KNOWLEDGE STRUCTURE DIFFERENCES BETWEEN MORE EFFECTIVE AND

Sujan, Harish; Sujan, Mita; Bettman, James R.

JMR, Journal of Marketing Research; Feb 1988; 25, 1; ABI/INFORM Global

pg. 81

Research Notes

and Communications

HARISH SUJAN, MITA SUJAN, and JAMES R. BETTMAN*

A study of salespeople working for a telephone marketing operation indicates that more effective (above average) salespeople have richer and more interrelated knowledge structures about their customers than do less effective (below average) salespeople in terms of both customer traits and strategies for selling to the customers. No significant differences are found between effective and less effective salespeople on the number of categories used to classify customers. A longitudinal study that tracked entering salespeople over time, from the less effective to the more effective stage, validates the findings of the cross-sectional study. Implications of these findings for sales management practice and the small but growing literature on real-world competence are discussed.

Knowledge Structure Differences Between More Effective and Less Effective Salespeople

The importance of sales knowledge for effective selling performance has been recognized by both researchers and practitioners. For example, Weitz, Sujan, and Sujan (1986) proposed that salespeople's knowledge about their customers and selling strategies critically affects their performance. Several sales training programs (e.g., Ingram 1981) teach elaborate knowledge structures to inexperienced salespeople in the belief that such knowledge will make them more effective. The assumption linking knowledge and performance is supported by research showing that "tacit" or working knowledge is important in enabling managers to cope competently with practical issues related to their jobs (Wagner and Sternberg 1985).

Though knowledge has been recognized as critical to salespeople's performance, empirical work in the area is lacking. We therefore examine the knowledge structures of salespeople to identify aspects of knowledge that distinguish more effective from less effective salespeople. To address this issue, two studies were conducted. The first was a cross-sectional comparison of above average and below average performers in a salesforce and the

*Harish Sujan and Mita Sujan are Assistant Professors of Marketing, College of Business Administration, The Pennsylvania State University. James R. Bettman is the Burlington Industries Professor of Business Administration, Fuqua School of Business, Duke University.

The research was supported in part by a grant from the Division of Research, College of Business Administration, The Pennsylvania State University.

Journal of Marketing Research

Vol. XXV (February 1988), 81–6

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.
second tracked salespeople over time to monitor changes in knowledge structures with increasing experience and effectiveness.

**KNOWLEDGE STRUCTURES AND EFFECTIVE PERFORMANCE**

Research that has examined differences in knowledge structures between effective and less effective performers suggests three sorts of differences are possible. First, effective performers simply might have more categories to describe the domain. Simon and Gilmartin (1973) estimated that a chess master has roughly 50,000 chessboard configurations in memory, a good club player 1000, and a poor player very few. In person perception, Brewer, Dull, and Lui (1981) found that a category such as “the elderly” is subdivided further (e.g., “the grandmother type,” “the statesman type”) with increasing familiarity. Similarly, more effective salespeople might use more specific categories to classify their customers (e.g., “small-scale entrepreneurs,” “small family businesses”) rather than broad categories (e.g., “large” vs. “small” customers). More customer categories might allow more precise classification and hence more appropriate behaviors. Some sales training programs (e.g., Ingrasci 1981) are based implicitly on the assumption that providing salespeople with several specific categories for classifying customers improves effectiveness.

However, the notion that higher performers use more categories is not supported unanimously. A study of experienced and inexperienced probation officers has shown that the experienced officers use fewer categories to describe criminal offenders (Lurigio and Carroll 1985). Lurigio and Carroll (1985) suggest that high performers may use fewer categories if such categories are more “functional” for describing the environment. (The issue of what makes categories functional is discussed subsequently.) However, in keeping with most of the evidence, we hypothesize that:

\[ H_1: \] More effective salespeople use more categories to classify customers than do less effective salespeople.

A second possible difference between more and less effective performers might be the internal structure of their categories. For example, Lurigio and Carroll (1985) found that though higher performers had fewer categories, those categories were more fully developed, with more information units associated with each category. Two types of information are associated with categories—declarative and procedural knowledge (e.g., Weitz, Sujan, and Sujan 1986). Declarative knowledge is the set of facts used to describe the category, whereas procedural knowledge consists of the strategies or heuristics used to guide behavior. Virtually all of the research on the richness of categories has examined declarative knowledge (e.g., Lurigio and Carroll 1985; Murphy and Wright 1984). The general finding is that declarative knowledge increases with skill. For salespeople, an important aspect of declarative knowledge is knowledge of the traits, motives, and behaviors of the different types of customers encountered. Several researchers (e.g., Wagner and Sternberg 1985) have argued that procedural knowledge accounts for major differences in performance levels, though that possibility has not been tested empirically. For salespeople, procedural knowledge corresponds to knowledge of sales strategies to be used with each type of customer. Hence we hypothesize that:

\[ H_{2a}: \] The customer categories of more effective salespeople contain more information about customers than do those of less effective salespeople.

\[ H_{2b}: \] The customer categories of more effective salespeople contain more sales strategies than do those of less effective salespeople.

A third possible difference between more and less effective salespeople is the interrelationship among the categories used to describe a domain. Empirical evidence about this difference is mixed. One set of findings (e.g., Homa, Rhoads, and Chambless 1979) suggests that effective performers’ categories are more differentiated. For example, more effective salespeople might see rebuy and new buy customers as very distinct categories and might use vastly different approaches for selling to the two types, whereas less effective salespeople might use similar approaches for these customer types. Evidence to the contrary comes from one of the few studies that has examined real-world effectiveness. Murphy and Wright (1984) found that skilled clinical psychologists’ descriptions of different categories of emotionally disturbed children had many more features that were common to two or more categories than did less skilled clinicians’ descriptions. They argued that studies showing less overlap between the categories of more effective performers were laboratory studies using artificial stimuli such as letter strings, and therefore the subjects had no intuitive theories to connect objects. Further, the goal for subjects in these experiments was to discriminate between objects, whereas the goal in the real world may be to discover general principles with broad application.

In selling, the goal of effective salespeople might be consistent with the goal of subjects in experimental tasks—to discriminate between different types of customers—and their customer categories might be more distinct. Alternatively, the goal of effective salespeople might be to uncover underlying similarities between customers who are overtly different (e.g., both rebuy and new buy customers are responsive to price deals) so as to use best the sales strategies available to them. Hence, their customer categories might be more overlapping. Though making predictions about category distinctiveness is difficult given the mixed results in this area, we expect effective salespeople to behave like skilled performers in the real world and show more intercategory overlap. Therefore we hypothesize that:

\[ H_{3a}: \] More effective salespeople show greater customer category overlap in information descriptive of cus-
Product product information (e.g., use of funds, gift-matching schemes, etc.) and methods of handling objections. Of the 45 callers who worked with the telefund, 41 participated in the study. Subjects were recruited for three separate one-hour sessions spread over a one-week period. They were paid $15.00 for their participation.

Tasks

Subjects were told that the purpose of the first session was to understand the kinds of categories or groupings they used to “differentiate” among the alumni they called. They were asked to think about the different types of alumni they encountered on the phone and to jot down those different types on a sheet of paper using short descriptive labels. They were assured that there were no “correct” types of categories or number of categories.

After writing down the different alumni categories they perceived, subjects were asked to describe each category in terms of (1) characteristic traits—the demographic and personality traits and the behavior patterns that were typical of the category and (2) strategies used to deal with the category—the strategies and behaviors that they, as callers, used while interacting with this type of customer. Subjects described each category in writing on a separate page. Subjects wrote about 65 words per page, 35 words descriptive of customer traits and 30 words descriptive of selling strategies.

Subjects were told that the purpose of session 2 was to “quantify” some of their responses from session 1. Each subject was given an individualized questionnaire containing (1) a trait table and (2) a strategy table. The tables consisted of rows and columns. The column heads, which were filled in before the session, were the idiosyncratic alumni categories that the subject had identified in session 1. The rows were descriptors (traits or strategies) that were relevant for describing alumni and were common across all subjects. Subjects were asked to score each descriptor on a 10-point “definitely appropriate” to “definitely not appropriate” scale for each category. Ten traits (e.g., friendly, likely to give) and 10 strategies (e.g., talk about sports, welcome small contributions) most commonly mentioned by subjects in a pretest were used as descriptors. Subjects again were assured that there were no correct answers and that we were interested only in their perceptions.

In session 3, some personal information was collected (e.g., age, sex, major, sales experience prior to the telefund). Subjects also filled in the revised self-monitoring scale (Lennox and Wolfe 1984). Subjects were debriefed at the end of this session and paid for their participation.

Knowledge Measures

The number of categories of alumni listed in session 1 was counted for each subject. The descriptions for each of the categories were coded by two independent judges blind to the hypotheses. The judges first independently divided each respondent’s descriptions into individual statements (e.g., “friendly,” “businesslike” for traits and
“give concrete examples of use of funds” for strategies. Responses conveying essentially the same meaning were counted as one unit. Disagreements were resolved by discussion (interjudge reliability = .89). Category richness for each subject was computed as the number of unique traits (trait richness) and strategies (strategy richness) used to describe a category, averaged across all the categories described by the subject.

Judges also compared the individual statements in each of the category descriptions generated by a subject. If an individual statement appeared in two descriptions generated by a subject, it was scored as a shared feature across the two categories. A statement was considered to be the same across two descriptions if either the same wording was used or close synonyms were employed. Disagreements were discussed until a consensus was reached (interjudge reliability = .77). Category overlap between any two categories was computed as the proportion of shared to shared plus distinctive features (Tversky 1977). The category overlap or similarity score for a subject was computed separately for traits and strategies by averaging across all possible category pairs generated by the subject.

The data from session 2 were used to compute a second overlap index. Subjects rated the appropriateness of each of 10 traits and strategies as descriptors for each of their categories. A uniform rating for a descriptor across categories would indicate that subjects saw the descriptor as equally applicable (or inapplicable), and thus the categories were overlapping for this descriptor. A highly variable rating would indicate that subjects perceived the categories to be non-overlapping on this descriptor. Thus, for each subject a variance score was computed for each descriptor and the variance scores then were averaged across the 10 traits (alpha = .92) and the 10 strategies (alpha = .79).

In sum, three sets of knowledge measures were computed for each subject: (1) the number of customer categories perceived, (2) the richness of categories on (a) customer traits and (b) selling strategies, and (3) the overlap of categories on (a) customer traits and (b) selling strategies. Measures 1 and 2 were based on the open-ended customer descriptions. Measure 3 was computed by using both the open-ended customer descriptions (to calculate a similarity score across categories) and the numerical ratings of appropriateness of descriptors for customer categories (to calculate a variance or distinctiveness score).

Effectiveness

The immediate supervisor rated all subjects on a 10-point performance scale (where 10 indicated best performance). Research on performance appraisal (e.g., Landy and Farr 1980) suggests that supervisor evaluations often are superior to “hard” performance measures because supervisors integrate across many facets of performance, some of which are not readily quantifiable. The supervisor was extremely familiar with each subject’s performance. For example, she frequently listened in on sales calls and provided regular performance feedback. On the basis of a median split, subjects rated as 8 or above were classified as above average performers and subjects rated as 7 or below were classified as below average performers. In our study, as in other real-world studies (e.g., Lurigio and Carroll 1985), experience was associated with expertise (r = .59, p < .01). Below average performers averaged 11 weeks of experience (range 1 to 32 weeks) and above average performers averaged 27.4 weeks of experience (range 3 to 72 weeks).

Results and Discussion

We hypothesized that more effective salespeople would have more customer categories (H1) and that these categories would be richer (H2) and more overlapping (H3). Effective salespeople produced, on average, 6.3 customer categories in comparison with 6.7 categories for less effective salespeople (t(39) < 1.0; n.s.). These results do not support H1, but are consistent with recent evidence suggesting that effective performers do not necessarily have more categories (cf. Lurigio and Carroll 1985). Effective salespeople, however, did produce significantly more descriptors per category, both for customer traits (4.6 vs. 3.7; t(39) = 2.0, p < .05) and sales strategies (3.5 vs. 2.4; t(39) = 2.8, p < .01), supporting H2a and H3a.

H3a and H3b suggest that at least part of the greater richness of the categories of more effective salespeople may be due to their perceiving more of the common features across categories. This hypothesis was tested by using the two measures of overlap described before. On the basis of the similarity score (computed as the proportion of shared to total features from the open-ended descriptions), overlap of customer traits is not significantly different between more and less effective salespeople (10% vs. 8%; t(39) < 1.0; n.s.). However, on the basis of the distinctiveness score (computed from the numerical ratings of appropriateness), more effective salespeople show significantly less across-category variance (greater overlap) for customer traits (6.3 vs. 9.0, t(39) = 2.3, p < .05).

For sales strategies, the similarity score indicates that effective performers’ categories overlap by 18% in comparison with an average overlap of 13% for less effective performers. This difference is in the hypothesized direction, but is not significant (t(39) = 1.1, p < .14). However, the distinctiveness score clearly indicates that more effective performers show significantly less across-category variance (more overlap) on selling strategies (3.6 vs. 5.3, t(39) = 2.2, p < .05). Thus, H3a and H3b are not supported by the similarity score, but are supported by the distinctiveness index, as a measure of overlap.

The reason the similarity scores do not produce stronger results may be partially methodological. The descriptive task that yielded the similarity score required subjects to provide categories that enabled them to differentiate among their customers. Hence subjects might have focused on differentiating rather than common cues. Consequently the rating task, which asked how appropriate a given set
of descriptors was for each category, may have provided a better measure of category overlap.

In sum, the data from study 1 indicate that more and less effective salespeople do not differ in the number of categories spontaneously generated; however, above average performers’ categories contain more descriptors of both customer traits and strategies. There is also some evidence that above average performers’ categories are more overlapping in terms of sales strategies and customer traits.

As noted before, these knowledge structure differences between more and less effective salespeople could be due to some other variable. We considered the personality trait of self-monitoring as one such variable. Though self-monitoring and supervisor performance ratings are significantly correlated ($r = .30$, $p < .05$ and $r = .27$, $p < .09$ for the two components of the self-monitoring scale), the knowledge structure differences between more and less effective salespeople remain significant when the self-monitoring components are used as covariates. Effectiveness and knowledge structure are related even when effects of self-monitoring are partialed out.

A more convincing case for the relationship between effectiveness and the structure of knowledge can be made with a longitudinal study. If an individual’s knowledge structure for a domain can be demonstrated to change in the hypothesized directions with the acquisition of skill, other stable traits (e.g., intelligence, personality) are less likely to be driving the observed knowledge differences. The purpose of study 2 therefore was to track individuals over time and to assess the changes in knowledge structure that occurred in conjunction with increasing effectiveness.

**STUDY 2: LONGITUDINAL STUDY OF KNOWLEDGE AND EFFECTIVENESS**

**Subjects**

Subjects were student callers who had just joined the university telephone operation described in study 1. Though 32 callers completed the training program, only 12 remained at the end of the 15-week period when the knowledge measures were collected from subjects for the second time.

**Task**

The knowledge measures were collected by means of a modified version of the method of session 1, study 1. Subjects were asked to write down the different categories of alumni they encountered on the phone and to describe each category in terms of the alumni’s traits and the sales strategies used to deal with that category of alumni. Rather than being asked to focus on characteristics that enabled them to differentiate between types of alumni, subjects were asked specifically to think of both the “differentiating” and “common” features characterizing types of alumni.

Subjects were run individually. They were contacted after the training program and an appointment was scheduled for the following week so they would have about a week’s experience when they filled out the knowledge measures for the first time. They were paid $5.00. At the first session, subjects were unaware that they would be repeating the task. Subjects were recontacted after 13 weeks and another appointment was scheduled. They were told merely that we were interested in their perceptions of the telefund operation now that they had worked for the operation for a semester. They then completed exactly the same task that they had performed earlier. They were paid $10 for the second phase of data collection and debriefed.

**Knowledge Measures**

The data from the two sessions were coded similarly to the open-ended data from study 1 by two independent judges blind to the hypotheses. The judges counted the number of categories used, independently divided the descriptions into individual statements (interjudge reliability = .82), and computed trait and strategy richness for each subject for each session. Judges also determined for each subject for each session whether trait and strategy statements were uniquely descriptive of one category or descriptive of two or more categories (interjudge reliability = .75). Thus, three knowledge measures were computed: (1) the number of customer categories spontaneously generated, (2) the richness of categories on traits and strategies, and (3) the similarity overlap between categories on traits and strategies. The change in task instructions (i.e., asking subjects to report both the differentiating and common features of alumni) was believed to overcome the problems in study 1 with using the open-ended descriptions to compute overlap scores. The numerical rating method was not used for logistical reasons, because it would have necessitated multiple sessions with subjects as a basis for developing the idiosyncratic questionnaires.

**Effectiveness**

The immediate supervisor rated 11 of the 12 subjects who completed both phases of the study as “above average” performers at the end of the 15-week period. Because the supervisor felt that all callers are relatively ineffective when they start, the results reported are for the 11 subjects whom we were able to track from their initial less effective stage to their final more effective stage.

**Results and Discussion**

The results of the longitudinal study are consistent with those of the cross-sectional study. Because a repeated measures analysis was used, the t-tests reported are paired t-tests. Though the number of categories does not change with increasing effectiveness (6.5 vs. 6.3; $t(10) < 1.0$, n.s.), there is an increase in the average richness of categories, both for customer traits (4.4 vs. 3.4; $t(10) = 2.1, p < .05$) and for selling strategies (3.3 vs. 2.5; $t(10) = 2.0, p < .05$). Further, for customer traits, category overlap increases with effectiveness (14% vs. 9%; $t(10)$
For selling strategies, category overlap increases (24% vs. 14%), but this increase is only marginally significant (t(10) = 1.6, p < .07).

GENERAL DISCUSSION

Both a cross-sectional and a longitudinal study suggest that more effective salespeople have richer and more overlapping knowledge structures about customer types, in terms of both customer traits and strategies for selling to those customers. However, there are no significant differences between more and less effective salespeople in the number of categories used to classify customers. Because the salespeople used as subjects were students who worked part time in a telephone sales operation, validation with other salesperson populations is important.

With that caveat, our findings add to the literature on competent performance in several ways. First, they suggest that effectiveness is not necessarily related to a proliferation of categories, but to a change in the qualitative nature of categories (cf. Lurigio and Carroll 1985) to contain more detailed information and more strategies to guide behavior. Second, effective salespeople also seem to perceive greater similarities across categories of customers. This finding corroborates Murphy and Wright’s (1984) notion of differences between real-world experts and “experts” in experiments and suggests that a focus on real-world expertise might lead to new and interesting insights about what factors allow for competent performance (Wagner and Sternberg 1985). Finally, ours is the first study of which we are aware that has tracked the development of knowledge structures over time as individuals progress from being less effective to being more effective.

The findings also have important sales management implications. More effective salespeople show less variance in their behaviors than do less effective salespeople. This finding does not suggest that effective salespeople do not vary their behavior (in fact their overlap on sales strategies on average is only about 25%), but that they vary it less than do less effective salespeople. This finding is consistent with the literature on bootstrapping (e.g., Dawes 1979), which suggests that when individuals deviate from a given policy they may over-adjust to the idiosyncrasies of the situation and make poorer decisions.

Training programs could incorporate our findings to teach salespeople specifically to interrelate their customer categories, to understand any inherent similarities among them, and to use general strategies to exploit such commonalities. Training programs also could attempt to train salespeople to create categories that are functional (i.e., highly informative with strong links between customer traits and selling strategies).

Finally, all of our findings should be verified with other types of salesforces. If these findings generalize, the impact of training programs and other practices that impart the types of knowledge structures we discuss should be assessed. This type of research would be important, particularly because our studies do not establish whether the development of certain types of knowledge structures leads to skilled performance or whether skilled performers perceive the world differently. Hence, research that attempts to affect knowledge structures would be important both managerially and in establishing causality.

REFERENCES


