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Reducing the Negative Effects of Uncontrollable Factors When Designing New Courses

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Abstract

This paper seeks to introduce a novel course design method in academic literature. It uses advanced experimental designs to capture student preferences. It distinguishes between controllable and uncontrollable design factors and seeks to minimize the negative impact of uncontrollable design factors, ensuring a successful course introduction. We propose and test a design method that combines Taguchi experimental designs with discrete choice estimation where choice probabilities are used as input data for Taguchi's inner and outer arrays. Design efficiency is measured by calculating signal to noise (S/N) ratio, which accounts for the mean and variance of choice probabilities. Using the S/N ratio, designers were able to choose the most robust design. Test results show grading and attendance policies and experiential learning as the three most factors in students' selection of an undergraduate elective course at a business school.

***Key Words*:** Course Design**,** Taguchi Methods, Discrete Choice Analysis, Robust Design

Relevance to Marketing Educators, Researchers and/or Practitioners

Designing and improving courses is one of the most critical tasks performed by marketing educators. They should find this paper helpful as it introduces a structured methodology for designing/improving new and existing courses. In addition, it highlights some critical design factors educators should consider when designing or reviewing their courses.

Introduction

A steady decline in state and federal funding to the universities (Pew, 2019) has resulted in a strong push for administrators' to increase enrollment and improve student retention as a countermeasure for the lost funding. In reality, the problem of low enrollment will only worsen in the near future. A decline of up to 15% is estimated between the years 2025-2029, primarily due to the demographic shift towards decreased birth rates triggered by the financial crisis of 2008. (Grawe, 2018, Conley, 2019). Designing and offering new courses deemed attractive by students has been seen as one of the many possible strategies to improve enrollment and retention (Graham et al., 2020).

Consistently delivering a high-quality course, semester after semester, is a challenge. Since an academic course can be considered a service encounter involving humans - both faculty and students - performance variation is deemed normal and unavoidable. Course quality varies from instructor to instructor and from semester to semester. This variation is often caused by factors beyond the instructor's control. Students' varied academic abilities or the energy/enthusiasm in evening classes for working students are examples of such uncontrollable factors. Even when faculty consistently delivers high-quality content and assessment, the end quality may be negatively impacted by factors outside their control. As a consequence of this variation, many courses suffer from low enrollment and are dropped, resulting in wasted effort and discouragement of faculty innovation.

The issue of performance variation is not new and has been addressed extensively in academic literature, where the focus is on improving controllable factors. Weakening the negative impact of uncontrollable factors is not emphasized much. The potential of uncontrollable factors to cause serious performance problems is often underestimated, and as a result, we notice no strategy to counter the negative effect of these factors. Recently, however, we have seen the introduction of robust design in the manufacturing sector that focuses on weakening the negative impact of uncontrollable factors first before strengthening controllable factors. It is not to suggest that controllable factors are less important, but focusing on controllable factors alone can make service performance vulnerable to high variation.

One of the design methods that explicitly considers the active management of failure factors ahead of success factors is the Taguchi Design method, named after a famous Japanese engineer. This method helped produce high-quality products despite environmental fluctuations. It can easily be adapted to design services such as an academic courses. The primary concept underlying Taguchi methods is that while variation cannot be eliminated, it can be managed. Since the complete elimination of variability due to noise factors is often impossible, Taguchi methods seek to at least minimize such adverse effects. Reducing the impact of uncontrollable factors by selecting optimum controllable factors forces desirable quality characteristics to stay close to the target value.

This paper attempts to introduce Taguchi experimental designs in (academic) course design literature to reduce variation in course quality by determining the optimal combination of factors that minimize the effects of uncontrollable design factors.

The rest of the paper is structured as follows. First, we introduce the concepts of Taguchi design and discrete choice analysis. Second, present a literature review of the course design selected for the study. Later, we detail the methodology, results, and discussions.

Taguchi Robust Designs and Discrete Choice Analysis

Taguchi methods, also known as robust design methods, have been used to develop products that can achieve high-quality standards despite environmental fluctuations. These methods are usually considered a superior alternative to relatively expensive process control methods. Taguchi (1984, 1985, 1986, 1993) recommends the signal-noise ratio (S/N ratio), where the term signal represents the controllable factors and noise represents uncontrollable factors. The S/N ratio's objective is to determine an optimum set of operating combinations of controllable and uncontrollable factors.

Orthogonal arrays (OA), linear graphs, and signal-to-noise ratio are three basic concepts Taguchi designs. Orthogonal arrays are a unique set of Latin square designs in which rows represent experimental runs and columns represent factors or variables. Factors in these designs are considered orthogonal to each other, where orthogonality refers to the property that these designs are balanced and not mixed. Linear graphs help the experimenter easily assign factors and their interactions to appropriate columns in an OA without confounding interactions with main effects. The third significant contribution of Taguchi methods is using a single measure of performance, i.e., signal-to-noise (S/N) ratio, where the term signal represents the controllable component. In contrast, the term noise represents the uncontrollable component.

The idea of Discrete Choice Analysis (DCA), introduced initially by McFadden (1974) in economics, is now well established in the areas of marketing (Louviere et al.,2000), transport economics (Hensher, 1994), and sociology (Finch and Mason, 1990). It refers to various experimental design techniques, data collection, and statistical procedures that analyze the consumer choice process. In choice experiments, customers, in our case, the students, choose among the available courses by obtaining information about salient course attributes. Then, they make value judgments through a trade-off process that involves assigning relative weights to course attributes, forming an overall impression, and developing a choice set by eliminating less attractive alternatives. To run a DCA experiment, we need to compile a list of explanatory variables, design factors in our case, that could explain the students' choices.

This list needs to be as exhaustive as possible. However, the final number of explanatory variables included in the DCA experiment should balance completeness with complexity. DCA is well suited to provide this required balance. It can accommodate many explanatory variables without becoming too complicated for understanding the trade-off process among various alternatives in a choice set. In addition, many models are available for analyses within DCA. Of these, the Multinomial Logit Model (MNL) is the most popular among practitioners and academicians (Manski and Mcfaden, 1981; Louveire and Woodworth,1983).

Course Design Factors

Extensive research in student evaluation of teacher (SEP) or student ratings of teaching (SRT) provided the best leads for identifying course design factors. The variables deemed important in SRTs and SEPs represent student expectations from their courses and can therefore serve as ideal course design factors. Most studies in this area have shown a positive relationship between course selection, SRTs, and student satisfaction. For example, in one of the more critical studies in this area, Babad, Darley, and Kaplowitz, 1999, content analyzed the Princeton Course Guide that included information on instructor and course characteristics and subject matter descriptors. The authors found that different course guide variables accurately predicted course selections. In a subsequent study, Babad, 200, expanded the list of course selection factors to include student considerations such as contribution to the future occupation, day, hour, and the number of credits.

Other studies documented significant relationships between instructors' characteristics (expertise, style, humor, enthusiasm), class policies (workload, grading, class size, scheduling), and SETs. For example, using hierarchical regression, Radmacher & Martin, 2001, found teachers' extraversion to be a strong predictor of student evaluations. Similarly, Marks, 2000, using structural equation modeling, found that instructor liking and concern loaded significantly on student evaluations. Factors that were only weakly to moderately related to SETs were instructors' gender and expertise.

Regarding class policies, most researchers report a weak relationship between workload difficulty and SETs, while some have reported a strong relationship between the two (Bacon & Novotny, 2002). Other class policies, such as grade leniency, is strongly related to SET (Bacon &

Novotny, 2002). Tarasewich and Nair 2000, included laboratory work, homework frequency, use of paper or project, presence or absence of case studies, participation grade, class topics, and computer software as factors important in designing a well-rounded course.

In addition to incorporating student and instructor preferences, research has also focused on incorporating employer preferences. For example, Tracy et al., 2014, used a survey instrument to collect data on both business students' and employers' preferences. It alerted them to the faculty's tendency to predominantly design courses that reflect student preference and ignore student employability. Their research included 14 variables in the survey relating to content, delivery mode, grading policies, and assessment types. They found significant differences between the emphasis placed on these factors by students and employers. It was important to note that there were some consensus factors, but the faculty should consider both stakeholders when designing the course.

In summary, many courses related variables are linked to SETs. In selecting design factors for our study, we ran a small focus group of students and instructors. This group picked pedagogy (case method vs. simulation), scheduling (once or twice a week), grading (absolute vs. curved), assessment (single vs. multi-instrument), workload difficulty (high vs. low), instructor's availability outside class (yes, no), class attendance (mandatory vs. voluntary), student heterogeneity (high vs. low) as essential in designing a well-rounded course. Below we include a brief discussion on each of these factors.

Case Method vs. Simulation

Teaching marketing concepts with the case study method (made famous by Harvard Business School) remains one of the most widely used pedagogical tools (Lapoule and Lynch, 2018). It requires active student participation in discussing a specific marketing situation and providing recommendations (Mesny 2013). A case study is meant to be engaging and allows students to investigate organizations in detail and search for patterns that may result in developing both theory and practice (Gawel, 2012). It helps students develop a reflective and critical approach to understanding complex marketing concepts and techniques (Gill, 2011).

Instructors have increasingly deployed marketing simulations in their classrooms as an experiential learning tool. They allow students to make business decisions that mimic the real organizational environment (Tiwari et al., 2014). In addition, simulations deliver the most comprehensive experiential learning by forcing students to think critically, take risks, and decide on problem solutions (Salas et al., 2009).

In experiential learning, marketing instructors have used the case study method and simulation with good results. Extant research has not answered these tools' relative effectiveness (Lapoule and Lynch, 2018). Both of these tools are effective in teaching marketing, particularly in teaching multidimensional and inter-temporal concepts.

The effect of scheduling on student's performance has received limited attention in educational research. However, attention span and spacing effects are critical when deciding on class scheduling (once, twice, or thrice a week). During uninterrupted long lectures, for example, once a week, meeting for two hours and forty-five minutes, students have been shown to experience a series of attention lapses with increasing frequency. (Johnstone and Percival 1976, Goss Lucas & Bernstein, 2005). Therefore, researchers have recommended embedding class activities every 15-20 minutes (Chaney, 2005; Olmsted, 1999).

Based on the encoding variability theory, the spacing effect implies that learning is more effective when studying in sessions that are separated from each other rather than being crammed together (Dempster, 1988, Ewer et al., 2002). This theory also posits that information is stored in small chunks in different parts of the brain when learning in paced sessions, making memory retrieval much faster and more comfortable (Bray et al., 1976; Glenberg,1979).

Research in this area is not conclusive. Some studies show a significant difference in learning between once, twice, and thrice-weekly schedules. Three days a weekly schedule produces better learning outcomes (Trout, 2018; Carrington, 2010; Gallo and Odu, 2009). However, each session duration of 55 and 75 minutes did not produce significantly different learning outcomes (Schultz and Sharp, 2008).

Absolute Vs. Curved Grading

There are two grading systems currently in use; absolute and relative. Absolute grading has three unique characteristics. One, students are graded solely on individual performances, independent of their peers' performance. Two, every student can either excel or perform poorly. Three, grade distribution can take on any shape. As opposed to absolute grading, relative grading, aka "curved grading," is based on the student's performance relative to their peers. Relative grading is more prevalent in the United States than in continental Europe (Karran, 2004).

One can find more than one rationale for implementing relative grading. It has been used to correct lower-than-expected class grades, to provide incentives for encouraging competition among students, and as a mechanism to control grade inflation. It has been chiefly used to adjust the low-class scores in an overly difficult class where students may not fully understand the content and hence may perform poorly on examinations. In this case, curved grading is more beneficial for students at the bottom of the class. The rationale for increased competition among students is based on the hypothesis that relative grading creates an environment similar to a sports tournament (Lazear & Rosen, 1981), where students fight hard to get a few spots reserved for the best students. Most law schools in the USA use relative grading. However, the response to incentives under relative grading has not been universal. Research on the impact of curved grading on student performance is equivocal and varies in terms of ability and gender (Czibor et al., 2016). The effort level of high ability students increases while it decreases for students of low ability (Brownback, 2018). It has also been reported that the relative grading does not work well with small sample sizes (Andreoni and Brownback, 2017).
Protection against grade inflation has been cited as another advantage of relative grading, as it limits the number of "A" grades in the class.

There are many ways to curve the grade; in some cases, grades may go up, while in others, grades may come down. However, the general perception of curved grading among students is that curves make their scores go up, and it serves as a safeguard against failing a difficult class.

Assessment Methods-Single vs. Multi-instrument

Instructors in marketing classes have adopted multiple assessment tools, including MCQs, essays, individual/group projects, etc. These tools measure different aspects of a student's learning. Answering MCQ's does not require deep learning as opposed to essay questions that delve into deeper understanding. Therefore, MCQ's are considered reasonable for measuring subject knowledge, whereas essay types better measures the critical thinking aspect of student learning (Scouller, 1998). Most students prefer MCQ over short answer questions (Holzinger et al., 2020). Projects measure the application part of learning objectives.

Measurement theory, in general, encourages a multidimensional assessment strategy. The rationale behind multiple measurements is the assumption that various measures would improve deconstruct validity. It means that the assessment scores based on multi-measures provide a more comprehensive view of students' progress. To decide whether a student is doing a good job, we need to consider several different achievement measures.

Workload Difficulty

There is no consensus in the literature on the relationship between workload difficulty and student satisfaction and the resulting faculty evaluation. Results range from negative relationships between two (Marsh, 1987, Greenwald 1997; Greenwald & Gillmore, 1997, Babad 2003, Pritchard, & Potter 2011) to no relationship (Thornton et al., 2010) to some positive relationships (Marsh & Roche, 2000). Results from March & Roche should be interpreted carefully as the student's favorable evaluation of teaching increases as workload increases to a certain optimal level while declining with excessive workload.

Now, suppose the workload difficulty influences the students' post-course evaluations, both positive and negative, to such an extent. In that case, we can deduce that workload difficulty will also figure prominently among the factors influential in original course selection (Babad 2003). It is also well known that students expressly seek information about course difficulty before making selecting a course.

Instructor's Availability Outside Class

While student-faculty interaction outside class is considered one of the most desired elements of a student's college experience (Cox and Orehovec, 2007), it is the least practiced among the five significant benchmarks of effective educational practice, as reported by the national survey of student engagement. The student-faculty interaction outside the classroom is also strongly related to student satisfaction (Astin, 1977). The desired level of these Interactions, however, remains elusive (Cox and Orehovec 2007).

Students appreciate access to instructors and mention it as a contributor to a positive learning environment. The mere perception of instructor availability outside the classroom has also been shown to have a statistically significant positive relationship with student evaluation of class instructions (Reynolds & Ludlow 2020). This means that instructors can improve students' satisfaction with increased availability to students outside of class. Although five major types of interactions have been delineated, including disengagement, incidental, functional, personal, and mentoring, our focus in this study is limited to functional interaction, which is directly or indirectly related to academic activities and concerns.

Mandatory Class Attendance

Research on the relationship between mandatory class attendance and various performance measures and evaluations has produced contradictory results (Burns and Ludlow, 2006). A lack of relationship between attendance and student performance and acquisition of knowledge has been reported (Hyde & Flournoy, 1986; Berenson et al.,1992). On the other hand, Davidovitch & Soen, 2006 found a positive relationship between class attendance and students' evaluation of instructors, while Marburger, 2006, found that a mandatory attendance policy significantly improves exam performance. Street, 1975 and Kooker, 1976 also reported a negative relationship between absenteeism and student performance. Despite the lack of clarity about the relationship between attendance and several performance indicators, instructors have to make the decision whether to require mandatory attendance or not, and therefore remains a crucial design factor.

Student Heterogeneity

College instructors frequently deal with the high variability of academic preparation on the student's part. This heterogeneity in the academic preparation impacts student learning and presents a challenge for the instructor in setting the rigor level. Research has shown that students with extensive K-12 academic preparation are likely to achieve high academic success (Kurlaender and Howell, 2012), while learning is hindered for those with faulty foundations or inaccurate knowledge (Ambrose et al., 2010). This disparity can further lead to friction between students in the course required group work.

Methodology

In this paper, we report the combined use of two different but related techniques of DCA and Taguchi experimental designs for collecting and analyzing the data. An L_8 Taguchi design was used to develop the experimental stimulus for students to make choices among eight different versions of a hypothetical course. A predictive MNL model was estimated based on choice responses. We then used the choice probabilities obtained from DCA analysis as an input to calculate Taguchi's S/N ratio.

The first step in this experiment was to design a choice stimulus. As mentioned earlier, we included seven controllable and two uncontrollable factors in our experiment. Table 1(a) lists the factors and their levels. In constructing the choice stimulus, we used the Taguchi design that requires the combined use of inner and outer arrays. The controllable factors were arranged in the inner array. We used an L_8 arrangement where an inner array is in 2^7 formats and the outer array is in 2^2 arrangements.

Table 1(b) shows the design matrix and description of factors and their levels. The factor levels were evenly spaced and described in detail to the respondents. Each student was presented with four sets of eight alternative choices. These choices were designed so that each row of controllable factors, taken at a time, was combined with every single row of uncontrollable factors. The idea was to test each combination of noise factors with all combinations of signal factors and determine a combination of controllable and uncontrollable factors that give the maximum S/N ratio.

Table…1(a)
Factor Level Description

Controllable Factors

	Test Factors	Level (1)	Level (2)
A	Experiential learning	Case Method	Simulation
B	Assessment methods	Single	Multi-instrument
C	Grading	Absolute	Curved
D	Workload difficulty	Low	High
E	Meeting frequency	twice a week	once on week
F	Class attendance	Mandatory	Voluntary
G	Instructor's availability	Yes	No

Noise Factors

H	Student heterogeneity	Low	High
I	Class scheduling	Any Time	9.00 a.m.- 4.00 p.m.

Table…1 (b)
Design Matrix

2^2 Outer Array

$L_8(2^7)$ Inner Array

							Heterogeneity	High	Low	High	Low
							Schedule	Any time	Any time	9am-4pm	9am-4pm
No.	Experiential Learning	Workload	Grading	Assessment	Frequency	Attendance	Availability				
1	Case	Low	Absolute	Single	Once	Mandatory	No				
2	Case	Low	Absolute	Multiple	More than Once	Optional	Yes				
3	Case	High	Curved	Single	Once	Mandatory	Yes				
4	Case	High	Curved	Multiple	More than Once	Optional	No				
5	Simulation	Low	Curved	Single	Once	Mandatory	Yes				
6	Simulation	Low	Curved	Multiple	More than Once	Optional	No				
7	Simulation	High	Absolute	Single	Once	Mandatory	No				
8	Simulation	High	Absolute	Multiple	More than Once	Optional	Yes				

Data were collected from 218 students who responded to a course choice survey. Multistage Stratified Random Sampling was used for selecting respondents from different business majors in the school of business. Each business major was taken to represent a stratum. Student listings for five business majors were used as the basis for the random selection of students.

For calculating choice probabilities, we followed Kuhfeld's (1996) recommendations. In the conditional logit model, the probability that an individual *j* chooses the alternative *i* from all possible alternatives, *k*, is given by:

$$P(y_{ij}) = \frac{1}{\sum_{i=1}^{k} exp[\beta + \gamma(z_{ij})]}$$, i=1,2,………g and j=1,2,….n

Where $z_{ij} = (z_{ij}1, z_{ij}2, ..., z_{ij}t)$ represents t explanatory variables, and beta and gamma are unknown constants. The following choice model was used for calculating choice probabilities for different combinations of service design:

$$P_i = \frac{e^{v_i}}{\sum_{i=1}^{k} e^{v_i}},$$

where $P_i =$ Probability of choosing alternative ***I,*** $v_i =$ Utility of alternative ***I and***

$\sum_{i=1}^{k} e^{v_i} =$ Combined utility of all alternatives in the experiment.

It is important to note that in this discrete choice experiment, the dichotomous response variable was expressed on a nominal scale and was subsequently converted into a choice probability so that the parameters could be interpreted. The choice probabilities were used in Taguchi design when the larger, the better (maximizing choice probabilities) were considered appropriate. The following formula was used for calculating the "larger the better" S/N ratio:

$$S/N = -10 \log \left[\sum_{i=1}^{n} \left[1/y_i^2 \right] / n \right]$$

where y_i is the response variable, which in our case is the choice probability, and n is the number of choice sets.

Results

Table 2(a) presents the goodness-of-fit statistics (GOF) and parameter estimates from conditional logit regression. The GOF results include the likelihood ratios and McFadden's σ^2 (pseudo R^2) for aggregate and individual-level choice. The likelihood ratio is a test similar to the F-test for linear regression. It tests the null hypothesis of no relation between choice and design factors. Its value represents the difference between a model with no explanatory variables and a model with all explanatory variables. Likelihood ratio, χ^2 distributed with seven degrees of freedom, for the four sets were estimated at 44.19, 48.20, 71.32, and 88.19 ($p<.05$), respectively. These values suggested that design factors in the model were significant predictors of customer choice at the .05 level. McFadden's σ^2 is a transformation of the likelihood ratio, which mimics an R^2. Typically, σ^2 values tend to be much lower than R^2. A low σ^2 value, however, does not necessarily imply a poor fit (Hensher and Johnson, 1981). The aggregate and individual level σ^2 values for the four models were 0.81, 0.75, 0.79, 0.76, and 0.26, 0.23, 0.28, 0.26, respectively. This indicated that multinomial models correctly predicted between 75 and 81 percent of aggregate and 23 to 28 percent of individual choice.

Table…2 (a)
Goodness of Fit Statistics

Set 1	Set 2	Set 3	Set 4
Model χ^2 -2 Log L 44.91	Model χ^2 -2 Log L 48.20	Model χ^2 -2 Log L 71.32	Model χ^2 -2 Log L 88.19
σ^2 Aggregate level 0.81 σ^2 Individual level 0.26	σ^2 Aggregate level 0.75 σ^2 Individual level 0.23	σ^2 Aggregate level 0.79 σ^2 Individual level 0.28	σ^2 Aggregate level 0.76 σ^2 Individual level 0.26

Table 2(b) presents the logit model's parametric results for all four sets of experiments. The regression coefficients (β) indicate which design factors significantly discriminate between choice or otherwise. Class policies on grading, attendance, workload difficulty, and scheduling contributed significantly to course choice in all four experiment sets. Coefficients for all controllable factors carried positive signs, which means that students preferred higher factor levels. High mean values for grading and class attendance policies (0.55 and 0.53) were not surprising. Preference for flexibility in attendance can be explained by students' desire to learn on their schedule. Recently, Universities have seen a surge in asynchronous online class enrollments. Similarly, the importance of grading policy and strong preferences for curved grading reflects students' desire to understand their performance compared to their cohort rather than an absolute standard set by the faculty.

It is important to note that coefficients for both uncontrollable factors carried negative signs. A negative parameter sign suggests that the probability of choice will decrease with a corresponding increase in factor value. In this experiment, student heterogeneity refers to the difference in academic and professional preparation levels before the student takes the course. Its factor levels one and two refer to low and high student heterogeneity, respectively. Similarly, levels one and two of class scheduling refer to classes during regular hours (9:00 am-4:00 pm) and outside these hours, respectively. This means that the probability of selecting courses decreases with high student heterogeneity and with classes being scheduled outside the regular time. It is also worth noting student heterogeneity had the highest absolute coefficient value in addition to its negative sign. This suggests that this uncontrollable factor weighed heavily on students' minds when making course selections.

Table…2(b)
Parametric DCA Results

	Set 1			Set 2			Set 3			Set 4			
Design Factors	β	>p	$e^{(\beta)}$	β	>p	$e^{(\beta)}$	β	>p	$e^{(\beta)}$	β	>p	$e^{(\beta)}$	Mean β
Grading	0.63	.000	1.88	0.42	.000	1.52	0.67	.000	1.95	0.46	.006	1.94	0.55
Workload difficulty	0.42	.001	1.52	0.61	.000	1.84	0.41	.000	1.51	0.36	.000	1.79	0.45
Experiential learning	0.38	.007	1.46	0.36	.058	1.43	0.51	.000	1.67	0.48	.053	1.79	0.43
Assessment methods	0.39	.268	1.48	0.28	.031	1.32	0.33	.035	1.39	0.53	.234	1.67	0.38
Meeting frequency	0.51	.531	1.67	0.46	.075	1.58	0.39	.000	1.48	0.28	.068	1.63	0.41
Class attendance	0.61	.031	1.84	0.33	.000	1.39	0.61	.045	1.84	0.55	.000	1.75	0.53
Instructor's availability	0.36	.000	1.43	0.49	.079	1.63	0.24	.021	1.27	0.29	.007	1.48	0.35
Student heterogeneity	-0.64	.061	0.53	-0.71	.000	0.49	-0.85	.076	0.43	-0.45	.059	0.50	-0.66
Class scheduling	-0.35	.000	0.7	-0.57	.000	0.56	-0.56	.000	0.57	-0.28	.000	0.64	-0.44

Table 2(c) lists the choice probabilities calculated from odd ratios for all eight alternatives in four sets of experiments. These probabilities are outcomes of a trade-off process that involves making sacrifices by diminishing or losing an attribute in return for gains in other attributes. For students making course choices, this process involves obtaining information about dominant course attributes, comparing various available options, and making a holistic choice. In our case, alternatives # 6 and # 1 have the highest and lowest choice probabilities, respectively. The lowest mean probability for alternative # 1 was expected as it had low levels for all factors.

Table…2 (c)
Choice Probabilities for Alternatives

	Set 1	Set 2	Set 3	Set 4	Mean	
	% Choice Probabilities	% Choice Probabilities	% Choice Probabilities	% Choice Probabilities	Choice Probabilities	Rank
1	2.32	6.21	1.67	3.56	3.44	**8**
2	13.00	10.20	7.30	11.90	10.60	**5**
3	12.40	7.81	10.20	7.98	9.60	**6**
4	11.67	8.42	18.62	17.30	14.00	**4**
5	18.70	17.31	17.72	16.70	17.61	**2**
6	15.43	16.28	22.45	18.20	18.09	**1**
7	8.65	9.64	9.63	7.01	8.73	**7**
8	13.40	17.30	10.23	15.50	14.11	**3**

Table 3(a) presents the design and resultant S/N ratios. In selecting a design alternative, we will consider the choice probabilities and the variance of these probabilities across four sets of experiments. An alternative with lower choice probabilities and low variation may be preferred over an alternative with relatively higher choice probabilities with greater variation. Comparing the choice results DCA experiments and S/N ratio, we find that the S/N ratio is a better predictor of students' choice as it considers both mean and standard deviation in choosing the best alternative. We can see that based on S/N ratio, alternative # 5 was ranked ahead of alternative #6 even though alternative # 6 had a higher mean choice probability than alternative # 5 i.e.18.09 vs. 17.61. This was so because alternative # 5 had a lower standard deviation of 0.84 as compared to 3.13 in alternate # 6. The use of the S/N ratio helped us to improve the predictive power of DCA.

Table 3(b) presents the relative importance of seven controllable factors based on the S/N ratio. The factor importance is indicated by the difference in combined S/N ratio scores for two design levels. For example, in calculating the relative importance of experiential learning, we first look at the experimental design. Experiential learning occurs equally, i.e., four times each for eight alternatives. We sum up the S/N ratio scores for all four instances when the lower level (1 in the design…case study) is indicated in the design. We got a combined score of 68.54, i.e., 7.9+19.86+19.19+21.6. We repeated the same process for the higher design level (2 in design…simulation) and got a combined score of 90.85. Finally, we subtract 68.54 from 90.85 to get a difference of 22.31. This, incidentally, was the largest difference among all factors. We also rank the design factors for their importance.

Table…3(a)
Taguchi S/N Ratio

2^2 Outer Array

$L_8(2^7)$ Inner Array

							H	**1**	**2**	**1**	**2**				
							I	**1**	**1**	**2**	**2**				
No.	*A*	*B*	*C*	*D*	*E*	*F*	*G*	**Set1**	**Set2**	**Set3**	**Set4**	Mean	SD	S/N Ratio	Rank
1	1	1	1	1	1	1	1	2.32	6.21	1.67	3.56	3.44	2.01	7.90	**8**
2	1	1	1	2	2	2	2	13.00	10.20	7.30	11.90	10.60	2.48	19.86	**5**
3	1	2	2	1	1	1	2	12.40	7.81	10.20	7.98	9.60	2.16	19.19	**6**
4	1	2	2	2	2	2	1	11.67	8.42	18.62	17.30	14.00	4.79	21.60	**4**
5	2	1	2	1	2	1	2	18.70	17.31	17.72	16.70	17.61	0.84	24.89	**1**
6	2	1	2	2	1	2	1	15.43	16.28	22.45	18.20	18.09	3.13	24.89	**2**
7	2	2	1	1	2	1	1	8.65	9.64	9.63	7.01	8.73	1.24	18.60	**7**
8	2	2	1	2	1	2	2	13.40	17.30	10.23	15.50	14.11	3.04	22.47	**3**

Table…3(b)
Relative Factor Importance Based on S/N Ratio

	Experiential Learning	Workload	Grading	Assessment	Frequency	Attendance	Availability
Low	68.54	77.53	68.82	70.57	74.45	70.57	72.98
High	90.85	81.86	90.57	88.82	84.94	88.82	86.41
Difference	22.31	4.33	21.75	18.24	10.49	18.24	13.43
Rank	**1**	**7**	**2**	**3**	**6**	**3**	**5**

These results provide us with two operational guidelines. First, the S/N ratio for different factor levels can be used to segregate more important factors from those deemed not very important. In most cases, increasing course selection probability does not necessarily require simultaneously addressing all design factors. Instead, faculty can focus on a vital few. In our case, we can concentrate on the three most important factors: experiential learning, grading policy, and assessment methods. For example, using simulation, curved grading, and multiple assessment methods can increase course selection probability. Although student heterogeneity was treated as an uncontrollable factor in this study, instituting standardized admission tests can help reduce student preparation variation.

Second, it alerts us about the adverse impact of uncontrollable factors such as class scheduling on customer choice probabilities. In this case, the strategy would be to minimize the effect of these seemingly uncontrollable factors by adopting policies to make them more controllable. For example, separate classes can be arranged for working and full-time students in the evening or very early morning.

Contributions

In this paper, we make important methodological and operational contributions to the course design literature.

Methodology

First, we report the use of advanced, efficient experimental design. Although basic experimental designs for use in the conjoint analysis are not new to academic course design literature yet, it has been reported sparsely. Even when reporting these experiments, researchers hardly discuss the need to employ advanced, efficient, orthogonal designs.

This paper introduces the use of orthogonal arrays, a unique set of Latin square designs, in which rows represent experimental runs and columns represent factors or variables. Factors in these designs are considered orthogonal to each other, where orthogonality refers to the property that these designs are balanced and not mixed. In a balanced design, each factor is supposed to have an equal number of levels; in our example two, and each column, each factor level occurs four times, but the sequence of their occurrence varies from factor to factor. This unique sequence of occurrences results in a design where the relationship between factors is such that the factor levels remain the same in half of the experiments when comparing any two factors. In contrast, in the other half, they contrast each other.

Second, we report a design that arranges the controllable (signal) and uncontrollable (noise) factors into inner and outer Taguchi arrays. The use of robust design to detect and minimize noise factors' effect on performance variation has not been previously reported. The use of Taguchi's inner and outer arrays in our study resulted in a better understanding of the sources of variation resulting in a significant reduction of performance variation. It improved the predictive power of DCA by making it less sensitive to noise factors.

Third, the S/N ratio -- a single, composite measure of design robustness -- has been incorporated into course design. It is used as the sole selection criterion when comparing alternatives. Previously, only mean choice probabilities have been used as the criterion for selecting the best design in a DCA experiment. In contrast, the S/N ratio considers both mean and variation in measuring robustness. With the S/N ratio's help, we selected the design that simultaneously maximized the choice probabilities and minimized performance variation.

Course Design Guidelines

One should be careful in drawing straightforward inferences based on the trade-off process. A design experiment can only be explained in terms of factors/levels included. We recognize that no single design experiment can include all possible factors. So, the results will have a generalizability problem. Having said that, we note that experiential learning is the most important factor in course selection. That importance can easily be understood as business students want college experiences as close to the real world as possible. Internships provide the best hands-on, real-world experience, while business simulations are the next best solution. Simulations let students make business decisions and see their impacts in real-time. While case studies also provide some understanding of how the business world operates, students can't see the results of their recommendations. Simulations are known to achieve the best student engagement, a prized goal for any course. Prado et al., 2019, find the simulation a more effective experiential learning tool than case studies. Faculty should consider including simulation in their courses whenever possible.

Grading policy was the second most important factor, with a shown preference for curved grading. Although not directly related to learning outcomes, grading policy can determine students' chances of completing a challenging course. Curved grading is seen as a protective backup against failing challenging courses. Under absolute grading, a student will fail the class even when everyone in the class performs poorly because either the content was too hard to grasp or was not taught properly. Curved grading provides some protection against this situation. Although students perceive curved grading to be fairer compared to absolute grading, it might not be accurate. A curve may be fair for students with poor performance but may be discriminatory to students with better performance. There is nothing worse than a hardworking student who has become demotivated because of the perceived inability to receive a decent grade as some very high-achieving peers move the curve upwards. This unfairness in curved grading intensifies further if a class has a high-level heterogeneity in academic preparation. Important factors of class difficulty and student heterogeneity must be considered while deciding on grading policy.

Class attendance policy was ranked the third most important factor. Its ranking can easily be explained by the peculiar nature of the student sample. The majority of the students in the sample were working full time and, with increased time constraints, would like flexibility in terms of learning on their own schedule. Even when they are not working full time, students like to be in control of their time. They argue that there are many ways to learn materials teachers want them to learn and that a lot of learning happens outside the classroom. Students usually make a distinction between "physically present" and "mentally present." Mandatory attendance will not contribute to learning if the student is not engaged in the classroom. Students believe they should be allowed to make their own attendance decisions and not punished for non-attendance. Some courses at business school, such as data analytics or basic accounting, might work better with mandatory attendance, but for most other courses, the faculty are advised to be flexible in the attendance policy.

One needs to remember that in choosing a course, students make a holistic decision while simultaneously considering many course characteristics. In our experiment, the winning alternative used a business simulation, curved grading, low workload, once-a-week schedule, single assessment method, non-mandatory attendance, and no access to the instructor outside class. Based on the literature review, we know that instructors' access outside class is highly desired, but students were willing to make the trade-off. Students are willing to put up with less desirable characteristics such as lack of instructor's access or being assessed with a single assessment instrument as long as the course uses business simulation and curved grading. The implication for course designers is that if they just focus on a few of the most important factors, students will choose their course even when it has some less favorable characteristics.

Further research should involve two principal areas. One, replicating this method across various services and situations can help us assess its generalizability. Second, it would be interesting to study the interaction between design factors. An improved understanding of the Interaction between controllable and uncontrollable factors can help us improve service robustness. To study interactions, more complicated designs may have to be used.

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