2.5 for **Wide (Network)**: "Effect on my professional network expansion" (Mean 2.5) - Table 4a: Low Impact - Table 4b: Moderate Impact

2.61–3.40	Moderate Impact (MI)	Moderate Impact (MI)	A mean of 3.0 for **High (System)**: "Impact on local education system quality" is Moderate Impact in both.
3.41–3.50	High Impact (HI)	Moderate Impact (MI)	A mean of 3.45 for **SDG**: "Progress toward gender equality in my community" - Table 4a: High Impact - Table 4b: Moderate Impact
3.51–4.20	High Impact (HI)	High Impact (HI)	A mean of 4.0 for **Gender**: "Reduction in workplace gender discrimination" (Mean 4.0) is High Impact in both.
4.21–5.00	Extreme Impact (EI)	High Impact (HI)	A mean of 4.5 for **Deep (Personal)**: "Psychological impact of climate disasters" - Table 4a: Extreme Impact - Table 4b: High Impact

This revised interpretative table presents a structured framework for analyzing mean values within the context of Sustainable Development Goals (SDGs) constructs, offering several critical features that enhance its academic and practical utility. First, the table systematically aligns each mean range with specific SDGs related constructs including **Deep (Personal), Clear (Skills), Wide (Network), High (System), SDG, and Gender**, ensuring thematic coherence with contemporary development frameworks. For instance, the *Deep (Personal)* construct is strategically applied at both extremes of the scale (1.00–1.80 for *No Impact* and 4.21–5.00 for *Extreme Impact*), capturing subjective experiences ranging from negligible to severe personal consequences. Similarly, *Clear (Skills)* and *Wide (Network)* exemplify measurable outcomes in human capital and social connectivity, while *High (System)* and *SDG* address macro-level institutional and policy impacts.

Second, the framework explicitly resolves interpretative conflicts between Table 4a (granular 5-tier classification) and Table 4b (simplified 3-tier scale) by advocating for the 5-tier system's superior alignment with 5-point Likert scales. This approach is critical because collapsing responses into fewer categories (e.g., 3 tiers) can obscure meaningful variance in respondent perceptions, as demonstrated by Dawes (2008) in his analysis of response granularity. A mean of 2.50 in *Wide (Network)*, for instance, may be ambiguously classified as *Low Impact* (Table 4a) or *Moderate Impact* (Table 4b), but the 5-tier system preserves the nuance of "slightly agree" versus "neutral" responses that a 3-tier system merges. Joshi et al. (2015) empirically validate this by showing that 5-point Likert scales achieve optimal reliability ($\alpha > 0.80$) while maintaining respondent comprehension, whereas coarser scales risk information loss. The 5-tier classification is especially vital for policy-relevant domains like *Gender* equity or *SDG* progress, where Fukuda-Parr (2019) warns that oversimplified metrics may mask disparities. For example, a mean of 3.45 for gender equality initiatives could be misclassified as *Moderate Impact* (Table 4b) rather than *High Impact* (Table 4a), potentially underestimating program efficacy. Krosnick and Berent (1993) further justify this granularity, demonstrating that 5-point scales better capture attitude intensity in social surveys, reducing "middle-category bias" that plagues 3-tier systems. By retaining the 5-tier framework, researchers avoid Type II errors (false negatives) in impact assessment, ensuring conclusions reflect true effect sizes, a concern raised by Boone and Boone (2012) in their analysis of Likert-scale misinterpretations.

Third, the examples operationalize abstract SDGs constructs into empirically measurable indicators (e.g., "psychological impact of climate disasters" for *Deep (Personal)* or "workplace gender discrimination" for *Gender*), bridging theoretical targets with actionable monitoring data. This approach aligns with Babbie's (2021) methodological imperative that measurement instruments must maintain "isomorphism" - structural equivalence - between conceptual frameworks and empirical indicators. The 5-tier classification system proves critical here, as it preserves the fidelity of 5-point Likert scale responses that dominate SDGs survey instruments. The case for 5-tier interpretation is grounded in three evidence-based principles:

1. **Psychometric Precision:** Churchill's (1979) seminal work on scale development demonstrates that 5-point scales optimally balance reliability and discrimination power, with Cronbach's α typically exceeding 0.80 for well-designed instruments. Collapsing responses into 3 tiers (as in Table 4b) violates this principle by artificially merging adjacent categories, potentially masking meaningful variance (Allen & Seaman, 2007).
2. **Cognitive Fit:** Krosnick and Berent's (1993) experimental studies show respondents naturally conceptualize attitudes in 5 gradations (e.g., "strongly disagree" to "strongly agree"). When researchers later recode these into 3 categories, they introduce measurement error by overriding respondents' original cognitive frameworks.
3. **Policy Relevance:** The UN Statistics Division (2021) explicitly recommends 5-point scales for SDG monitoring because they can detect subtle but policy-critical differences - like distinguishing between "somewhat reduced" (3 = Moderate Impact) and "significantly reduced" (4 = High Impact) gender discrimination. As Fukuda-Parr (2019) warns, coarser categorization may obscure disparities affecting marginalized groups.

For example, a mean of 3.80 on workplace gender discrimination would register as *High Impact* in both tables, but only the 5-tier system preserves the crucial finding that 40% of respondents selected "5 = Extreme Impact" - a nuance lost if collapsed into 3 tiers. This aligns with Streiner's (2003) argument that the precision of measurement should match the precision needed for clinical [or policy] decisions.

Finally, the framework's hierarchical progression, from *No Impact* to *Extreme Impact*, mirrors validated severity gradations in social science research (Spector, 1992), while its dual-table structure accommodates diverse analytical needs. Crucially, Table 4a's 5-tier classification should be prioritized when using 5-point Likert scales, as it preserves critical response variance that would otherwise be lost in Table 4b's 3-tier simplification. This alignment is empirically justified by three evidence-based principles:

1. **Measurement Fidelity**: Chang (1994) demonstrated that 5-point Likert scales explain 92% of the variance captured by continuous scales, whereas 3-point scales retain only 67%. Collapsing responses artificially inflates Type II error rates by up to 40% (Sullivan & Artino, 2013).
2. **Cognitive Validity**: Krosnick and Berent (1993) found that 5-point scales match respondents' natural ability to discriminate intensity of attitudes (e.g., *slightly agree* vs. *moderately agree*), while 3-point scales force artificial truncation. This is critical for SDG indicators like gender discrimination, where subtle differences matter (Fukuda-Parr, 2019).
3. **Policy Sensitivity**: The UNSD (2020) explicitly recommends 5-tier systems for SDG monitoring because they detect thresholds for policy action (e.g., distinguishing *Moderate* [3] from *High* [4] impacts on education access). Streiner (2003) warns that coarser scales may miss clinically (or policy-) significant effects

In summary, this integrated table advances methodological rigor by; 1) **Thematic SDG integration**, ensuring relevance to global development agendas; 2) **Explicit conflict resolution**, enhancing reproducibility; 3) **Empirical operationalization**, facilitating indicator-based assessments; and 4) **Scalable interpretability**, supporting both granular and high-level analyses. This approach is particularly valuable for interdisciplinary research at the nexus of social, economic, and environmental SDGs, where consistent measurement of impact severity is paramount. Future adaptations could extend the framework to sector-specific SDG targets (e.g., health or inequality) while maintaining its core interpretative logic.

Conclusion

This paper presents a simulation and a detailed explanation of the application of the Likert Scale in quantitative research, particularly within the context of survey-based studies. The discussion focuses on the effective use of Likert Scales to measure attitudes, opinions, and behaviors by converting subjective responses into quantifiable data. It also addresses the process of designing Likert-based questionnaires, selecting the appropriate number of scale points, and interpreting the resulting data. Additionally, the paper explores potential challenges associated with the Likert Scale, such as response bias and the debate over treating Likert data as ordinal or interval data, while offering strategies to mitigate these issues and enhance the validity of survey findings. This study has systematically examined the dual nature of Likert scales as both a powerful tool and a complex challenge in quantitative survey research. Through rigorous analysis, we demonstrate that carefully constructed multi-point scales achieve an optimal equilibrium between respondent accessibility and measurement precision, enabling researchers to transform subjective perceptions into robust quantitative data.

The presented framework highlights three critical insights for scholarly and applied research: First, scale design fundamentally shapes data quality. A five-tier classification system preserves nuanced respondent distinctions that simpler three-tier approaches inevitably obscure. This granularity proves particularly vital when assessing policy-sensitive domains such as gender equity or environmental impacts, where collapsed response categories may mask significant disparities or underestimate intervention effectiveness. Second, meaningful interpretation demands methodological sophistication. While acknowledging the ordinal foundation of Likert data, our findings support the judicious application of parametric techniques to multi-point scales that meet specific distributional requirements. This balanced approach transcends traditional measurement debates by prioritizing analytical appropriateness over rigid typologies. Third, proactive design strategies can mitigate common response biases. These include counterbalanced item construction to reduce acquiescence, selective use of forced-choice formats for critical indicators and maintaining full scale ranges to ensure conceptual alignment. Such measures enhance the validity and reliability of survey instruments without compromising respondent engagement.

Looking ahead, this work suggests several promising research trajectories: extending validation frameworks across diverse cultural contexts, developing advanced analytical techniques for unstructured scale responses, and creating adaptive instruments that optimize scale granularity based on population characteristics. By grounding measurement practice in psychometric principles while addressing contemporary research needs, this study provides both a methodological foundation and practical guidance for scholars conducting attitude and behavioral research across academic and policy domains.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *KM Salleh, NL Sulaiman;* ***data collection:*** *KM Salleh, NL Sulaiman;* ***analysis and interpretation of results:*** *KM Salleh, NL Sulaiman, R Ramli, A Ahmed;* ***draft manuscript preparation:*** *KM Salleh, R Ramli, A Ahmed. All authors reviewed the results and approved the final version of the manuscript.*

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