The Multifaceted Nature of Online MBA Student Satisfaction and Impacts on Behavioral Intentions

MEGAN L. ENDRES
SANJIB CHOWDHURY
CRISSIE FRYE
EASTERN MICHIGAN UNIVERSITY, YPSILANTI

CHERYL A. HURTUBIS
ALTA COLLEGES
DENVER, COLORADO

ABSTRACT. The authors analyzed surveys gathered from 277 students enrolled in online MBA courses at a large university in the Midwest. As the authors expected, student satisfaction in the survey comprised 5 factors: satisfaction with faculty practices, learning practices, course materials, student-to-student interaction, and course tools. Student satisfaction predicted student intention to recommend the course, faculty, and university to others. Varying types of online satisfaction that were revealed in the factor analysis predicted each type of student intention. The authors provide a discussion of results and implications for future research.

Keywords: online learning, MBA studies, satisfaction

More than 200 institutions now offer online graduate degrees (Pethokoukis, 2002), and one of the fastest growing online fields is MBA study (Lankford, 2001; Smith, 2001). Online MBA programs are attracting a new market comprising nontraditional students who work full-time and are often sponsored by organizations (Mangan, 2001; Smith). Organizations are also using more online business courses, which professionals view as a viable alternative to face-to-face options (Arbaugh, 2004; Kyle & Festervand, 2005). Difficulties that have arisen with the sudden proliferation of online MBA courses are improper course management and a lack of attention to the special needs of online students (Bocchi, Eastman, & Swift, 2004; Mangan). More specifically, research on students' satisfaction with regard to MBA course delivery is limited, despite a recent increase in publications on the topic (Arbaugh, 2002).

Student satisfaction is most often studied as a unidimensional construct, but research suggests that multiple dimensions may exist in online classes (Arbaugh, 2000b). For example, according to Benbunan-Fich, Hiltz, and Harasim (2005), online student satisfaction is affected by "all aspects of the educational experience . . . satisfaction with course rigor and fairness, with professor and peer interaction, and with support systems" (p. 31). Therefore, a challenge researchers face is how to incorporate multiple facets of online business courses into research models (Arbaugh & Benbunan-Fich, 2005).

Another challenge researchers face is how to investigate multiple courses as opposed to only one course, specifically in the business disciplines (Arbaugh, 2000b). Past research of online business courses is also limited by problems with small sample size (Arbaugh, 2000a), a lack of theoretical basis (Arbaugh, 1998; Hiltz & Wellman, 1997), a lack of data (Bocchi et al., 2004; Leidner & Jarvenpaa, 1995), and a general lack of statistical rigor (Arbaugh & Hiltz, 2005). Few researchers have collected large data sets for empirical analysis (Alavi & Gallupe, 2003; Webster & Hackley, 1997).

In response to the current state of research, our first goal in the present study was to investigate the multifaceted nature of student satisfaction in online graduate business courses. Our second goal was to determine how these different facets of satisfaction are differentially important to the students' intention to recommend the course, faculty, or university to others. In the present article, we first discuss relevant literature. Second, we describe the method and data collection, followed by an analysis. Last, we discuss results, study limitations, and implications for future research.

Literature Review: Student Satisfaction With Online Business Courses

Researchs of online business courses have often focused on the instructor's behaviors, attitudes, and impact on students (Arbaugh, 2000b, 2001; Bocchi et al., 2004; Webster & Hackley, 1997). However, researchers have suggested that student satisfaction is comprised of multiple dimensions and is not influenced by instructors alone (Arbaugh, 2000a).

Miles (2001) stated that student satisfaction is affected by instructor elements (flexibility and interaction), course elements (asynchronous learning and meaningful learning objectives), and access (ability for low-bandwidth access). The Sloan Consortium (2005) noted similar influences, including involvement of the learning community and interaction with other students.

Empirical research also suggests that online student satisfaction with business courses is multifaceted (Arbaugh, 2000a, 2001, 2002, 2005; Arbaugh & Duray, 2002; Bocchi et al., 2004; Marks, Sibley, & Arbaugh, 2005; Webster & Hackley, 1997). Webster and Hackley studied online courses from several disciplines (including business) and six universities. They found multiple aspects of the online experience to be positively related to overall student satisfaction, including high quality technology, high media richness, positive instructor attitude, high instructor control over technology, interactive teaching style, positive classmate attitude, comfort with images, high involvement and participation, cognitive engagement, and positive attitude toward technology. These findings illustrate the important impact of noninstructor elements on student satisfaction.

Arbaugh (2000a) also concluded that student satisfaction regarding online business courses may be because of the instructor, student, course, or medium. In a multicourse online MBA study, Arbaugh found that different facets of the course were important in predicting satisfaction, depending on the course type. Student satisfaction was affected by a range of factors including flexibility of the medium and ability of the instructor to use it interactively. Because most studies of online courses use a single course and one medium for delivery, Arbaugh suggested that questions are still unanswered regarding the sources of student satisfaction.

As in past research, student interaction with the instructor and with other students is promoted as having the largest impact on student satisfaction. In one of the most robust online MBA studies to date, Marks et al. (2005) used structural equation modeling on a sample of courses over a 4-year period. In comparing different types of student interaction, Marks et al. found that student–instructor interaction had the largest impact on outcomes. Student–student interaction also had an important impact. The effect of student–content interaction, such as streaming audio and video, was insignificant, but this may have been because of limited use of the course elements.

Bocchi et al. (2004) discovered that online faculty's use of frequent feedback and interaction with students promoted MBA students' satisfaction. Behavioral characteristics of the courses that allow students to interact and participate appear to be more important to MBA students than technological characteristics, such as ease of use of the software (Arbaugh, 2001, 2002; Arbaugh & Duray, 2002). For example, Arbaugh and Duray reported that MBA students' satisfaction was positively affected by higher perceived flexibility and smaller class sizes that allowed interaction. Although interaction appears to have a primary influence on satisfaction, technological characteristics of the course also affects satisfaction.

Other course characteristics may be significant predictors of online student satisfaction, such as the length of the course (Arbaugh, 2001). For example, course-specific effects explained more variance in course outcomes than the specific business discipline from which the course was generated (Arbaugh, 2005).

In summary, past researchers focused most often on the role of the instructor in the online MBA learning environment. However, recent research findings suggest that online student satisfaction is multifaceted and dependent on instructor, course, and technology elements.

Research Model and Hypotheses

Our study design follows the virtual-learning environment model (Alavi & Gallupe, 2003; Piccoli, Ahmed, & Ives, 2001). This model presents two dimensions as important to virtual learning environments: human and design. The human dimension may include students, instructors (Piccoli et al.), and administrators (Alavi & Gallupe). The human dimension affects the design of the virtual environment and may include learning, teaching, and organizational practices. Assessment of these practices determines effectiveness in terms of performance and satisfaction.

The research model, modified for the present study, is presented in Figure 1. The student input is represented by the gray arrows in the model because students' attitudes toward the practices were assessed on the basis of online course dimensions suggested in the literature. Arbaugh (2000b) suggested that future research assess additional dependent variables to student satisfaction. Therefore, we hypothesized the following:

Hypothesis 1 (H_1): Student satisfaction with online courses comprises multiple factors, including satisfaction with faculty practices, course materials, learning practices, student-to-student interaction, and online tools.

Researchers have suggested that student satisfaction with faculty members should be based on the faculty members' use of online tools, their attitudes, and their interactions with students (e.g., Arbaugh, 2000a) and that this satisfaction predicts the students' behavioral intention to recommend the faculty. Thus, we hypothesized the following:

H_2: Student behavioral intention to recommend the faculty is predicted by faculty practices and course materials, but not by satisfaction with learning practices, student-to-student interaction, or online tools.

Miles (2001) suggested that course objectives and information should affect student satisfaction with the online course. Because a single course is often investigated in online student-satisfaction research, specific impacts on course satisfaction are not known (Arbaugh, 2000b). Therefore, we hypothesized the following:

H_3: Student behavioral intention to recommend the course to others is

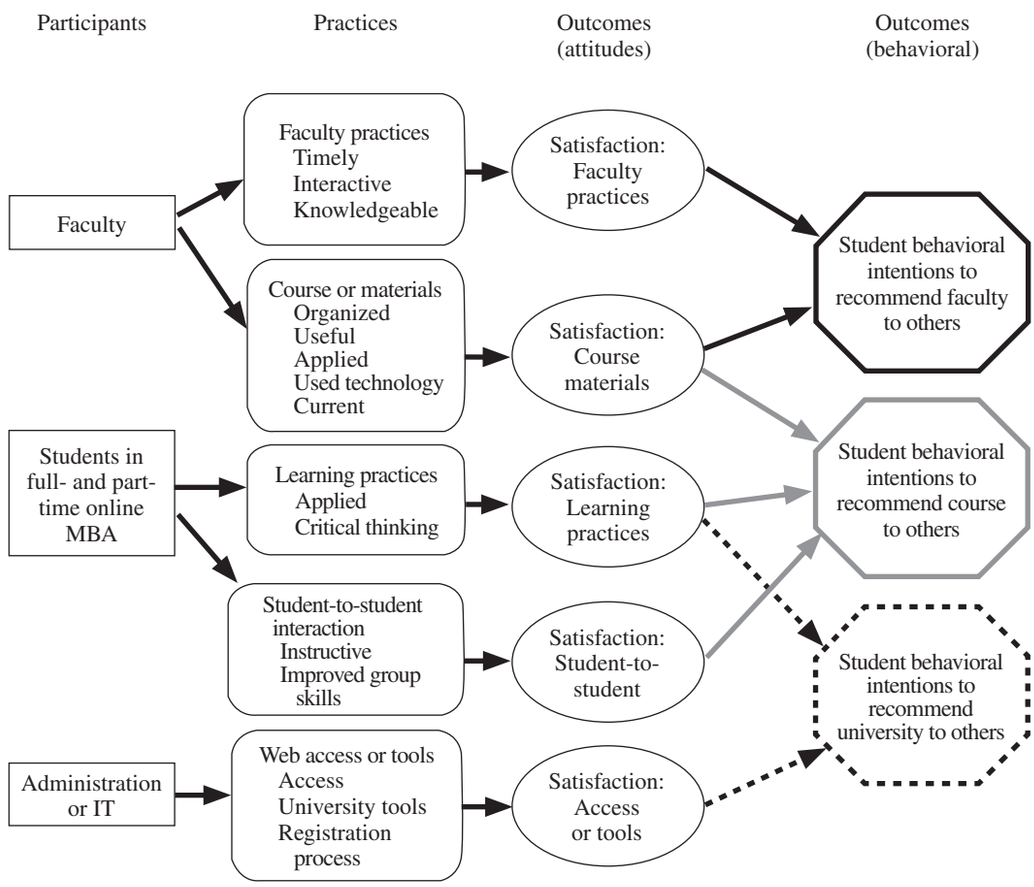

FIGURE 1. Virtual learning environment research model: Theoretical model (Adapted with permission from G. Piccoli, R. Ahmed, & B. Ivers, 2001, and M. Alavi & R. B. Gallupe, 2003).

predicted by their satisfaction with course materials, learning practices, and student-to-student interaction, but not by their satisfaction with faculty practices or online tools.

Last, we proposed that students' satisfaction with online tools predicts their intention to recommend the university. Although student satisfaction with the university was not addressed in previous literature, researchers have suggested that technology type (Arbaugh, 2001, 2002; Arbaugh & Duray, 2002) and media richness (Webster & Hackley, 1997) are important aspects of university online programs, and these aspects are not related to certain courses or faculty. In addition, students' satisfaction with the university may increase when technology allows students to efficiently interact with other students and faculty (Arvan, Ory, Bullock, Burnaska, & Hanson, 1998). Therefore, we hypothesized the following:

H_4: Student behavioral intention to recommend the university to others is predicted by satisfaction with online tools, but not by learning or faculty practices, course materials, or student-to-student interaction.

METHOD

Sample and Survey Administration

At an accredited university in the midwestern United States, school administrators e-mailed 866 questionnaires to the students who took online MBA courses. A total of 277 questionnaires were returned (32%). The sample was taken from 31 MBA courses at the university from March 2002 to August 2004.

The administrators then asked students to fill out the student satisfaction survey after completing their course and directed them to click on a hyperlink to the online survey. Students were allowed to respond to more than one survey, but not for the same course or instructor. Therefore, every response is unique and relates to the most recent course and instructor. All students were enrolled in the university's MBA program.

Survey Instrument

The online survey instrument analysis includes 20 questions regarding student satisfaction. A team of administrators and faculty PhDs used current literature to form the items. The sections of the survey reflect the specific university's MBA program needs and areas that the Sloan Consortium (2005) listed as affecting student satisfaction: These areas are technology, learning issues, course-specific issues, and interaction with faculty and students.

The survey was divided into five areas: faculty practices (six questions), learning practices (five questions), course materials (four questions), student-to-student interaction (three ques-

tions), and online tools (two questions). Students were asked to indicate their satisfaction with the statements on a 5-point Likert-type scale ranging from 1 (*very dissatisfied*) to 5 (*very satisfied*), with the option of indicating not applicable (NA). Example survey questions from each area of the survey are provided in Table 1. The alpha coefficient for the 20 questions is high ($\alpha = .95$). Responses of NA were removed from the sample and not analyzed.

Research has shown that planned behavior could be validly assessed through a question of behavioral intention (Ajzen, 1991). In three questions, we asked students for behavioral intentions to be used as the dependent variables in the study:

1. Will you recommend the course to others?
2. Will you recommend this faculty member to others?
3. Will you recommend the university to others?

Students were asked to circle *yes* or *no* as a response to each question.

RESULTS

Analysis

We analyzed H_1 with principle component factor analysis and Hypotheses H_2, H_3, and H_4 with discriminant analysis. We used a discriminant analysis because it enabled us to determine the relative importance of independent variables (student satisfaction) in predicting the dichotomous dependent variable (behavioral intention).

H_1 was supported by a principle component factor analysis with varimax rotation (see Appendix A). Online student satisfaction was multifaceted in five factors. H_2 stated that five factors of student satisfaction would emerge: faculty practices, learning practices, course materials, student-to-student interaction, and online tools. These five factors were confirmed. All factor loadings were clear except Question 12 ("the course was thought provoking"), which included a loading of .595 on Factor 2 (learning practices) and a loading of .548 on Factor 3 (course materials). The question was loaded on Factor 2 because of its theoretical similarity with the other questions in that factor.

The five factors each had an eigenvalue of > 1.0, and cumulative variance for all five factors was 80.55% (see Appendix B). The five factors each accounted for variance of at least 9.0% of the total, suggesting that each was a significant addition to the model. The two factors accounting for the most variance included faculty (24.23%) and learning practices (20.83%).

H_2 was partially supported by using a discriminant analysis. When asked, "Will you recommend the faculty member to others?" 185 students responded *yes* (67.0%) and 91 responded *no* (33.0%). As we expected, satisfaction with faculty practices predicted student intention to recommend faculty. Unexpectedly, learning practices also predicted student intention to recommend faculty (marginal significance at $p < .10$). Course materials did not predict intention as we had hypothesized.

Table 2 shows that Wilks's lambda and F values indicated that students' satisfaction with faculty and learning practices significantly influenced their intention to recommend the faculty member. Satisfaction with course materials, student-to-student interaction, and online tools were not valuable predictors according to these statistics. The canonical discriminant function (as independent predictors) and factor matrix coefficients (as joint predictors) showed that students' satisfaction with faculty and learning practices were the only predictors of intention to recommend the faculty.

The eigenvalue reports the Pearson correlation between the discriminant scores and the dependent variable (intention to recommend the faculty member). An eigenvalue of 1.53 explains 100% of the variance in the prediction equation, and the canonical correlation of .78 represents a significant correlation of the independent variables with the dependent variable. The effect size is calculated by squaring the canonical correlation and is medium-sized by Cohen's (1988) standards ($d = 0.61$).

Last, Wilks's lambda ($\lambda = .40$) showed that the independent variables effectively separated the dependent variable into groups (1 = *yes*, 2 = *no*). Also, it indicated that the model was a better predictor than what researchers would have expected to occur by chance, $\chi^2(5, N = 275) = 251.91$, $p < .00$. H_3 was partially supported by discriminant analysis. When asked, "Will you recommend the course to others?", 221 students (79.8%) responded *yes*, and 56 (20.2%) responded *no*. As we expected, satisfaction with course materials and learning practices predicted students' intention to recommend the course. Contrary to expectations, satisfaction with faculty practices was also a significant predictor. Also contrary to H_3, satisfaction with student-to-student interaction was not a significant predictor of intention to recommend the course.

First, Wilks's lambda and F values indicated that satisfaction with faculty practices, course materials, and learning practices significantly influenced the students' intention to recommend

TABLE 1. Example Survey Questions With Proposed Factor Assignments

Number of questions	Category	Example question	Proposed factor
4	Course materials	Print readings aided my learning in this course.	Course materials
6	Faculty performance	The instructor returned grades in a timely manner.	Faculty practices
5	Learning practices	I can apply what I have learned in this course to my job.	Learning practices
3	Student-to-student interaction	Other students contributed to my learning in the course.	Student-to-student interaction
2	Access or tools	Books and other materials for this course arrived on time.	Access or tools

the course (see Table 3). Satisfaction with student-to-student interaction and online tools were not valuable predictors according to these statistics. The canonical discriminant function (as independent predictors) and factor matrix coefficients (as joint predictors) showed that satisfaction with faculty practices, course materials, and learning practices are the only predictors of intention to recommend the course.

The eigenvalue reports the Pearson correlation between the discriminant scores and the dependent variable (intention to recommend the course). An eigenvalue of 0.77 explains 100% of the variance in the prediction equation, and the canonical correlation of 0.66 represents a significant correlation of the independent variables with the dependent variable. The effect size is calculated by squaring the canonical correlation and is medium-sized by Cohen's (1988) standards (d = 0.44).

H_4 was partially supported. When asked, "Will you recommend the university to others?" 254 students (91.7%) responded *yes*, and 23 (8.3%) responded *no*.

Consistent with H_4, students' intention to recommend the university to others was predicted by their satisfaction with online tools. Contrary to our expectations, students intention to recommend the university was negatively and marginally predicted by satisfaction with course materials ($p < .09$), meaning that the higher the satisfaction with course materials, the higher the chance that students' may not recommend the university. Also contrary to H_4 was the finding that students' satisfaction with learning practices predicted their intention to recommend the university.

Wilks's lambda and F values showed the relative importance of online tools, course materials, and learning practices as predictors (see Table 4). Students' satisfaction with faculty practices and student-to-student interaction was not a valuable predictor.

The canonical discriminant function (as independent predictors) and factor matrix coefficients (as joint predictors) verified the Wilks's lambda and F statistics. Students' satisfaction with online tools was the strongest predictor; students' satisfaction with learning practices satisfaction was the next strongest predictor; and students' satisfaction with course materials was a negative, although marginal, predictor of students' intention to recommend the university to others

An eigenvalue of 0.09 and canonical correlation of 0.29 specify that the relation between the independent and dependent variables is not as strong as that relation in H_3 and H_4. The squared canonical correlation gives an effect size of 0.08, which also proposes a weak relation. Wilks's lambda is also large (λ = 0.92) and indicates that the function does not effectively discriminate between the *yes* and *no* responses. However, the model was a better predictor than what one would have expected to occur by chance, $\chi^2(5, N = 276) = 23.95$, $p < .00$.

Summary

In summary, H_4 was partially confirmed. Satisfaction with online tools predicted students' intentions to recommend the university. Unexpectedly, students' intentions were also predicted positively by their satisfaction with learning practices and negatively (although marginally) by their satisfaction with course materials. However, the discriminant function was weak and lacked statistical power, which was most likely because of the small number of *no* responses in the dependent variable.

TABLE 2. Discriminant Analysis Statistics for Hypothesis 2: Intention to Recommend the Faculty

Category	Wilks's λ	*F*	*p*	Canonical function coefficient	Structure matrix (pooled predictors)
Faculty practices	0.41	389.49	.00	1.01	0.96
Learning practices	0.99	2.83	.10	0.21	0.08
Course materials	1.00	0.92	.34	0.10	0.05
Student-to-student interaction	1.00	0.62	.43	0.10	0.04
Online tools	1.00	0.56	.45	0.09	0.04

Note. For all *F*s, *df* = 274.

TABLE 3. Discriminant Analysis Statistics for Hypothesis 3: Intention to Recommend the Course

Category	Wilks's λ	*F*	*p*	Canonical function coefficient	Structure matrix (pooled predictors)
Faculty practices	0.96	12.08	.00	0.99	0.24
Learning practices	0.72	108.28	.00	0.09	0.72
Course materials	0.89	33.20	.00	0.31	0.40
Student-to-student interaction	1.00	0.52	.47	–0.06	–0.05
Online tools	1.00	0.26	.61	–0.08	0.04

Note. For all *F*s, *df* = 275.

DISCUSSION

The present study is an empirical test of an adaptation of the virtual learning environment models introduced by Piccoli et al. (2001) and Alavi and Gallupe (2003). First, we met our research goals by establishing that student satisfaction comprised five distinct factors: satisfaction with faculty practices, course materials, learning practices, student-to-student interaction, and online tools.

Second, we met our goals by showing that students' behavioral intention to recommend the course, faculty, and university were predicted by different types of satisfaction. Figure 2 shows the final research model, revised to represent the study results.

Faculty practices predicted students' intention to recommend a faculty member to others, as we expected. However, course materials did not predict students' intention to recommend faculty. Unexpectedly, learning practices predicted student intention to recommend faculty at a marginal significance level. Learning practices questions included topics such as practical application of course materials, learning critical thinking skills, and providing a thought provoking course. These aspects of the course may be attributed to the faculty member's discretion, especially if the faculty member expresses to students that he or she uses certain practices or methods specifically for teaching critical thinking or practical application. However, course materials was not important in predicting students' intention to recommend faculty. These questions, such as satisfaction with the current nature and usefulness of reading materials, may be attributed more to the institution. The faculty member may even apologize to students for the book choice, as he or she may not have chosen the book. These informal apologies may become typical in a situation in which the faculty does not pick a standardized course book or materials.

TABLE 4. Discriminant Analysis Statistics for Hypothesis 4: Intention to Recommend the University

Category	Wilks's λ	*F*	*p*	Canonical function coefficient	Structure matrix (pooled predictors)
Faculty practices	0.99	2.34	.13	0.33	0.30
Learning practices	0.98	5.47	.02	0.50	0.47
Course materials	0.99	2.87	.09	–0.36	–0.34
Student-to-student interaction	1.00	1.37	.24	0.25	0.23
Online tools	0.96	11.74	.00	0.71	0.68

Note. For all *F*s, *df* = 275.

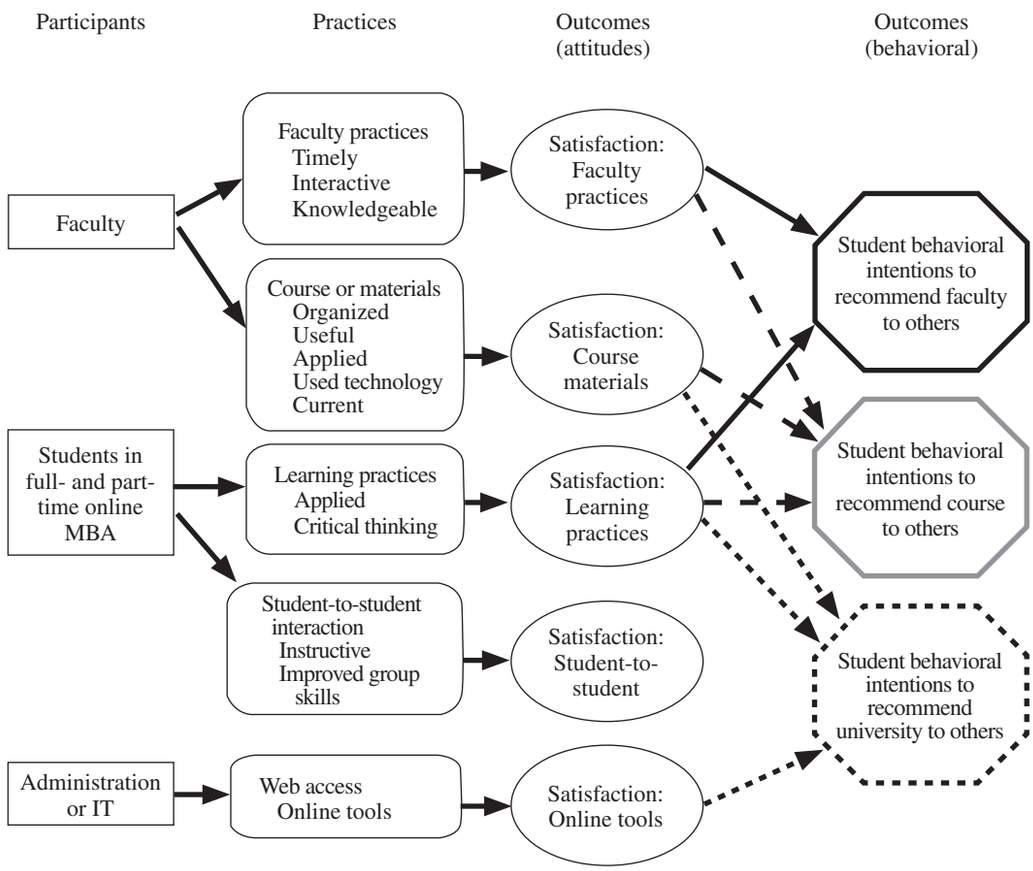

FIGURE 2. Virtual learning environment research model: Study results (Adapted with permission from G. Piccoli, R. Ahmed, & B. Ivers, 2001, and M. Alavi & R. B. Gallupe, 2003).

As we hypothesized, students' intention to recommend the course to others is predicted by faculty practices, course materials, and learning practices. We did not hypothesize that faculty practices would predict students' intention to recommend the course, but its inclusion as a significant predictor illustrated the importance of the faculty member to online students. Several research articles suggested that the instructor's approach may be the most important element in an online course (Arbaugh, 2001; Bocchi et al., 2004; Marks et al., 2005). Other researchers stated that the instructor bears a broader responsibility in online learning than in traditional face-to-face learning settings (Brower, 2003; Shrivastava, 1999). The instructor appears to significantly affect students' attitudes toward the course, even though the course material and syllabus may not have been developed by the faculty member who taught the course. Therefore, one possible explanation for the importance of faculty practices on students' recommendation of the course is that online students may assume that the faculty member facilitating the course also developed the course. This information was not measured in the present article, but a future study may ask students about their perception of the course content's developer.

Intention to recommend the university was predicted by learning practices, by online tools, and marginally by course materials. The effects of learning practices and online tools were hypothesized on the basis of the literature presented in the present article, especially given the importance students place on online tools and the presentation of material. We did not hypothesize the significance of course materials as a factor in predicting students' intentions to recommend the university, although the significance could be explained by the perception that the university has some control over the materials used. However, this may be counter to the students' supposition that the faculty develop their own courses, as noted previously. Or, students may believe that the university has the ultimate responsibility to oversee the course content. Future researchers may investigate students' perceptions of accountability for course content.

Interestingly, satisfaction with student-to-student interaction did not predict intention to recommend the faculty, course, or university. Further research is needed to determine what importance student-to-student interaction holds for online classes.

Limitations

A major benefit of the present study was that the data set comprised multiple graduate business courses and many responses. In addition, the factor analysis revealed the strength of the survey instrument and a high alpha coefficient. However, some limitations may have affected the results.

First, no control variables were available for the current data set. Control variables distinguish students in online environments and are important to the statistical relevance of results (Arbaugh & Hiltz, 2005; Bocchi et al., 2004). In particular, gender has been an important control variable in online MBA studies (Arbaugh, 2000c, 2000d). Future studies should attempt to find multiple dimensions of student satisfaction while considering important controls such as gender. Furthermore, the lack of information about nonrespondents limits our knowledge of bias in the survey. Individuals who responded to the survey may have tended toward high or low satisfaction in some or all of the areas of the questionnaire. Because we do not have information about these nonrespondents, we cannot conclusively say that our results are unbiased. However, the large size of the data set and its collection over a 3-year period lends support for the validity of our results.

Second, a dichotomous dependent variable limits the range of explanation that is available. Behavioral intention is a valid measure, as indicated in past research (Ajzen, 1991), but future research may expand on this study by including ordinal dependent measures and objective measures such as student performance.

Results for H_2 and H_3 display adequate statistical power and effect sizes, according to Cohen's (1988) standards. However, the range of responses limited the statistical power in the analysis of H_4. Despite the large data set that we analyzed (n = 277), few students responded that they would not recommend the university (n = 23, 8.3%). The limited data affected how well the discriminant function could predict a *yes* or *no* answer. In addition, a student may want to give a response that corresponds to *it depends* or *to some people*. Therefore, future researchers may use a continuous scale to measure behavioral intention.

Conclusion

In conclusion, online MBA student satisfaction appears to be multifaceted. The study results confirm that online MBA students' satisfaction with their faculty, courses, and university is not straightforward. To affect each intention, universities must focus on a variety of different courses, faculty, learning tools, and online learning tools. The lack of online MBA students' intention to recommend any one of these areas can be more directly targeted with knowledge of the importance of each online satisfaction facet. With resources more efficiently directed, intervention in raising student satisfaction can be more effective.

NOTE

Megan L. Endres is an associate professor of organizational behavior at Eastern Michigan University. Her research focuses on individual self-beliefs and their formation, particularly in challenging and novel situations. She is a member of the Academy of Management.

Sanjib Chowdhury is an associate professor of strategic management and entrepreneurship at Eastern Michigan University. His research focuses on safety, customer interaction, human capital, and entrepreneurial teams. He is a member of the Academy of Management and U.S. Association of Small Business and Entrepreneurship.

Crissie Frye is an associate professor of human resource management at Eastern Michigan University. Her research focuses on examining the influence of individual differences on job-related attitudes, job performance, and team interpersonal processes. She is a member of the Academy of Management, the Society for Industrial and Organizational Psychology, the Management Faculty of Color Association, and the National Association of African Americans in Human Resources.

Cheryl A. Hurtubis is a manager of institutional effectiveness and assessment for Alta Colleges, Inc. Her research experience includes online learning in higher education and disability awareness in higher education.

Correspondence concerning this article should be addressed to Megan L. Endres, Eastern Michigan University, Department of Management, 466 Owen Building, Ypsilanti, MI 48197, USA.

E-mail: mendres2@emich.edu

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50,* 179–211.

Alavi, M., & Gallupe, R. B. (2003). Using information technology in learning: Case studies in business and management education programs. *Academy of Management Learning and Education, 2,* 139–153.

Arbaugh, J. B. (1998). An exploratory comparison of student learning and class participation in a traditional classroom and an asynchronous Internet-based MBA course. *Academy of Management Best Papers Proceedings*, B1–B7.

Arbaugh, J. B. (2000a). Virtual classroom characteristics and student satisfaction in Internet-based MBA courses. *Journal of Management Education, 24,* 32–54.

Arbaugh, J. B. (2000b). How classroom environment and student engagement affect learning in Internet-based MBA courses. *Business Communication Quarterly, 63*(4), 9–26.

Arbaugh, J. B. (2000c). Virtual classroom versus physical classroom: An exploratory study of class discussion patterns and student learning in an asynchronous Internet-based course. *Journal of Management Education, 24,* 213–233.

Arbaugh, J. B. (2000d). An exploratory study of the effects of gender on student learning and class participation in an Internet-based MBA course. *Management Learning, 31,* 503–519.

Arbaugh, J. B. (2001). How instructor immediacy behaviors affect student satisfaction and learning in Web-based courses. *Business Communication Quarterly, 64*(4), 42–54.

Arbaugh, J. B. (2002). Managing the online classroom: A study of technological and behavioral characteristics of Web-based MBA courses. *Journal of High-Technology Management Research, 13,* 203–223.

Arbaugh, J. B. (2004). Distance training: How innovative organizations are using technology to maximize learning and meet business objectives. *Academy of Management Learning and Education*, *3,* 117.

Arbaugh, J. B. (2005). Is there an optimal design for online MBA courses? *Academy of Management Learning and Education*, *4,* 135.

Arbaugh, J. B., & Benbunan-Fich, R. (2005). Contextual factors that influence ALN effectiveness. In S. R. Hiltz & R. Goldman (Eds.), *Learning together online* (pp. 123–144). Mahwah, NJ: Erlbaum.

Arbaugh, J. B., & Duray, R. (2002). Technological and structural characteristics, student learning and satisfaction with Web-based courses: An exploratory study of two online MBA programs. *Management Learning, 33,* 331–347.

Arbaugh, J. B., & Hiltz, S. R. (2005). Improving quantitative research on ALNs. In S. R. Hiltz & R. Goldman (Eds.), *Learning together online* (pp. 81–102). Mahwah, NJ: Erlbaum.

Arvan, L., Ory, J., Bullock, C. D., Burnaska, K. K., & Hanson, M. (1998). The SCALE efficiency projects. *Journal of Asynchronous Learning Networks*, *2*(2). Retrieved March 7, 2009, from http://www.sloan-c.org/publications/jaln/index.asp

Benbunan-Fich, R., Hiltz, S. R., & Harasim, L. (2005). The online interaction learning model: An integrated theoretical framework for learning networks. In S. R. Hiltz & R. Goldman (Eds.), *Learning together online* (pp. 19–37). Mahwah, NJ: Erlbaum.

Bocchi, J., Eastman, J. K., & Swift, C. O. (2004). Retaining the online learner: Profiles of students in an online MBA program and implications for teaching them. *Journal of Education for Business, 79,* 245–253.

Brower, H. H. (2003). On emulating classroom discussion in a distance-delivered OBHR course: Creating an online learning community. *Academy of Management Learning and Education, 2,* 22–36.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Earlbaum.

Hiltz, S. R., & Wellman, B. (1997). Asynchronous learning networks as a virtual classroom. *Communications of the Association for Computing Machinery, 40*(9), 44–49.

Kyle, R., & Festervand, T. A. (2005). An update on the high-tech MBA. *Journal of Education for Business, 80,* 240–244.

Lankford, K. (2001). Web MBAs make the grade. *Kiplinger's personal finance, 55,* 84–88.

Leidner, D. E., & Jarvenpaa, S. L. (1995). The use of information technology to enhance management school education: A theoretical view. *MIS Quarterly, 19,* 265–291.

Mangan, K. S. (2001, October 5). Expectations evaporate for online MBA programs. *Chronicle of Higher Education,* p. A31.

Marks, R. B., Sibley, S. D., & Arbaugh, J. B. (2005). A structural equation model of predictors for effective online learning. *Journal of Management Education, 29,* 531–563.

Miles, L. (2001, February 1). Marketers warm to electronic learning. *Marketing UK*, 35.

Pethokoukis, J. M. (2002, June 24). E-learn and earn. *U.S. News & World Report, 132*(22), 36.

Piccoli, G., Ahmed, R., & Ives, B. (2001). Web-based virtual learning environments: A research framework and a preliminary assessment of effectiveness in basic IT skills training. *MIS Quarterly, 25,* 401–426.

Shrivastava, P. (1999). Management classes as online learning communities. *Journal of Management Education, 23,* 691–703.

Sloan Consortium (2005). Retrieved July 30, 2005, from http://www.sloan-c.org/

Smith, L. J. (2001). Content and delivery: A comparison and contrast of electronic and traditional MBA marketing planning courses. *Journal of Marketing Education, 23,* 35.

Webster, J., & Hackley, P. (1997). Teaching effectiveness in technology-mediated distance learning. *Academy of Management Journal, 40,* 1282–1312.

APPENDIX A
Factor Analysis Results

Question	Faculty practices	Learning practices	Course materials	Student-to-student interaction	Online tools
Q1	.178	.214	**.780**	.230	.109
Q2	.163	.420	**.730**	.163	.047
Q3	.333	.352	**.655**	.196	–.006
Q4	.305	.257	**.755**	.058	.174
Q5	**.681**	.310	.308	.111	–.005
Q6	**.851**	.309	.115	.106	.061
Q7	**.887**	.147	.139	.104	.132
Q8	**.839**	.292	.133	.047	.194
Q9	**.830**	.061	.280	.209	.065
Q10	**.742**	.321	.312	.195	.043
Q11	.329	**.745**	.266	.008	.253
Q12	.303	**.595**	.548	.096	.125
Q13	.224	**.822**	.346	.117	.071
Q14	.272	**.846**	.325	.143	.127
Q15	.302	**.802**	.297	.186	.062
Q16	.382	.481	–.019	**.616**	.142
Q17	.273	.318	.171	**.810**	.031
Q18	.040	–.088	.311	**.782**	.167
Q19	.125	.041	.032	.134	**.902**
Q20	.107	.249	.185	.078	**.852**

Note. Factor loadings are presented in bold. The extraction method used was a principal component analysis with varimax rotation. Rotation converged in five iterations. Q = question.

APPENDIX B
Total Variance Explained

Component	Total	Variance (%)	Cumulative (%)
Faculty practices	4.85	24.23	24.23
Course materials	4.17	20.83	45.07
Learning practices	3.31	16.53	61.60
Student-to-student interaction	1.99	9.94	71.54
Online tools	1.80	9.01	80.55

Note. The extraction method used was a principal component analysis with varimax rotation. Rotation converged in five iterations.