

# Fuzzy Scale Table: An Effective Research Tool

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## INTRODUCTION

Surveys are the most commonly used data collection technique/ tool for business management research for getting a snapshot of the current state of affairs in a given group or population (Janes, 2001). Zikmund (2000) defines survey as 'a research technique where information is obtained from a sample of people by use of a questionnaire.' The questionnaire survey is a data collection method which involves quantification of response data, using a formally designed schedule of questions (listed with appropriate scales such as nominal, ordinal, and interval) for which the answers are provided by the respondent (Ticehurst & Veal, 2000; Kumar, 1996). The goals of the questionnaire survey are to collect data with maximum reliability, accuracy and validity; and these goals are applicable for all types of surveys including household surveys, postal/mail surveys, customer surveys, organizational surveys and online/ email surveys (Fricker & Schonlau, 2002). As the respondents are expected to read questions, understand, interpret and respond at any time and from anywhere, surveys provide quick, inexpensive, effective and efficient response (Zikmund, 1997).

As the individual characteristics such as emotion, involvement, attitude and motivation play a role in responding to a questionnaire item (Hitchen & Watkins, 2011), the respondents' views may range from optimistic to pessimistic as each respondent's knowledge base is different. Similarly, the response time may also vary. For instance, a respondent may recollect only a

limited knowledge base and may give a qualitative judgment for a questionnaire item by taking lesser time. Whereas another respondent may spend more time in recollecting a larger part of his/her expertise for analyzing different aspects of the construct in order to arrive a response for a question. In some instances, the respondent is constrained to express his/her view and forced to choose an option when there are no choices available in the scale of a questionnaire-item. Though survey questions could bias participant judgments and answers (Andrews, Nonnecke, & Preece, 2003; Schwarz, 1999), time taken for understanding and interpreting a questionnaire item may also vary. A respondent with sharp memory may take less time for answering a question; and another respondent may take considerable amount of time for responding to each item in the questionnaire. At the same time, there is a chance that the respondent who answers quickly, simply might not pay more attention to the questionnaire item and just wants to finish the task by randomly responding to each item. This variability in response may end up in capturing inaccurate data as all the responses are treated equally without considering the efforts made by a respondent in responding to a question. Therefore, though interactive questionnaire generation framework is available for capturing the variability of users' responses (La Rosa, Aalst, Dumas, & Hofstede, 2009), there is a lack of standard mechanism to capture the variability in expressing views and uncertainties in responding to a questionnaire item.

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Besides, for answering a questionnaire item of a construct, the respondent is not given any opportunity to think in terms of its sub-dimensions, types, classifications, categories and other intangible factors. As a result, the survey may fail to collect rich data on these hidden aspects of a construct and self-selecting bias may emerge in responses (Warwick & Lininger, 1975). Moreover, there may be uncertainties/ambiguities in answering a questionnaire item and there is a lack of mechanism to capture the uncertainty in responses. To facilitate the responding process and for easy recollection, the questionnaire should be accompanied with some kind of check list in which the sub-dimensions of the construct are given. This is equivalent to providing some personal support in administering a questionnaire survey. To standardize the responding process, it will be more convenient if the dimensions and quantitative conversions of qualitative judgments are given to the respondent beforehand. This approach facilitates a respondent to recollect his/her experience and to synthesize the response on a standardized scale. In this way, for obtaining a qualitative judgment, the respondent is required to think in two steps. In the first step, the respondent has to obtain a response for each dimension of a construct by recollecting his/her knowledge base. In the second step, the dimension-wise responses are to be aggregated to obtain a final qualitative judgment for the construct.

Furthermore, responding to qualitative variables in a crisp way may be subject to risk, because reference points are confounded by various characteristics of the respondents. Even some times the qualitative judgments about a construct could be biased because of subjective evaluation as the process of triggering that response often varies from person to person. In order to alleviate this problem, fuzzy sets and fuzzy logic could be used. As fuzzy quantifiers can capture the ambiguities and impreciseness in the interplay of qualitative variables, using possibility values to gauge the inclusion of membership in the standardized scale is recommended. A standardized scale fol-

lows a uniform procedure for all respondents for collecting, scoring, aggregating and interpreting numerical data by facilitating the respondent to respond in a synthesized manner. The standardized scale tabulates the possibility values (usually between 0 and 1) for each dimension and qualitative values (say Very High, High, Moderate, Low and Very Low) of a construct. In other words for each qualitative value, there is a corresponding fuzzy set comprised of possibility values representing each dimension of the construct. So when a respondent responds to a questionnaire item, there is an associated fuzzy set from the standardized scale table which could be used for data analysis. This fuzzy set data is useful for conducting data analysis not only for the constructs but also for the dimensions of the construct given in the model/hypothesis. This gives more insight into the constructs and the relationships with other constructs. This type of dimension-wise analysis is feasible as the data has been collected in terms of fuzzy sets for the dimensions of the variables. Furthermore, these fuzzy set responses could be used for testing the relationships between the dimensions. Thereby the data analysis becomes richer and gives more understanding about the relationships. The remaining part of this chapter discusses the steps for formulating a standardized scale table.

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## **BACKGROUND**

### **A Brief Overview of Fuzzy Set Theory**

Fuzzy logic has been widely used for designing decision and control systems where “rules of thumb” are easily conceptualized and implemented compared to precisely defined decision making criteria. Some of the application areas are automatic control, decision analysis, data classification, robotics and pattern recognition (Fuller, 2000; Awad, 1996; Klir & Yuan, 1995; Zimmermann, 2001). The applications of fuzzy logic in real life are manifold. For example any control system can

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