Journal of Forecasting
J. Forecast. **25**, 303–324 (2006)
Published online in Wiley InterScience
(www.interscience.wiley.com) **DOI**: 10.1002/for.989

The Evolution of Sales Forecasting Management: A 20-Year Longitudinal Study of Forecasting Practices

TERESA M. MCCARTHY,[1]* DONNA F. DAVIS,[2]
SUSAN L. GOLICIC[3] AND JOHN T. MENTZER[4]
[1] *College of Business and Economics, Lehigh University, Bethlehem, Pennsylvania, USA*
[2] *Texas Tech University, Lubbock, Texas, USA*
[3] *University of Oregon, Eugene, Oregon, USA*
[4] *University of Tennessee, Knoxville, Tennessee, USA*

ABSTRACT

This paper presents results of a survey designed to discover how sales forecasting management practices have changed over the past 20 years as compared to findings reported by Mentzer and Cox (1984) and Mentzer and Kahn (1995). An up-to-date overview of empirical studies on forecasting practice is also presented. A web-based survey of forecasting executives was employed to explore trends in forecasting management, familiarity, satisfaction, usage, and accuracy among companies in a variety of industries. Results revealed decreased familiarity with forecasting techniques, and decreased levels of forecast accuracy. Implications for managers and suggestions for future research are presented. Copyright © 2006 John Wiley & Sons, Ltd.

KEY WORDS forecasting techniques; forecasting management; accuracy; satisfaction; familiarity

INTRODUCTION

The business environment has changed dramatically over the past two decades with increasing globalization, widespread adoption of information technology, and the advent of e-business. Factors stemming from these environmental changes such as time-based competition (Golicic *et al*., 2002) and product proliferation (Bayus and Putsis, 1999; Parker, 2002) have a direct impact on forecasting practices and processes (Moon *et al*., 2003), thereby making it important to consider how forecasting management practices have changed since studies conducted in the 1980s (Mentzer and Cox, 1984) and 1990s (Mentzer and Kahn, 1995).

More than 20 years ago, Makridakis *et al*. (1989, p. 13) suggested the greatest gains to be made in forecasting would result from research focused on forecasting management practices: ‘While there undoubtedly will be some improvements in available methodologies, it is management’s knowledge

* Correspondence to: Teresa M. McCarthy, College of Business and Economics, Lehigh University, 621 Taylor Street, Bethlehem, PA 18015-3117, USA. E-mail: tem3@lehigh.edu

and use of existing methods, in their specific organizational context, that hold the greatest promise.' This view is echoed by other researchers who suggest specific areas of forecasting management that need more attention (Armstrong, 1988; DeRoeck, 1991; Mahmoud *et al*., 1992). For example, globalization has caused many companies to become more decentralized; therefore, the administration and functional integration of the forecasting process should be examined. Increased research on systems used for forecasting is necessary due to the advent of e-business, advancements in information technology, and product proliferation. In addition, recognition of the potential for improved performance to be gained by collaborative forecasting (Helms *et al*., 2000; McCarthy and Golicic, 2002) has resulted in a need to examine how collaborative forecasting is incorporated into forecasting processes and practices within companies.

The purpose of this research is to report the results of a 20-year retrospective study of sales forecasting management and practices using the same measures employed by Mentzer and Kahn (1995) and Mentzer and Cox (1984), along with additional questions to obtain more detail on the impact of the changing business environment on management and performance of forecasting in firms. The current study concentrated on the original four objectives of familiarity, satisfaction, usage, and application of forecasting techniques in determining whether the sales forecasting practices of the early 2000s parallel those of the early 1990s and 1980s. Within the context of the original objectives, additional questions explored the adoption of collaborative forecasting within firms, accountability for forecast accuracy, and the use of system hardware and software. The following sections describe the research methodology, present and discuss the findings, and outline implications for forecasting management and future research.

METHODOLOGY

To guide the extension of the previous studies, we first reviewed empirical research on forecasting practices published since 1994[1] (Table I). The overview was limited to empirical research on forecasting *practice,* excluding those that focused on methodological issues such as the development of more accurate forecasting techniques. Mentzer and Cox (1984) and Mentzer and Kahn (1995) focused on the relationships among sales forecasting technique familiarity, satisfaction, usage and application. Several subsequent studies examined practices in specific disciplines (e.g., pharmaceuticals in Choo, 2000; purchasing in Wisner and Stanley, 1994; accounting and law in Peterson and Jun, 1998). These studies principally focused on administration of forecasts and the techniques used within firms from the perspective of a specific discipline. The more general studies covering a broad range of industries (Sanders and Manrodt, 1994; Lam, 1996; Duran and Flores, 1998; Mady, 2000; Jain, 2001; Klassen and Flores, 2001) are summarized in Table I along with the results from the Mentzer and Cox (1984) and Mentzer and Kahn (1995) studies.

Following the review of prior research, a web-based questionnaire was developed and e-mailed to a random sample of forecasting executives from 480 companies. The e-mail included an introductory cover letter containing a URL-embedded link to the survey, as well as an option to print a PDF hard copy of the survey to be completed manually and returned by fax. The introductory letter requested that the survey be forwarded to the appropriate person if the original recipient was not the individual in charge of the forecasting process within their company. The same list of forecasting

[1] See Mentzer and Cox (1984) and Mentzer and Kahn (1995) for reviews of forecasting practices research prior to 1994.

DOI: 10.1002/for

Table I. Surveys on sales forecasting practices since 1994

	Mentzer and Cox (1984)	Sanders and Manrodt (1994)	Mentzer and Kahn (1995)	Jain (2001)
Population	US forecasting managers	US forecasting managers	US forecasting managers	IBF conference attendees
Methodology	Mail survey	Mail survey	Mail survey	Survey
Response rate	160 (32%)	96 (19.2%)	207 (43%)	Not reported
Familiarity	Majority of respondents familiar with all techniques except – Box Jenkins, life cycle analysis, and classical decomposition Techniques learned from (1) conferences, (2) textbooks, (3) trade journals	Majority of respondents familiar with all techniques except Box–Jenkins and classical decomposition	Majority of respondents familiar with all techniques except Box–Jenkins, classical decomposition, expert systems and neural networks Techniques learned from (1) colleagues and textbooks, (2) conferences and trade journals	
Satisfaction	Majority satisfied with regression, exponential smoothing, moving average, trend-line analysis, classical decomposition, simulation, jury of executive opinion Majority dissatisfied with Box–Jenkins time series	Majority satisfied with jury of executive opinion, manager's opinion, moving average, regression and simulation Majority dissatisfied with naïve technique	Majority satisfied with exponential smoothing, trend-line analysis and classical decomposition Majority dissatisfied with straight line projections	
Usage	Majority use subjective techniques for short-range forecasts (less than 3 months) Jury of executive opinion favored across all time horizons and corporate levels of forecasts	Majority rely on subjective techniques far more than quantitative techniques for shorter-range forecasts (up to 1 year) Jury of executive opinion favored for longer-term forecasts (greater than 1 year) and all forecast levels except industry	Majority use both quantitative and qualitative techniques for shorter range (3 months–2 years) and qualitative for longer range (greater than 2 years) Qualitative methods favored for higher levels (industry and corporate) and quantitative favoured for lower levels (SKU, SKUL)	Time series models most often used

DOI: 10.1002/for

Table I. *Continued*

	Mentzer and Cox (1984)	Sanders and Manrodt (1994)	Mentzer and Kahn (1995)	Jain (2001)
Accuracy	Accuracy generally decreased as forecast level moved down to individual product forecasts Accuracy decreased significantly as time horizon increased Average accuracy across forecast levels and forecast periods was 85%		Accuracy generally decreased as forecast level moved down to individual product forecasts Accuracy decreased significantly as time horizon increased Average accuracy across forecast levels and forecast periods was 84%	Accuracy generally decreased as forecast level moved down to individual product forecasts Error increased for quarter horizon One-month SKU error 25%, category error 18% and aggregate error 14%
Evaluative criteria	Ease of use	Accuracy and ease of obtaining data	Accuracy and credibility	Monthly consensus meetings
Technology diffusion/systems	Some use of computer modeling		Some use of computer modeling	System use prevalent, Excel most widely used

Table I. *Continued*

	Duran and Flores (1998)	Klassen and Flores (2001)	Lam (1996)	Mady (2000)
Population	Mexican marketing and sales executives	Canadian senior-level marketing or production personnel responsible for forecasts	Hong Kong public firm COOs	Egyptian manufacturing firm general managers
Methodology	Mail survey	Mail survey	Mail survey	Mail survey
Response rate	54 (5.4%)	118 (20%)	62 (21%)	37 (76%)
Familiarity	Majority of respondents familiar with manager's opinion, sales force composite, and moving average	Majority familiar with naïve method, sales force composite, jury of executive opinion and intention surveys		Majority familiar with jury of executive opinion, sales force composite and simple average Large gap with USA in quantitative method familiarity
Satisfaction	Satisfaction was reported as 'average' for all techniques	Most satisfied (implied) with naïve method, jury of executive opinion and intention surveys		
Usage	Majority use manager's opinion, sales force composite and market research; use of techniques was hindered by difficult economic conditions	Majority use sales force composite, jury of executive opinion and moving average prepared monthly and quarterly at all market levels; majority use multiple techniques (very similar results to US firms)	Majority use linear regression, moving average and naïve extrapolation (respondents were not asked about qualitative methods); majority use more than one technique	Majority use jury of executive opinion and sales force composite with some use of simple average; use of techniques was hindered by lack of statistical skills
Accuracy	Most techniques were reported as having 'average' accuracy (on a 1- to 5-point Likert scale)	Visual monitoring most often used with some usage of error metrics Accuracy generally improved as the time horizon increased		
Evaluative criteria	Accuracy	Accuracy		
Technology diffusion/ systems		Majority use personal computers with in-house software		Majority do not use computers

DOI: 10.1002/for

technique definitions used in the previous studies was accessible on the web survey through hyperlinks. The overall design of the web survey took into account issues with using the Internet to collect organizational research data as discussed in Stanton and Rogelberg (2001).

Prior to the initial contact, a pretest questionnaire was administered to forecasting managers from 16 companies to check the appearance and readability of the questions and functionality of the web link. For the main study, multiple survey waves were distributed in accordance with the procedures described in Dillman (2000). Eighty-six completed surveys were submitted, resulting in a response rate of 18%. This response rate was deemed acceptable in comparison with the studies in Table I. Analysis revealed no demographic differences between early and late respondents, which lends support to the absence of non-response bias (Armstrong and Overton, 1977). A review of titles and job responsibilities reported in the responses confirmed that surveys were completed by individuals involved in the forecasting process, including CEOs (5%), vice presidents (12%), directors (28%), managers (50%), and analysts (5%).

RESULTS AND DISCUSSION

Analysis of corporate demographics reflected a nationally representative sample across multiple industries. Similar to the Mentzer and Kahn (1995) study, the largest single industry represented in this study was consumer package goods. The majority of responding firms were manufacturers with sales ranging from $101 million to $5 billion and more than 1000 employees. In addition to corporate demographics, respondents in this study were also asked to report on two key environmental factors: the level of technological change and intensity of competition in their industries. The majority reported moderate levels of technological change and high levels of competition. Chi-square analysis revealed no significant differences in responses for any corporate demographic variables, and very few for environmental variables. Significant findings related to environmental variables are presented in the sections below.

Forecasting management

As a starting point for understanding the current state of forecasting management, this study added a series of questions aimed at determining the organizational approach adopted by firms for managing the forecasting process. For 56% of responding companies, a cross-functional team was involved in developing the forecast. The majority of firms employing this approach (53%) used the team to reconcile multiple forecasts developed by different departments. For the remaining firms using this approach, the cross-functional team was charged with responsibility for developing a single forecast for the firm. Thirty-four percent of respondents did not utilize a cross-functional team; rather, they reported a single department was responsible for developing the final forecast. Among these firms, the majority (52%) assigned responsibility for developing the forecast to sales and marketing, and 15% assigned responsibility to finance. The remaining 10% of firms reported a decentralized approach, with each department in the company developing and using independent forecasts. Previous studies have indicated that firms at more advanced levels of forecasting effectiveness formally incorporate functional integration and consensus forecasting into the forecasting process (Mentzer *et al*., 1999; Moon *et al*., 2003).

Respondents were asked to identify functional areas that contributed information to the forecast (see Table II). Sales and marketing were named as contributors most frequently, followed by forecasting, executive leadership, and finance. The majority of respondents (72%) reported having four

DOI: 10.1002/for

Table II. Forecast responsibility by functional area

Function	Contribute information	Own the forecast
Sales	84%	43%
Marketing	81%	31%
Forecasting	52%	28%
Finance	48%	18%
Executive leadership team	50%	18%
Planning	43%	21%
Production	38%	4%
Logistics	24%	7%
Product management	29%	4%
Purchasing	12%	4%
R&D	6%	1%
Engineering	2%	0%

or more functional areas contributing information to the forecast, with 22% having contribution from four areas and another 22% from five areas, 12% from six areas, and 15% having contribution from seven or more functional areas. Previous empirical research has not reported statistics related to the number of functional areas contributing to the forecast; therefore this research provides a benchmark against which to compare trends in the future.

No significant relationships were found between the number of functional areas contributing to the forecast (average = 4.72) and the approach to developing the final forecast (e.g., cross-functional team, single department, or multiple independent forecasts). It should be noted that, even in companies where one department is responsible for developing the final forecast, many functional areas contribute information (average = 4.39). However, these findings indicate that firms collecting input from multiple functional areas are not necessarily adopting a consensus approach to developing the forecast, thereby presenting an area for improvement.

Asked which area owned the forecast, 43% identified sales, followed by marketing, forecasting, planning, finance, and executive leadership. Thirty-eight percent of firms reported a separate functional area for forecasting, employing an average of 10 people. Among these firms, 62% said the forecasting unit owned the forecast. Interestingly, in 16% of firms with a forecasting function, the forecasting unit did not contribute information to the forecast. One possible explanation is that the forecasting function for these responding companies performed primarily administrative tasks such as collecting and aggregating input from other functional areas.

Fifty-four percent reported participating in collaborative forecasting with customers. The majority of these (69%) limited collaboration to fewer than seven customers; however, 10% collaborated with more than 20 customers. In contrast, only 31% reported collaborative forecasting efforts with suppliers, illustrating one of the challenges of collaborative forecasting: those with the most information to share (i.e., downstream trading partners) appear to have the least motivation to share it. However, the correlation between collaborative forecasting with customers and suppliers was significant (p-value = 0.001, $r = 0.26$), demonstrating the emergence of demand planning in some supply chains. Neither the existence of a separate functional area for forecasting, nor any other demographic characteristic, affected the probability of participating in collaborative forecasting.

Asked to report their overall satisfaction with the current approach to forecasting management, the majority (61%) were satisfied with the current approach. All respondents that were extremely

DOI: 10.1002/for

Table III. Familiarity with forecasting techniques

Technique	% familiar			% somewhat familiar			% not familiar		
	M&C	M&K	PS	M&C	M&K	PS	M&C	M&K	PS
Qualitative									
Jury of executive opinion	81	66	57	6	16	17	13	18	26
Sales force composite	79	71	66	5	14	18	16	15	17
Customer expectations	73	64	62	7	19	21	20	17	17
Quantitative									
Moving average	85	92	84	7	6	16	8	2	0
Straight-line projection	82	85	71	11	11	20	7	4	9
Exponential smoothing	73	90	76	12	6	20	15	4	4
Regression	72	78	73	8	10	24	20	12	3
Trend-line analysis	67	73	69	16	16	23	17	11	7
Simulation	55	50	44	22	26	34	23	24	22
Life cycle analysis	48	50	49	11	22	25	41	28	25
Decomposition	42	43	38	9	20	16	49	37	46
Box–Jenkins time series	26	38	30	9	23	22	65	39	48
Expert systems		33	34		29	21		38	45
Neural networks		19	17		23	22		58	61

Notes: M&C, Mentzer and Cox (1984); M&K, Mentzer and Kahn (1995); PS, present study.

satisfied (4%) worked in firms with a separate functional area for forecasting. Overall satisfaction with the organizational approach to forecasting was positively correlated with the number of functional areas contributing to the forecast ($r = 0.252$, p-value $= 0.013$). Thus, it appears that a process involving many functional areas and managed by a separate forecasting area results in the highest levels of overall satisfaction. Twenty-two percent indicated they were dissatisfied with the current approach; however, dissatisfaction was more highly correlated with the information technology system used for forecasting than the organizational approach to forecasting management. These issues are discussed subsequently in the section on systems.

Familiarity

Examination of familiarity with various forecasting techniques reveals some similarities and several differences over the past 20 years (Table III). There has been little change overall in the techniques with which respondents are most familiar (i.e., generally the least sophisticated). Similar to findings in previous studies, moving average continues to be the most familiar quantitative forecasting technique, with all respondents in the present study indicating some level of familiarity. Although the order has changed slightly, the next four most familiar techniques—straight-line projection, exponential smoothing, regression, and trend line analysis—remained unchanged over 20 years for better than 80% of survey respondents. For these top five quantitative techniques, there appears to be a trend toward lower levels of familiarity as evidenced in the decrease among the percentage of respondents that were ‘familiar’ with the techniques, and an increase among the percentage ‘somewhat familiar.’

The percentage of respondents familiar with life cycle analysis remained consistent with previous studies, and the percentage not familiar with the technique continued to drop. In contrast, the percentage of respondents who were not familiar with simulation remained virtually the same compared to previous studies, while the percentage familiar with the technique continued to trend downward. When compared to the previous studies, familiarity with the more sophisticated techniques appears to be decreasing. For example, the percentage of respondents indicating they were familiar or somewhat familiar with decomposition, Box–Jenkins time series, expert systems, and neural networks decreased, while the percentage unfamiliar with these techniques increased. The only exception was expert systems, for which the percentage familiar increased slightly.

Similar to findings in 1995, familiarity with qualitative methods continued to drop. Those familiar with jury of executive opinion declined from 81% in 1984 to 66% in 1995 and 57% in the present study. Sales force composite and customer expectations declined less dramatically, dropping from over 70% in 1984 to 66% and 62%, respectively, in the present study.

Overall, for both quantitative and qualitative techniques, the level of familiarity appears to be decreasing when compared to the Mentzer and Kahn (1995) study. No relationships were found in the present study between level of familiarity and position within the company, ruling this out as a possible explanation for the differences between the two studies. However, this finding has serious implications for forecasting effectiveness if not addressed within firms. Cross-tabulations and correlations were calculated to determine if any relationships existed between familiarity with each technique and level of competition or level of technological change in the industry. Customer expectations (using customers' expectations of their needs and requirements as the basis for the forecast) was the only technique significantly related to level of competition ($r = 0.273$, p-value = 0.008). Specifically, respondents are more familiar with customer expectations in highly competitive environments, ($\chi^2 = 14.955$, p-value = 0.036). In increasingly competitive markets, firms are recognizing the importance of retaining customers and, thus, are moving toward building closer relationships with customers (Lemon *et al*., 2002). Logically, the use of customer expectations should increase in highly competitive markets.

In environments characterized by high rates of technological change, respondents were more familiar with regression ($\chi^2 = 14.698$, p-value = 0.005), exponential smoothing ($\chi^2 = 9.918$, p-value = 0.042), simulation ($\chi^2 = 10.832$, p-value = 0.029), and life cycle analysis ($\chi^2 = 13.598$, p-value = 0.009), and less familiar with these techniques when rates of technological change were low. High rates of technological change result in shorter product life cycles, and thus explain the increased familiarity with life cycle analysis. Furthermore, shorter product life cycles require more product introductions within shorter time horizons. Increased familiarity with quantitative techniques that can be executed very quickly in times of rapid technological change—such as regression, exponential smoothing, and simulation—would facilitate the need to produce greater quantities of forecasts in a short period of time. In addition, these three techniques allow forecasters to account for exogenous factors that, in times of high technological change, could provide important input to the forecast. The absence of a correlation between high rates of technological change and increased familiarity with qualitative techniques is not surprising as they tend to require more time and coordination.

Satisfaction

Respondents who were familiar with each technique were asked to indicate their levels of satisfaction. As shown in Table IV, respondents were most satisfied with exponential smoothing (69%), similar to respondents a decade ago. Exponential smoothing was the second most satisfactory technique in 1984. Regression, the most satisfactory technique in 1984, continued to be favorably rated in the 1995, with 66% indicating satisfaction with the technique; however, only 39% of respondents in this study indicated satisfaction with regression. Rather, trend-line analysis was the second most

DOI: 10.1002/for

Table IV. Satisfaction with forecasting techniques

Technique	% satisfied			% neutral			% dissatisfied		
	M&C	M&K	PS	M&C	M&K	PS	M&C	M&K	PS
Qualitative									
Jury of executive opinion	54	35	26	24	36	48	22	29	26
Sales force composite	43	34	43	25	27	38	32	39	19
Customer expectations	45	46	36	23	32	41	32	22	23
Quantitative									
Moving average	58	40	42	21	35	45	21	25	13
Straight-line projection	32	28	26	31	30	36	37	42	38
Exponential smoothing	60	72	69	19	24	27	21	4	4
Regression	67	66	39	19	29	56	14	5	6
Trend-line analysis	58	48	52	28	40	41	15	12	7
Simulation	54	50	32	18	42	64	28	8	5
Life cycle analysis	40	36	30	20	36	59	40	18	11
Decomposition	55	61	43	14	28	55	31	11	2
Box–Jenkins time series	30	44	33	13	45	62	57	11	4
Expert systems		45	21		47	74		8	4
Neural networks		38	18		49	76		13	6

Notes: M&C, Mentzer and Cox (1984); M&K, Mentzer and Kahn (1995); PS, present study.

satisfactory technique among respondents in the present study. Interestingly, this technique was among the top three techniques in the 1984 satisfaction analysis, but was displaced in the 1995 study by decomposition.

Decomposition and sales force composite were tied for the third most satisfactory techniques in the present study. The increase in satisfaction with sales force composite from 34% in 1995 to 43% in the present study is not surprising given that the sales department contributed to the forecast for 84% of respondents and owned the forecast for 43% of respondents (Table II). Furthermore, increased focus on collaborative forecasting also supports increased reliance on and improved use of sales force composite.

Cross-tabulations revealed no significant relationships between level of satisfaction and level of industry competition, and only one significant relationship between level of satisfaction and rate of technological change. Respondents were more likely to be satisfied and less likely to be dissatisfied with customer expectations in environments characterized by high degrees of technological change. This could be due to the perception that more information about customer expectations helps alleviate the uncertainty faced in an environment of technological change.

In general, satisfaction levels with various techniques appear to be declining. Twenty years ago, the majority of respondents reported satisfaction with seven of 12 techniques included in the survey. A decade ago, this dropped to four of 14 techniques presented. In the present study, only two techniques were rated as satisfactory by a majority of respondents. On the other hand, respondents in the present study indicated lower levels of dissatisfaction: less than 10% of respondents were dissatisfied with the majority of techniques whereas 20% of respondents reported dissatisfaction with all but two techniques in the 1984 study. Perhaps a maturity level is being reached in sales forecasting management, where techniques are not seen as the entire answer to sales forecasting (thus, lowering overall satisfaction levels), but rather as a part of the overall process (thus, also, decreasing dissatisfaction levels).

DOI: 10.1002/for

Table V. Forecasting techniques ranked in order of frequency of use across forecasting horizon

Technique	Short horizon ≤3 months			Mid horizon 4 months–2 years			Long horizon >2 years		
	M&C	M&K	PS	M&C	M&K	PS	M&C	M&K	PS
Qualitative									
Jury of executive opinion	1	5	na	1	2	1	1	1	1
Sales force composite	1	5	2	2	2	3	8	4	3
Customer expectations	3	3	1	5	8	4	4	7	na
Quantitative									
Moving average	4	1	6	6	6	7	10	9	na
Straight-line projection	8	3	6	8	9	8	6	10	6
Exponential smoothing	4	2	3	7	1	2	9	6	5
Regression	7	5	3	2	4	6	2	2	2
Trend-line analysis	6	8	3	4	5	5	3	3	4
Simulation	11	12	na	10	13	10	6	8	na
Life cycle analysis	12	12	6	12	10	11	5	5	na
Decomposition	9	8	na	9	7	8	10	10	na
Box–Jenkins time series	10	8	na	11	11	11	11	12	na
Expert systems	nm	12	na	nm	13	11	nm	11	6
Neural networks	nm	8	na	nm	12	11	nm	13	na

Notes: M&C, Mentzer and Cox (1984), sample size = 160; M&K, Mentzer and Kahn (1995), sample size = 186; PS, present study, sample size = 86; nm, not measured in the study; na, not applicable (no respondents indicated use of the technique for that time horizon).

Usage

Over the past 20 years, many similarities exist among the forecasting techniques used across various time horizons (see Table V). For techniques most frequently used in the shorter time horizon (≤3 months), customer expectations was the most frequently mentioned technique, increasing from the third most frequent in the past two studies. Sales force composite and exponential smoothing, which were the second and third most popular techniques, respectively, for short-horizon forecasting in the present study, were also among the top five most popular techniques in 1995 and 1984. Regression, which is tied with exponential smoothing and trend-line analysis for the third most popular short-horizon technique, increased in usage from fifth most popular in 1995 and was not among the top five in 1984. The rise in popularity of regression could be a result of increased ease of accessibility to systems that can perform regression analysis, including simple spreadsheet software. Among the less sophisticated techniques, trend-line analysis ascended into the top five for the first time, while moving average and straight-line projection dropped off the top-five list for short-horizon forecasting techniques. Jury of executive opinion, which dropped from most frequently used technique in 1984 to fifth most frequently used in 1995, is no longer among the top five in the present study for short-horizon techniques. Jury of executive opinion consists of combining top executives' views concerning future sales. Executives are typically involved in more strategic-level decision making, and short-horizon forecasts are often considered more tactical. As such, it is not surprising that jury of executive opinion is not frequently used for short-horizon forecasts.

For the mid-horizon forecasts (4 months to 2 years), jury of executive opinion and exponential smoothing were the first and second most frequently used techniques in the present study, respectively, and were the second and most frequently used in 1995. Sales force composite, which has con-

DOI: 10.1002/for

sistently been the second most frequently used technique in the prior studies, dropped to third in this study. Customer expectations, which had dropped off the top-five list in 1995, reappeared as the fourth most popular mid-horizon technique. Consistent with 1995 results, trend-line analysis remained as the fifth most frequently used technique. Regression dropped to sixth in frequency of use for mid-horizon forecasting compared to fourth in 1995 and second in 1984.

Techniques identified for long-horizon forecasting (>2 years) over the past 20 years illustrate some consistencies as well. Jury of executive opinion and regression remained as the first and second most frequently used long-horizon forecasting techniques, respectively, for all three studies. Sales force composite and trend-line analysis were the third and fourth most frequently used techniques in this study, respectively, which is very similar to their fourth and third positions, respectively, in 1995. Respondents indicated exponential smoothing was the fifth most frequently used long-horizon technique, replacing life cycle analysis for that spot in both 1995 and 1984.

Although jury of executive opinion continues to be among the most frequently used techniques for mid- and long-horizon forecasting, only 26% of respondents were satisfied with the technique (see Table IV). In fact, just as many respondents were dissatisfied with jury of executive opinion as were satisfied. Our data do not indicate the source of dissatisfaction with the technique. Two possibilities include: (1) dissatisfaction stemming from the level of accuracy associated with the technique; or (2) frustration resulting from 'executive overrides' that can alter forecasts developed with input from multiple sources using alternative techniques.

Customer expectations fell off the top-five list in 1995 for long-horizon forecasting, and similarly does not appear on the top-five list in this study either. Three of the techniques that appeared on the top-five list for all three time horizons—exponential smoothing, trend-line analysis, and sales force composite—were also rated as the first, second, and third most satisfactory techniques among respondents, respectively. Decomposition and moving average, which ranked as third (tied with sales force composite) and fifth in terms of level of satisfaction, did not appear in the top five most frequently used techniques for any time horizon. Overall it appears that firms are relying more heavily on qualitative methods for all time horizons. This could be a function of a general familiarity with these methods, which are often easier to understand and learn, regardless of the appropriateness of the technique for a particular situation.

Table VI displays the forecasting techniques most frequently used by forecasting level. Jury of executive opinion continued to be the most frequently used technique for industry and corporate level, but dropped to fifth most frequently used for product line as compared to first in 1995 and 1984. Jury of executive opinion also appeared as the fifth most popular technique at the SKUL level, which is surprising considering that SKUL is typically considered a more tactical level that would not require regular attention of executives. Sales force composite appeared as second or third most frequently used technique for every level. This is fairly consistent with the prior studies, with the exception of industry level, in which sales force composite did not appear among the top five in the prior studies. Exponential smoothing continued to be the most frequently used technique for the lower-level forecasts (SKU and SKUL), and increased from third most frequent in 1995 to most frequent for product line forecasting in the present study. Regression appears in the top five most frequently used techniques for all levels of forecasting. Overall, there does not appear to be any consistent pattern between use of qualitative versus quantitative techniques for horizon or level of forecasting. This could be a random function of the knowledge and familiarity of the specific contributors to the forecast at the different levels. For example, if finance is responsible for the forecast at the industry or corporate level in a particular company, they may use jury of executive opinion because that is the technique with which they are most comfortable.

DOI: 10.1002/for

Table VI. Forecasting techniques ranked in order of frequency of use across forecast level

Level Technique	Industry			Corporate			Product line			SKU			SKUL	
	M&C	M&K	PS	M&C	M&K	PS	M&C	M&K	PS	M&C	M&K	PS	M&K	PS
Qualitative														
Jury of executive opinion	1	1	1	1	1	1	1	1	5	4	6	8	7	5
Sales force composite	7	6	3	3	2	2	2	2	2	1	2	2	2	3
Customer expectations	4	6	6	5	6	4	6	7	3	3	8	2	8	2
Quantitative														
Moving average	8	12	6	7	7	7	4	6	7	6	4	4	4	9
Straight-line projection	6	6	3	6	10	8	8	9	8	8	8	11	9	na
Exponential smoothing	8	5	6	9	4	3	7	3	1	22	1	1	1	1
Regression	2	2	2	2	3	4	4	4	3	7	2	4	3	5
Trend-line analysis	3	3	3	3	5	4	3	5	6	4	4	6	5	4
Simulation	5	9	10	7	12	9	10	12	9	12	13	8	13	9
Life cycle analysis	8	4	6	10	7	10	10	8	na	10	10	na	12	na
Decomposition	11	9	10	10	7	10	9	9	9	9	7	6	6	5
Box–Jenkins time series	11	12	na	12	11	na	12	11	na	11	10	na	11	9
Expert systems	nm	9	10	nm	14	na	nm	na	na	nm	14	10	13	8
Neural networks	nm	12	na	nm	12	na	nm	na	na	nm	10	11	10	na

Notes: M&C, Mentzer and Cox (1984), sample size = 160; M&K, Mentzer and Kahn (1995), sample size = 186; PS, present study, sample size = 86; nm, not measured in the study; na, not applicable (no respondents indicated use of the technique for that time horizon).

DOI: 10.1002/for

Table VII. Percentage accuracy by level and horizon

Horizon Forecast level	Short-Horizon ≤3 Months			Mid-Horizon 4 Months to 2 Years			Long-Horizon >2 Years		
	M&C	M&K	PS	M&C	M&K	PS	M&C	M&K	PS
Industry	92 (n = 61)	90 (n = 1)	85 (n = 1)	89 (n = 61)	88 (n = 16)	84 (n = 10)	85 (n = 50)	87 (n = 36)	93 (n = 3)
Corporate	93 (n = 81)	72 (n = 2)	71 (n = 5)	89 (n = 89)	86 (n = 64)	84 (n = 31)	82 (n = 61)	88 (n = 42)	89 (n = 8)
Product line	89 (n = 92)	90 (n = 4)	88 (n = 6)	84 (n = 95)	86 (n = 83)	79 (n = 34)	80 (n = 60)	88 (n = 25)	79 (n = 5)
SKU	84 (n = 96)	82 (n = 14)	79 (n = 5)	79 (n = 88)	79 (n = 89)	64 (n = 36)	74 (n = 54)	86 (n = 10)	79 (n = 3)
SKU by location		76 (n = 17)	66 (n = 7)		75 (n = 58)	60 (n = 22)		87 (n = 5)	
Weighted average[a]	85	84	76						

Notes: M&C, Mentzer and Cox (1984), sample size = 160; M&K, Mentzer and Kahn (1995), sample size = 186; PS, present study, sample size = 86.
[a]Weighted average calculated by weighting each cell accuracy by the number responding.

Accuracy

The overall degree of forecast accuracy (defined in all three studies as one minus the average absolute percentage error experienced) for the present study reflects a weighted average of 76%, and is substantially lower that that of the 1995 and 1984 studies (Table VII). Examination of accuracy at more detailed levels is discussed below and lends some possible explanations as to why overall forecast accuracy has decreased in the last 10 years.

Accuracy by forecast level and horizon were compared across all three studies (Table VII), and there appear to be some patterns worthy of mention. The movement away from short-term forecasting found in the Mentzer and Kahn (1995) study is also reflected in the current study. As suggested by Mentzer and Kahn, the likely explanation for this phenomenon is that the increasing volatility of short-term market forecasting combined with emphasis on strategic linkages may lead to less emphasis on short-term forecasting.

For the lower forecast levels (product line, SKU, and SKUL), accuracy decreased across all horizons. Furthermore, when comparing the present study to the 1995 study, the reduction in accuracy was greater for the mid-term and long-term horizons than for the short-term horizon. For example, when compared to 1995, product line forecast accuracy in the present study decreased for the short-horizon forecast by only 2%, for the mid-horizon forecast by 7%, and for long-horizon forecast by 9%. Similar patterns hold for the SKU and SKUL level forecasts, with the exception of the SKUL level accuracy for the long-horizon forecast, for which accuracy was not reported.

One possible explanation for decreases in accuracy is that familiarity with forecasting techniques appears to have decreased, as mentioned earlier (Table III), which could mean these techniques are not being used properly. Another possible explanation is product proliferation. Approximately 40% of the respondent firms produced more than 1000 forecasts at the SKU level, with 8% producing between 10,001 and 100,000 and 5% producing more than 100,000. Academic and trade literature

DOI: 10.1002/for

Table VIII. Measures of forecast accuracy

Accuracy measure	Percentage of respondents using measure of accuracy[a]	
	M&K	PS
Mean absolute percentage error	52	45
Mean absolute deviation	25	20
Mean squared error	20	6
Deviation	4	36
Percentage error	3	45

Notes: M&K, Mentzer and Kahn (1995), sample size = 186; PS, present study, sample size = 86.
[a]Respondents were allowed to list more than one measure.

suggests product proliferation is an issue of increasing concern (Parker, 2002; Bayus and Putsis, 1999) as it adds considerable complexity to the forecasting process, thereby increasing the potential for error (Moon *et al*., 2003). A third possible explanation is that forecast accuracy has not actually changed, but the method for measuring forecast accuracy has changed, resulting in the appearance of decreased accuracy levels.

To determine differences in measures used for forecast accuracy, respondents were asked to indicate all methods used by their firms to measure accuracy. Results revealed the two most frequently used methods were mean absolute percentage error (MAPE) and percentage error (PE) (Table VIII), which were each identified as being used by 45% of respondents. The percentage using MAPE decreased from the 1995 study, and the percentage using PE increased dramatically. However, among those using PE, 75% use the measure in combination with other methods, with 47% using it in combination with MAPE. The combined use of MAPE and PE can be beneficial. Since MAPE only provides an overall metric of forecasts, with no indication of whether the forecast has been high or low, or high during certain seasons and low during others, the MAPE measure supplemented with PE plots offers a useful diagnostic tool. The use of deviation as a measure of accuracy also increased in the present study. Fifty-eight percent of those using deviation also use MAPE as a measure of accuracy. Although use of accuracy measures between the two studies was compared, we were not able to determine the percentage of respondents in 1995 that used a combination of measures; therefore, it is difficult to discern the impact this may have on overall level of accuracy.

Another factor impacting accuracy is the degree to which individuals involved in the process are held accountable for accuracy levels. Thirty-three percent of respondents agreed that individuals in their firm were held accountable for forecasting performance, and 23% agreed that rewards were provided as incentives for improving forecasting performance. In previous research, companies incorporating these practices into their approach to forecasting have been characterized as showing a higher level of sophistication in the management of the forecasting process (Mentzer *et al*., 1999; Moon *et al*., 2003). For companies looking to make improvements in forecasting accuracy, holding individuals accountable and providing incentives for forecast performance could provide a source for improvement.

Another indication of firms showing a higher level of forecasting sophistication is recognition of the impact forecast accuracy has on other aspects of business performance. Almost half (48%) indicated they measured the impact of forecasting on inventory, 30% measured the impact on customer

DOI: 10.1002/for

Table IX. Criteria for evaluating sales forecasting effectiveness

Criteria	Percentage indicating criteria are 'important' or 'extremely important'	
	M&K	PS
Accuracy	92	82
Credibility	92	82
Customer service performance	77	69
Ease of use	75	63
Inventory turns	55	54
Amount of data required	46	52
Cost	41	41
Return on investment	35	27

Notes: M&K, Mentzer and Kahn (1995), sample size = 186; PS, present study, sample size = 86.

service, and 19% measured the impact on supply chain costs. Nearly all of those that measured the impact on customer service (90%) and supply chain costs (95%) also measured the impact on inventory.

Table IX illustrates that accuracy and credibility continued to be the top criteria for evaluating sales forecasting effectiveness, although 10% fewer respondents indicated such in the present study. Similar to the 1995 study, the majority of respondents continued to identify customer service performance, ease of use, and inventory turns as important criteria, although a lower percentage of respondents indicated such for each criteria. Respondents in the present study considered cost and return on investment as lesser criteria to evaluate forecasting effectiveness. These findings are consistent with Mentzer and Kahn (1995), and indicate forecasting techniques are often not valued for the potential impact on corporate financial measures. It is interesting that firms recognize and measure the impact of forecasting on customer service and supply chain costs as previously discussed, but do not take this further and link these measures to the bottom-line impact. Companies that can illustrate a direct link between forecast accuracy and improved financial performance are more likely to get senior management to see forecasting as an area worthy of investment rather than as an expense.

Systems

Additional important considerations in forecasting management practice are the software and hardware combinations used to support the sales forecasting function. When asked to identify the types of software used for forecasting, the largest percentage (41%) used spreadsheet programs, followed by commercial forecasting packages (38%), applications developed in-house (30%), and customized applications by an outside vendor (22%). In the majority of cases, combinations of software packages were used. For example, among those using spreadsheet programs, 15% used it in combination with a customized application by an outside vendor, 24% used it in combination with an application developed in-house, and 37% used it with a commercial forecasting package. However, the remaining 24% (10% of the total sample) used spreadsheet programs exclusively.

Respondents were also asked to identify how information was input into the forecasting system and then transmitted to the production planning system (Table X). The largest percentage of respon-

DOI: 10.1002/for

Table X. Method of data transmittal (percentage of respondents[a])

Type of transmission	Input into forecasting system	Transmit to production planning system
Manual entry	37.8	15.9
Electronic download	26.7	36.4
Customized electronic interface	18.9	25.0
Integrated software interface	16.7	22.7

[a] $n = 80$.

Table XI. Satisfaction with system based on type of system used and method of data transmittal (mean score[a])

Type of transmission	Input into forecasting system	Transmit to production planning system
Manual entry	3.26[b]	3.14
Electronic download	2.83	2.88
Customized electronic interface	2.53	2.55
Integrated software interface	2.27[b]	2.65

[a] 5-point Likert-type scale; 1 = extremely satisfied, 2 = satisfied, 3 = neutral, 4 = dissatisfied, 5 = extremely dissatisfied.
[b] Significantly different at $\alpha = 0.05$; Bonferroni adjustment for multiple comparisons.

dents indicated data were entered into the forecasting system manually, followed by electronic download, customized electronic interface, and integrated software interface. Considerably fewer respondents reported using manual transmission of forecasting data into the production planning system, with most respondents indicating electronic download as the method of transmittal into the production planning system.

When asked to report their overall satisfaction with the existing sales forecasting system, less than half (43%) were satisfied with the current system, and only 4% were extremely satisfied. Twenty-two percent indicated they were dissatisfied, and 5% were extremely dissatisfied. Mean scores of overall satisfaction with the system by method of data transmittal were compared using one-way ANOVA. Significant differences were found when comparing the means for the method of data input into the forecasting system, but no significance was found for the means by method of data transmittal into the production planning system (Table XI). Specifically, those who enter data into the forecasting system manually were significantly more dissatisfied than those using an integrated software interface (p-value = 0.010). The same pattern was revealed when testing for significant differences between the means in satisfaction with approach to developing the forecast (Table XII). This question was positioned in the survey after questions related to approach, but several pages before questions related to systems. Therefore, the results are unlikely an artifact of order effect. It is more likely that dissatisfaction associated with manual entry reflects perceptions of the entire forecasting process and is not limited to assessment of the system.

The results indicating dissatisfaction with the forecasting system and approach when manual entry is required are not surprising. Manual entry provides opportunities for human error that can be

DOI: 10.1002/for

Table XII. Satisfaction with approach to forecasting based on type of system used and method of data transmittal (mean score[a])

Type of transmission	Input into forecasting system	Transmit to production planning system
Manual entry	3.06[b]	3.14
Electronic download	2.67	2.63
Customized electronic interface	2.47	2.41
Integrated software interface	2.00[b]	2.33

[a]5-point Likert-type scale; 1 = extremely satisfied, 2 = satisfied, 3 = neutral, 4 = dissatisfied, 5 = extremely dissatisfied.
[b]Significantly different at $\alpha = 0.05$; Bonferroni adjustment for multiple comparisons.

reduced with electronic forms of data entry. Error stemming from manual entry result in reduced forecast accuracy levels, and thus reduced overall satisfaction with the forecast. Firms looking to increase accuracy levels should minimize reliance on use of spreadsheet forecasting system and other systems that require manual entry of data.

IMPLICATIONS AND FUTURE RESEARCH

This study has many implications for firms seeking to improve forecasting management practice. For example, regarding the organizational approach to managing the forecasting process, 10% of respondents indicated their firms adopt an independent approach to forecasting where each functional area develops and uses its own forecast. Such functional disconnects among departments hinder efforts toward developing an accurate forecast (Moon *et al*., 2003). The absence of other departmental perspectives leads to forecasts biased toward the specific requirements of the developing department. As an example of an independent forecasting environment, the production forecast would not incorporate marketing's promotional schedule or logistics' knowledge of customers' delivery requirements. One step toward improving forecast accuracy in firms adopting this approach is to establish formalized communication mechanisms whereby information is shared among all functional areas.

Furthermore, although the large majority of respondents indicated input was collected from multiple functional areas, a consensus approach to developing the forecast was adopted by only 29% of companies. A true consensus process involves a systematic, coordinated effort among members of an interfunctional team to develop a forecast derived by team members based upon the information provided from their multiple perspectives. As such, the goal of each member of the consensus team is forecasting accuracy. The consensus approach avoids bias in the case where one department is responsible for developing the final forecast based on information collected from multiple departments. It can also mitigate undue influence and political pressures that can occur in the case where several departments negotiate based on their individual goals rather than a common, consensus goal of forecast accuracy. Previous benchmarking research has indicated that firms at a more advanced level of forecasting sophistication use a consensus approach (Mentzer *et al*., 1999). The present research indicates a potential area for improvement (and potential competitive advantage) for the

DOI: 10.1002/for

majority of companies that can work towards implementing this approach to improve existing forecasting practices.

Another serious implication for managers is the decreasing overall level of familiarity with both quantitative and qualitative techniques. Lack of familiarity with an array of techniques can lead to reliance on only those techniques with which an individual is familiar and improper application of techniques in general. A related finding with potentially distressing consequences is the fact that forecast accuracy is decreasing. Decreased familiarity with forecasting techniques is likely a factor contributing to decreased accuracy. Firms attempting to improve forecast accuracy rates can provide adequate, ongoing training for their forecasting personnel through enrollment in certification programs, forecasting seminars, conference attendance, local college courses, or other sources. As forecasting management and best practices evolve, continuing education is essential to ensure that state-of-the-art forecasting processes and techniques are considered for implementation within a firm to continually strive for improved forecasting performance.

Results reported on the type of systems used for forecasting indicate another potential area for improvement. Ten percent of firms used spreadsheet programs exclusively for developing the forecast, and an additional 31% used spreadsheet programs in combination with other types of software programs. Furthermore, 38% of respondents indicated data were entered manually into the forecasting system and 16% reported manual transmission of the forecast into the production planning system. Use of spreadsheets as a primary method of creating and communicating forecasts throughout the company and reliance on manual transfer of data introduces opportunity for error into the process, thereby increasing the possibility of reduced accuracy. This scenario can result in a lack of confidence in the integrity of the numbers among users of the forecast. Functional divisions that rely on the forecast as input into their decision-making processes (e.g., production planning, logistics, purchasing) may not trust that manual entry and transfer of data were conducted accurately. Also, spreadsheet systems allow for idiosyncratic use of data, formatting, techniques, and processes in developing the forecast that may not hold consistent meaning across forecasts and users. Companies facing these situations should implement one integrated solution that eliminates the need for spreadsheets and provides real-time, end-to-end data with a report function that permits users to view the forecast data and format that are relevant to them.

It should also be noted that use of an integrated forecasting software package does not relieve forecasters of the need to be familiar with a variety forecasting techniques. While forecasting systems facilitate ease of use of myriad techniques, it is the forecaster that ensures appropriate application of those techniques, tempered by their own insights about the business environment and its impact upon demand.

Only 55% of respondents believed that forecasting performance was formally evaluated in their companies. Moreover, more than two-thirds of respondents reported an absence of accountability for forecast accuracy, and three-quarters indicated there was no reward structure in place as an incentive for improving forecast accuracy. Implementation of a meaningful reward and/or recognition program for all functional areas that contribute to the forecast can work toward creating an environment of continuous improvement. However, such a program cannot work effectively without a formal, systematic evaluation of forecast performance. Until forecast performance is accurately measured and reported, individuals creating the forecast have no basis for improvement. Implementing measurement and reward processes are critical first steps to improving forecast accuracy.

Results of this study also revealed areas of opportunity for future research. In particular, the decline in familiarity with techniques and forecast accuracy over the past 20 years is alarming. Future

DOI: 10.1002/for

research should delve into the reasons behind these trends. For example, is decreased familiarity with techniques a result of inadequate training? Is it a result of blind dependence upon software packages (the 'black box' syndrome)? What types and how many years of training do forecasters have within companies? Is there a correlation between training and 'black box' forecasting? If several functional areas are contributing to the forecast, what types of training are appropriate for each of these areas, and how often is training provided? Research exploring these questions can shed light on the impact of training on forecast accuracy.

Future research should also focus on the underlying causes of decreased forecast accuracy. As suggested above, this phenomenon could be a result of inadequate training. Other possible causes could include product proliferation and a rapidly changing competitive landscape. Future research can explore the alternative solutions companies are adopting to counter these business trends to determine which are the most effective. For example, it would be interesting to know the impact of production postponement on forecast accuracy at various levels, such as product line, SKU, and SKUL. A qualitative research design such as multiple case studies, which is conducive to examining contemporary phenomena in context, could provide rich insights into how companies are combating forecast accuracy issues in today's evolving business environment.

CONCLUSIONS—TRENDS OVER A TWENTY-YEAR PERSPECTIVE

Over a 20-year time span, with considerable improvement in the tools at the disposal of sales forecasters, why have we not gotten any better at sales forecasting? The number and sophistication of techniques available to sales forecasters have improved. The change in computers during this time span—from mainframes to personal computers, wide area networks, the World Wide Web, and astounding increases in software efficiency and effectiveness—has been nothing less than amazing. Given all this, however, accuracy has not improved, technique and systems understanding and use has not improved, and satisfaction with techniques, systems, and management processes has not improved.

Again, taking a 20-year perspective, we think the answer lies in our not concentrating on the critical elements of sales forecasting management—processes, training, and performance measurement and rewards. There is a tendency in sales forecasting research to concentrate on the development of techniques. There is a tendency in sales forecasting management to concentrate on the selection of a package that will 'solve our sales forecasting problems.' Both lead us to ignore fundamental facts about sales forecasting management.

A lack of familiarity by users with techniques leads to 'black box' forecasting; i.e., users do not know what the package does, so they assume it must be right. Alternatively, 'black box' forecasting leads to an over-reliance on qualitative forecasting. Both lead to misuse of sales forecasting systems, and neither leads to an effective sales forecasting process. With proper training, sales forecasters realize what techniques are included in the package they are using, what factors in the sales forecasting environment each technique considers, and, based upon this information, what qualitative adjustments they should be making to quantitative forecasts.

Lack of satisfaction with sales forecasting systems also leads to their circumvention. Manual data entry, lack of understanding of the systems, and uninterpretable results all lead users to resort to what they do understand, i.e., spreadsheets. With the considerable sophistication of sales forecasting packages today, spreadsheets should not be the most common sales forecasting package among users. It is the fact that we in sales forecasting management have not made these packages under-

DOI: 10.1002/for

standable, nor have we provided users with the training to facilitate this understanding process, that has led to the ongoing use of spreadsheets as the sales forecasting systems of choice.

It should not be surprising to anyone schooled in management that these problems occur. At the heart of this lack of performance improvement is the fact that most personnel involved in sales forecasting are not held accountable for performance (67%), nor does sales forecasting performance affect their compensation (77%). The best systems and techniques in the world will not result in improved sales forecasting performance if the personnel charged with using this technology are not rewarded for doing so.

Finally, and related to the last point, is the disjointed approach most companies take to managing the sales forecasting function. Lack of involvement in the sales forecasting process of the numerous functions that have information critical to effective sales forecasting, lack of creation of a recognized sales forecasting function, and multiple, unreconciled sales forecasts in the same company have all led to an ongoing lack of satisfaction with the sales forecasting process from respondents over a 20-year time span of study.

The message is clear. Sales forecasting performance will not improve until companies commit the resources to create an adequately funded, cross-functional sales forecasting process that is populated with personnel trained in the use of sales forecasting techniques (both qualitative and quantitative), packages, and systems, and properly measured and rewarded for performance—performance that is measured in terms of sales forecasting accuracy, and its impact on customer satisfaction levels and supply chain costs.

REFERENCES

Armstrong JS. 1988. Research needs in forecasting. *International Journal of Forecasting* **4**: 449–465.

Armstrong JS, Overton TS. 1977. Estimating nonresponse bias in mail surveys. *Journal of Marketing Research* **14**(August): 396–402.

Bayus BL, Putsis WP. 1999. Product proliferation: an empirical analysis of product line determinants and market outcomes. *Marketing Science* **18**(2): 137–155.

Choo L. 2000. Forecasting practices in the pharmaceutical industry in Singapore. *Journal of Business Forecasting Methods and Systems* **19**(2): 18–22.

DeRoeck R. 1991. Is there a gap between forecasting theory and practice? A personal view. *International Journal of Forecasting* **7**: 1–2.

Dillman DA. 2000. *Mail and Internet Surveys: The Tailored Design Method* (2nd edn). Wiley: New York.

Duran JA, Flores BE. 1998. Forecasting practices in Mexican companies. *Interfaces* **28**(6): 56–62.

Golicic SL, Davis DF, McCarthy TM, Mentzer JT. 2002. The impact of e-commerce on supply chain relationships. *International Journal of Physical Distribution and Logistics Management* **23**(10): 851–871.

Helms MM, Ettkin LP, Chapman S. 2000. Supply chain forecasting: collaborative forecasting supports supply chain management. *Business Process Management Journal* **6**(5): 392–407.

Jain CL. 2001. Forecasting practices in corporate America. *Journal of Business Forecasting Methods and Systems* **29**(2): 2–3.

Klassen RD, Flores BE. 2001. Forecasting practices of Canadian firms: survey results and comparisons. *International Journal of Production Economics* **70**(2): 163–174.

Lam SSK. 1996. A survey of the forecasting practices of Hong Kong companies. *International Journal of Management* **13**(3): 300–305.

Lemon K, White B, Winer RS. 2002. Dynamic customer relationship management: incorporating future considerations into the service retention decision. *Journal of Marketing* **66**(January): 1–14.

Mady MT. 2000. Sales forecasting practices of Egyptian public enterprises: survey evidence. *International Journal of Forecasting* **16**(3): 359–368.

DOI: 10.1002/for

Mahmoud E, DeRoeck R, Brown RG, Rice G. 1992. Bridging the gap between theory and practice in forecasting. *International Journal of Forecasting* **8**: 251–267.
Makridakis S, Wheelwright SC, McGee VE. 1989. *Forecasting Methods for Management* (5th edn). Wiley: New York.
McCarthy TM, Golicic SL. 2002. Implementing collaborative forecasting to improve supply chain performance. *International Journal of Physical Distribution and Logistics Management* **32**(6): 431–454.
Mentzer JT, Bienstock CC, Kahn KB. 1999. Benchmarking sales forecasting management. *Business Horizons* May–June: 48–56.
Mentzer JT, Cox JE Jr. 1984. Familiarity, application, and performance of sales forecasting techniques. *Journal of Forecasting* **3**(1): 27–36.
Mentzer JT, Kahn KB. 1995. Forecasting technique familiarity, satisfaction, usage, and application. *Journal of Forecasting* **14**: 465–476.
Moon MA, Mentzer JT, Smith CD. 2003. Conducting a sales forecasting audit. *International Journal of Forecasting* **19**: 5–25.
Parker K. 2002. Events happen, but demand is always. *Manufacturing Business Technology* **20**(2): 40–43.
Peterson R, Jun M. 1998. Forecasting practices in accounting, law, and medical professions. *Journal of Business Forecasting Methods and Systems* **17**(2): 20–23.
Sanders NR, Manrodt KB. 1994. Forecasting practices in US corporations: survey results. *Interfaces* **24**(2): 92–100.
Stanton JM, Rogelberg SG. 2001. Using Internet/Intranet web pages to collect organizational research data. *Organizational Research Methods* **4**(3): 200–217.
Wisner JD, Stanley LL. 1994. Forecasting practices in purchasing. *International Journal of Purchasing and Materials Management* **30**(1): 22–28.

Authors' biographies:

Teresa M. McCarthy is an assistant professor of Supply Chain Management in the Marketing Department at Lehigh University. Dr. McCarthy's primary research interests include supply chain management, collaborative forecasting, demand management, and demand planning. Prior to her academic career, she worked in the retail industry in buying, forecasting, and inventory planning.

Donna F. Davis is an assistant professor of Marketing at Texas Tech University. Dr. Davis's primary research interests include supply chain management, brand management, and information management. Prior to her academic career, she was the Vice President for Admissions and Enrollment at Maryville College in Tennessee.

Susan L. Golicic is an assistant professor of Marketing at the University of Oregon. Dr. Golicic's primary research interests include supply chain management, business to business relationships, and logistics strategy. Prior to her academic career, she worked with DaimlerChrysler in the corporate logistics department.

John T. Mentzer is a Professor & Bruce Chair of Excellence in Business at the University of Tennessee. He has written more than 130 papers and articles, and co-authored six books in the areas of Supply Chain, Sales Forecasting & Demand Planning and Marketing Strategy. Dr. Mentzer has been recognized as one of the most prolific authors in his field.

Authors' addresses:

Teresa M. McCarthy, Lehigh University, College of Business and Economics, 621 Taylor Street, Bethlehem, PA 18015-3117.

Donna F. Davis, Room 806, Mail Stop 2101, Rawls College of Business, Texas Tech University, Lubbock, TX 79409.

Susan L. Golicic, Charles H. Lundquist College of Business, 1208 University of Oregon, Eugene, OR 97403-1208.

John T. Mentzer, Department of Marketing and Logistics, 310 Stokely Management Center, The University of Tennessee, Knoxville, TN 37996-0530.

DOI: 10.1002/for