Last-mile supply chain efficiency: an analysis of learning curves in online ordering

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Abstract

Purpose – As companies extend supply chains via direct delivery to consumers, supply chain efficiency depends upon the usability of the online ordering system. The purpose of this paper is to focus on customer order cycle efficiency gains through the “learnability” of web sites.

Design/methodology/approach – The paper analyzes empirical data using nonlinear regression from seven firms and over 4,000 customers to examine how order time – an important performance metric – changes within an online grocery ordering environment.

Findings – The evidence supports various forms of power-law learning for web-based ordering (i.e. the first few orders involve substantial learning). However, significant differences exist between web sites, and a portion of the ordering time may be irreducible.

Research limitations/implications – The research lends insight into how web sites influence last-mile supply chain efficiency via differing learning rates in the order cycle. Perceptual measures were used in order to assess customer beliefs.

Practical implications – Online order entry serves as the starting point for many supply chain actions. Managers can use this research to benchmark their web site performance and subsequently take action to improve the efficiency and service of their supply chain.

Originality/value – The empirically validated model allows researchers and web-based businesses to utilize the provided learning rate measure as an ease of use performance metric.

Keywords Supply chain management, Lead times, Electronic commerce

Paper type Research paper

Introduction

Many resources have recently been focused towards better understanding of the last-mile supply chain – that portion of the supply chain delivering products directly to the consumer. Numerous opportunities exist to increase customer convenience and operational efficiencies by delivering directly to the customer in a manner similar to the Dell direct model (Kraemer et al., 2000). These opportunities exist in all five components of the customer order cycle, viz.; order communication, order entry, order processing, order picking and packing, and delivery (Stock and Lambert, 2001). In this study, we focus on the first two components: order communication and order entry via an online ordering system. This interface normally occurs via a web site, which can either improve or damage both the convenience and efficiency of a supply chain’s last mile.

The web site for order entry serves as the customer doorway to a company – while doing away with physical stores can result in substantial reduction in costs due to the removal of tangible facilities, a web site that is difficult to use and learn sets
a substantial barrier to new customers. This is the physical equivalent of offering an unattractive and dirty store. In fact, a recent observation has been made that many customers of e-commerce sites are suffering from “technological Tourette’s syndrome,” a compulsion to grunt, swear, and shout at web sites (Travis, 2003). Dissatisfaction, disuse, and disloyalty are the likely results of such suffering, in addition to the inefficiencies that often are coupled with user-unfriendly processes (Johnson et al., 2003; Pace, 2004). The concept of usability and interface design has grown as a discipline to address the issue of user-friendly human-computer interface (HCI) design (Myers et al., 1996). Use of these concepts is helpful when analyzing how to improve the efficiency and effectiveness of a last-mile supply chain, as well as for attracting new customers, increasing web site visitation and converting browsers to buyers (Johnson et al., 2003; Moe and Fader, 2001; Moe and Fader, 2004).

This study seeks insights into how web sites influence last-mile supply chain efficiency via differing learning rates in the order cycle. We extend the current knowledge of an aspect of e-commerce usability known as learnability, by investigating various models that describe the phenomenon of users’ perceived learning. Accelerated web site learning will increase the efficiency of this customer entry point in the supply chain process. Understanding and measuring differences in learning rates should therefore lead to improved supply chain operations. The environment selected for this study was online groceries. This web-environment is attractive from a supply chain research standpoint due to its order-transaction orientation vs the browsing nature of other web-based environments (Johnson et al., 2003). Moreover, studying a single web site type allows for strong learnability comparisons. By focusing on one high order frequency e-commerce environment, we are able to make robust conclusions that can later be tested in more general settings.

Learning has been and continues to be a crucial concept in operational as well as supply chain literatures (Hirschmann, 1964; Yelle, 1979; Towill, 1985; Globerson and Levin, 1987; Boone and Ganeshan, 2001). However, previous studies investigating web site learning have used either controlled experiments (Mitta and Packebush, 1995; Lim et al., 1997) or indirect web-activity monitoring (Johnson et al., 2003). By contrast, the current study captures perceived learning through a large survey instrument, thereby allowing a stronger usability generalization to the population of last-mile supply chain customers.

The remainder of this paper is organized as follows: first, the background literature streams are presented, bringing together three distinct areas of study: last-mile supply chains, e-commerce usability, and learning curves. Second, previous studies relevant to learning in an HCI environment are reviewed. Third, learning theory-based research hypotheses are developed. Fourth, regression analysis is performed on the survey data. Finally, we discuss several implications for operations, HCI and marketing professionals, as well as limitations and future research issues.

**Literature review**

The following sections provide highlights of the three research streams pertinent to this study – supply chain management (SCM), e-commerce and learning curve theory. The intent is not to generate an exhaustive review, but to demonstrate how three seemingly separate research areas are related to the topic at hand.
Supply chain management

Extending supply chains. Starting with Ford Motor Company’s early attempts to manage supply chains, numerous opportunities and challenges in extending the boundaries of production and delivery have existed. However, the obstacles in understanding and reaping the potential benefits have left many firms unable to realize these opportunities. Recent developments in information technology and SCM techniques are diminishing these obstacles, and are allowing managers to uncover both subtle and evident outcomes of their strategies. The power of these techniques has been manifested in firms, such as Dell Computer Corporation (Kraemer et al., 2000), seeking to manage channels of supply previously untenable.

Last-mile supply chains. The past decade has seen a host of firms seeking to extend their supply chains directly to the end customer. Managing this portion of the supply chain – home delivery service for the customer – has been termed the “last-mile” issue (Punakivi et al., 2001) and has been a particular problem from a logistics infrastructure standpoint, most notably because of trade-offs between routing efficiency and customer convenience. Another issue, which firms must address when extending their supply chains to the last-mile, comes from the consumer standpoint. Specifically, the method by which consumers place orders can have a significant impact on transaction costs and customer service (Boyer et al., 2005). A successful last-mile supply chain initiative therefore seems to require attention to the customer order cycle.

Online grocery. A particularly interesting area of last-mile research is the advent of online grocers. This industry’s attempt at extending the supply chain demonstrates how a traditional, frequently performed action by consumers can be transformed through the use of an e-commerce platform. Traditional retailers recognized the “live” store-customer interface as a critically important element of the business (Newman and Foxall, 2003). For instance, “off-line” grocers in traditional settings have tried to add-value by improving retail layout, item availability, store atmosphere, and product assortment. This effort has served to diminish the so-called “distressful” events such as searching, waiting, and misplacing, and increase the “eustressful” events, defined as positive experiences such as pleasant atmosphere, product variety, and placement of like items (Aylott and Mitchell, 1999). Online grocers likewise have tried to enhance a customer’s e-purchase experience by saving past shopping lists, creating intuitive layouts and allowing product customization – such as cutting, packing and marinating meats to order (Boyer et al., 2005). In general, it has been found that the dominant reason for grocery shoppers to purchase online is convenience and time, followed by physical constraints and dislike for grocery stores (Morganosky and Cude, 2000). Not surprisingly, attempts by grocers to add-value to the e-purchase experience, albeit with mixed success, have focused on creating web site attributes that should save time (Boyer and Hult, 2006).

In general, as firms extend their SCM focus towards consumers they should experience increasing demands on the efficiency and effectiveness of their customer order cycle. Since, web sites are a primary medium in which order cycle management takes place, making improvements there can significantly improve a firm’s extended supply chain.

E-commerce

The current growth and popularity of e-commerce has affected many consumers’ everyday lives by providing a wider range of choices, more available information and
ease of purchasing. Simultaneously, retail firms have gained advantages by adopting e-commerce platforms through more efficient delivery of services and greater access to new consumer markets. How retailers traditionally interact with customers has been studied from the retail and distribution literature, but investigations into the customer-retailer electronic interface have emerged from the HCI and marketing fields.

Human-computer interaction. The HCI field of study originated in the 1960s (Shackel, 1969) and has evolved to examine how people design, use, and are affected by interactive computer systems (Myers et al., 1996; Griffith et al., 2001; Holzinger and Errath, 2004). The direct manipulation of graphical objects, multiple tiled windows and hypertext are all evolutions of HCI technology (Hewett et al., 2004). These successful interface tools have not only led system users to expect highly effective, easy-to-learn interfaces, but also have led researchers to develop new psychological theories of exploratory learning, also known as successful guessing (Polson and Lewis, 1990). Much of e-commerce depends upon successful exploratory learning because web site training is minimal at best, thereby allowing it to be considered a walk-up-and-use application aimed at permitting productive work on the first encounter (Polson and Lewis, 1990). Additionally, electronic retail shopping is not physical but a symbolic environment of shared representation, action, and feedback (Nadin, 1988). This non-physical environment, however, should possess many of the natural symbols and logical processes which are expected by the user (Nadin, 1988). Such features are critical to user-friendly web sites.

E-commerce usability. In fact, new sub-disciplines to HCI have emerged known as usability engineering (Nielsen, 1993) and e-commerce usability (Travis, 2003), which both focus on how to design web sites that ordinary people can use. Travis (2003) considered web site usability to be composed of:

- **Effectiveness.** Completeness of goal achievement.
- **Efficiency.** Goal achievement in relation to resources.
- **Satisfaction.** Low discomfort and positive attitudes.

Somewhat similarly, Nielsen (2003) identified five components of usability: learnability, efficiency, “memorability,” errors, and satisfaction. Hoffman and Novak (1996) and Pace (2004) both proposed theories that drew connections between web-interface quality and users attaining flow (Csikszentmihalyi, 1975), i.e. a state of consciousness when involved in an enjoyable activity. Flow has many elements: challenges that match skills, timely feedback, concentration, a sense of control, a loss of self-consciousness and a distorted sense of time (i.e. time seems to pass very quickly (Novak et al., 2000)). Recently, a broader concept of web site quality has materialized as a 12-component survey instrument termed “Webqual” (Barnes and Vidgen, 2001). Positive behavioral effects of high usability have been explained in other IT environments by the technology acceptance model and the task-technology fit model (Davis et al., 1989; Klopping and Mckinney, 2004). Although perspectives may vary, the message is clear that if web site usability is lacking, customers will leave and productivity will suffer; if web site usability is high, brand value will increase (Murray and Haubl, 2003) and customer service will cost less.

Learnability. Linking the desire for a positive customer-web site interaction and the aspiration for efficient last-mile processes is the notion of web site learnability, which has been defined as the ability to:
• learn a system within a specified time period; and
• relearn a system without undue stress (Shackel, 1986).

Learning in general has been linked with computer interface design in the past (Newell and Card, 1985; Polson and Lewis, 1990), and specifically with user time spent with web site functions and ease of use (Johnson et al., 2003; Nielsen, 2003; Travis, 2003). Given that the customer-web site interface is crucial within last-mile supply chains (Boyer et al., 2005), understanding and creating learnable web sites is an important component of efficient and effective extended supply chains. Managing web site learnability can be enhanced through learnability measurement, of which learning curve theory can be utilized (Johnson et al., 2003).

**Learning curves**

The curvilinear relationship between efficiency and practice has been studied since the early 1920s with regard to perceptual-motor skills (Snoddy, 1926), costs in aircraft construction (Wright, 1936) and memory retrieval (Anderson, 1983). This curvilinear relationship, also known as power-law learning (Anderson, 1982), is classically associated with motor skills, but has also been observed in the acquisition of cognitive skills and other types of skill acquisition (Newell and Rosenbloom, 1981). Newell and Rosenbloom (1981) point out that power-law learning experiences a mechanism that slows down the instantaneous rate of learning. This mechanism is mostly explained by exhaustion models – improvements become either harder to find, less available, less effective, or less applicable. Newell and Rosenbloom (1981) provide an explanation they refer to as a chunking theory of learning: humans memorize useful patterns within the task environment at a constant rate, but the patterns learned decrease in relevance. The initial rapid reduction in completion times is explained by a combination of increasing skill and perfection of tools (De Jong, 1957). Debate, however, is ongoing as to the actual learning mechanisms at play (Palmeri, 1999).

A learning index or rate is typically provided in exponent form as shown in the following equation (Belkaoui, 1986):

\[ \gamma = KX^n \]

where \( \gamma \) = time to complete the xth unit; \( K \) = time to complete first unit; \( X \) = cumulative unit number; \( n \) = learning index = \( \log f / \log 2 \); \( f \) = learning rate.

The learning index \( (n) \) has a negative value, and the learning rate \( (f) \) manifests as a percentage, typically between 70 and 90 percent of task time reduction after a doubling of repetition. That is, the second task performance is \( f \) percent of the first task performance, the fourth performance is \( f \) percent of the second, and so on.

Extensions upon the seminal research have been performed by exploring how learning can reach a limit (De Jong, 1957); how learning can improve profits (Hirschmann, 1964); where learning exists in non-manufacturing settings (Yelle, 1979; Newell and Rosenbloom, 1981; Boone and Ganesan, 2001); and what explains the phenomenon that has come to be called power-law learning (Newell and Rosenbloom, 1981; Anderson, 1982). Although most work seems to be focused on organizational or group learning, some research has examined individual learning (Fellner, 1969; Ross and Schulz, 1999; Nembhard and Uzumeri, 2000). Although the early work by Wright (1936) observed that design, albeit product design, influences learning rates, only
somewhat recently has research been devoted to exploring how the environment or design, specifically process design, influences learning rates (Mitta and Packebush, 1995; Johnson et al., 2003; Boone and Ganeshan, 2001; Sorenson, 2003). In fact, it has been suggested that learning rates can be used as a quantitative measure of how well a process, specifically a computer-based procedure, is designed (Mitta and Packebush, 1995; Johnson et al., 2003).

To summarize, extended supply chains, HCI and learning curves are three major research areas that provide background material for this study. The literature shows that as organizations connect their supply chains to individual consumers via an electronic medium, assuring an effective and efficient connection can be both a complicated and yet rewarding accomplishment.

**Previous related empirical studies**

Although many empirical studies of learning have been conducted in the past, only a handful have studied the rate of learning experienced by individuals in an HCI or e-commerce environment.

Mitta and Packebush (1995) conducted an HCI learning experiment to quantify the usability characteristic — learnability. Their test involved student subjects performing graphical user interface tasks that they repeated based upon their ability to complete tasks correctly. Learning rates were calculated based upon the probability of a subject transitioning within a task from a “guessing” state to a “learned” state. The authors found that tasks can be statistically grouped by learning rate, that completion time decreases as learning improves, that user type (occasional or frequent) has no effect on learning rate, and that interface quality can be measured using learning rates. A major contribution made by Mitta and Packebush (1995) was that they linked different computer interfaces with differences in user learning. Limitations to their study were that learning was based upon accuracy, not efficiency; learning rate was probabilistic, not related to learning curve theory; and completion times were actual measures, not perceptions of time as recommended by Travis (2003) for measuring usability. By contrast, the current study uses perceptual measures to describe efficiency and is grounded in learning curve theory.

A later study by Lim et al. (1997) sought to compare two types of exploratory computer learning methods: self-discovery vs co-discovery. The former method involves a single user, the latter method involves two users working together, and both methods seek learning without instruction. The authors used actual time and errors to judge which learning method was superior, but included a mediating variable that measured the degree to which users had a mental model — that is, a metaphoric picture like filing cabinets for electronic storage — of the system. Co-discovery was found to be superior mostly because of its ability to improve the user’s mental model. Lim et al.’s study underscored the learning benefits of web sites that mimic existing natural human operations (Polson and Lewis, 1990), while also providing insights into the self-discovery type of learning which most e-commerce users must confront. Usability inference limitations of the Lim et al., study are the linear assumption of learning rates and use of actual completion times.

Most recently, Johnson et al. (2003) studied the manifestation of power-law learning in an e-commerce environment, where web-browsing and web site visit durations were focused upon. Based upon a large sample of the actual seconds a web site was active,
and after a series of data cleansing steps to eliminate accidental visits or artificial durations (i.e., users away from computer with website active), the authors estimated learning rates by website. The authors applied three power-law functions, one being a log-linear regression that revealed an average learning index of $-0.19$ (i.e., an 88 percent learning rate), with a large range from 0.028 to $-0.602$. Johnson et al. (2003) helped introduce learning curve theory to website management. Their study created a measure for learnability and their subsequent documentation of various learning rates allowed for benchmarking in future learnability studies. A limitation of their study was that visits, not ordering times, were being measured. This creates inference difficulties because of task dissimilarity — that is, transactional vs. informational. Also, as with other studies, actual times were used instead of perceptions of time, which makes usability inferences more tenuous. Our study is different from Johnson et al. (2003) in the following ways:

- they examine browsing and not ordering as we do;
- they do not include first order time as most traditional learning models do;
- they do not investigate time incompressibility as some learning models do; and
- we use and emphasize the importance of subjective data while they use objective data from comscore.com

To summarize these past studies, it is evident that power-law learning exists in HCI and e-commerce, and that learning rates differ significantly by task environment. Past studies were either performed in a lab or web-browsing environment. What remains unclear is, first, how can web-based transactional task learning — critical to supply chain efficiency be characterized; and second, is the power-law evident for users’ perceptions of time, which is a closer proxy to usability than actual times (Travis, 2003; Pace, 2004)? Our study contributes to current knowledge by:

- assessing learning models untested in e-commerce environments (De Jong, 1957; Belkaoui, 1986);
- examining customer ordering specifically (not general visiting as did Johnson et al. (2003) and Moe and Fader (2004)); and
- testing learning models on subjective measures of time (an important indicator of usability (Travis, 2003)).

**Research hypotheses**

As traditional brick-and-mortar customers gain knowledge of a firm’s layout through repeated experiences (Park et al., 1989), so too online customers should gain knowledge of a firm’s website. The hypotheses we derived are divided into two categories. First, we propose a multiple linear regression model that tests a variety of factors (Ratkowsky, 1990) proposed to associate with perceived usage time. In addition, this model will serve as a base-case in which to compare the models that follow. The characteristics of online shopping are similar to other venues where power-law learning is present. Therefore, three nonlinear power-law models are developed and tested.

The following models propose formulations that predict the empirical phenomenon of decreasing ordering time through repetition. These models assume a consistent
underlying learning mechanism as described by Polson and Lewis (1990). That is, users of the grocer’s web site a priori know what ordering goals are desired and they seek possible online actions to meet those goals. Possible actions, such as a sequence of button clicks, are assessed and selected based upon cues or “labels” presented on the webpage. The selected action is carried out and the consequence is assessed for successful progress towards buyer ordering goals. A degree of success is retained in memory – defined as user knowledge – and is used for the next action selection. Future web site cues and updated user knowledge combine to help buyers improve successful action selection and consequently reduce the time required to attain ordering goals. Although this learning mechanism is difficult to validate, the following proposed empirical learning models relating ordering characteristics to ordering time should help improve the understanding of e-commerce learning.

**Linear model**

The first five hypotheses are developed with the expectation that factors will be linearly associated with perceived task efficiency. The unit of analysis is the individual customer and the associations are understood as linear coefficients.

Most models used to explain successive units’ completion time require incorporation of the time associated with the first unit (Belkaoui, 1986). In online ordering, the first unit time can be considered the initial order time ($T_1$) and successive units can be considered most recent order times ($T_N$). Customers should have similar ordering circumstances, therefore we posit $H1a$; a user’s reported time to complete the most recent order ($T_N$) is positively associated with the reported time to complete the first order ($T_1$).

Previous examinations of learning (Wright, 1936; Fellner, 1969; Adler and Clark, 1991; Boone and Ganeshan, 2001) highlight the major position of learning theory that task efficiency ($T$) will improve with experience, that is, task repetition. For this study, the number of orders ($N$) a subject has placed is used as a proxy for task repetition: repeated acts of web site use. Therefore, we posit $H1b$; a user’s reported time to complete the most recent order ($T_N$) is negatively associated with the number of online orders completed ($N$).

Observations have been made (Barnes and Vidgen, 2001; Travis, 2003) that firms’ web site designs will differ in interface quality, and subsequently in learnability and usability (Mitta and Packebush, 1995). Therefore, grocer web site differences should be manifest in perceived task time variance (Mitta and Packebush, 1995; Pace, 2004). Specifically, we expect $H1c$; a user’s reported time to complete the most recent order ($T_N$) is influenced by the grocer web site used ($G_i$).

The more advanced web site features – such as “saved list” options (Boyer et al., 2005) – improve ordering times after some repetition. However, each grocer uses advanced features differently. Therefore, we posit $H1d$; that an interaction of grocer ($G_i$) and the number of orders ($N$) exists to influence the user’s reported time to complete the most recent order ($T_N$).

As individuals repeat a given task, the amount of time required tends to approach a certain asymptotic limit, greater than zero, understood to be incompressible (De Jong, 1957). Although online ordering time is primarily comprised of human time, a portion of the process is computer/task design dependent and therefore a likely cause for incompressibility. If a user’s initial order time begins near the asymptote, less of the
compressible time will exist and less perceived learning will be evident. Stated more specifically is our \( H1e \); a user’s reported time to complete the most recent order \( (T_N) \) is negatively associated with the interaction between the number of orders \( (N) \) and the time to complete the first order \( (T_1) \).

At the conclusion of testing each of these hypotheses, a full linear model will result which shall be termed model A as shown in equation (1).

Model A:

Hypothesis: \( H1a \) \( H1b \) \( H1c \) \( H1d \) \( H1e \)

Direction: + - +/ - +/ - -

\[ T_N = \beta_0 + \beta_1 T_1 + \beta_2 N + \sum_{i=1}^{m} \beta_{3,i} G_i + \sum_{i=1}^{m} \beta_{4,i} G_i N + \beta_5 T_1 N \]  

where \( T_N \) = time to complete the \( N \)th order; \( T_1 \) = time to complete first order; \( N \) = number of orders completed; \( G_i = 1 \), for grocer and 0, otherwise; \( i = 1 \) to \( m \) grocers.

The next section will propose nonlinear efficiency relationships.

Nonlinear model

Although most past studies of individual HCI learning have tested linear relationships, individual nonlinear models may be more appropriate (Fellner, 1969; Nembhard and Uzumeri, 2000). The online ordering task environment involves various levels of task complexity from simple category drill down and item selection, to more complicated meal planning and compiling of reorder lists. Initial users should begin processing patterns of task completion immediately while achieving instantaneous speed improvements. At the completion of a user’s initial order, a certain time will be associated with that order that should encapsulate the characteristics of the user and the order. Upon returning to the web site for following orders, the user should have retained knowledge of previously learned patterns, and then begin learning new patterns, albeit with diminishing effect on improving order time. The above phenomena should be manifest as power-law learning model B, shown in equation (2).

Model B:

\[ T_N = T_1 N^\alpha \]  

where \( \alpha = \) learning index = \( \log \phi / \log 2 \), \( \alpha < 0 \); \( \phi = \) learning rate, \( 0 < \phi < 1 \).

Additionally, web site design should affect learning rates. Applicability to ever increasing pattern complexity likely dictates the rapidity of performance improvement (Newell and Rosenbloom, 1981), and therefore a web site designed to offer user-friendly task completion tools that enhance performance should demonstrate steeper learning curves. Since, a difference should therefore exist between web site learning rates, a binary grocer indicator variable \( (G_i) \) should be incorporated into model C as shown in equation (3).

Model C:

\[ T_N = T_1 N \sum G_i \alpha_i \]

where \( \alpha_i = \) learning index for the \( i \)th grocer.
Finally, as stated in $H_1$, a lower bound to improvement is likely where human and machine, in this case computer, interact within a task environment. Therefore, it is likely that a parameter estimating a lower bound will provide an improved model over the original learning model (2), which lacks a lower bound estimate. This asymptotic limit will be represented as recommended by De Jong (1957) in model D, as shown in equation (4).

Model D:

$$T_N = T_1[M + (1-M)N^\alpha]$$  \hspace{1cm} (4)

where $M =$ factor of incompressibility, $0 < M < 1$.

The hypotheses for the nonlinear models B, C, and D are based upon certain model “fitness” parameters as described in the methodology section. An improvement in model “fitness” is expected to occur starting from the linear model A, and ending at models C and D. More formally stated:

$H_{2a}$. The “fitness” of online customer learning model B will exceed model A.

$H_{2b}$. The “fitness” of online customer learning model C will exceed models A and B.

$H_{2c}$. The “fitness” of online customer learning model D will exceed models A and B.

Note that no theory based hypothesis is made stating whether model C or model D is superior. However, these will be compared in the empirical analysis.

**Methodology**

This section describes the procedures used for data collection and regression analysis.

**Survey instrument**

A survey methodology was selected in which to test the learning theory-based hypotheses. A survey provides a different perspective of actual use than a controlled experiment, incorporates important usability perceptions of time (Travis, 2003), allows for a large sample size and provides a breadth of multiple web sites.

Customer lists were obtained from seven major online grocers in the USA, UK and Canada. The grocers selected customers randomly within different experience levels. This was done to allow for analysis of the full range of experience. E-mails were then sent to these customers inviting them to complete a web-based survey. After an initial response, reminder e-mails were sent in an attempt to maximize response rates (Table I). Questions existed on the survey that did not pertain to this study. For the purposes of the present analysis, a response was considered complete if it contained data for both of the time measures described below.

The questions pertaining to this study asked the respondents to estimate the time duration in placing their first order ($T_1$) and their most recent order ($T_N$). Specifically, respondents were requested to state in minutes “how long did you spend on X grocer’s web site (including browsing and completing a grocery purchase)?” As stated earlier, using reported first and most recent order times as a proxy for multiple actual times has three benefits. First, it eliminates the need for data cleansing in order to filter out non-attended, active web site time. Second, it allows for a feasible large-scale study, which if all $N$ order times were requested would result in a much smaller sample and a likely biased sample to low $N$ values. Finally, a reported time is a perceptual measure
<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Grocer 1</th>
<th>Grocer 2</th>
<th>Grocer 3</th>
<th>Grocer 4</th>
<th>Grocer 5</th>
<th>Grocer 6</th>
<th>Grocer 7</th>
<th>Total</th>
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<tr>
<td>Customers contacted</td>
<td>3,379</td>
<td>10,418</td>
<td>2,078</td>
<td>500</td>
<td>2,500</td>
<td>1,159</td>
<td>2,000</td>
<td>5,000</td>
<td>23,655</td>
</tr>
<tr>
<td>Responses</td>
<td>620</td>
<td>1,066</td>
<td>475</td>
<td>373</td>
<td>690</td>
<td>396</td>
<td>460</td>
<td>877</td>
<td>4,337</td>
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<tr>
<td>Initial response rate (percent)</td>
<td>29.77</td>
<td>8.6</td>
<td>22.9</td>
<td>74.6</td>
<td>27.6</td>
<td>34.2</td>
<td>23.0</td>
<td>17.5</td>
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<td>499</td>
<td>718</td>
<td>429</td>
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<td>591</td>
<td>188</td>
<td>403</td>
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<td>3,496</td>
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<tr>
<td>Final response rate</td>
<td>24.40</td>
<td>6.89</td>
<td>20.64</td>
<td>66.60</td>
<td>23.64</td>
<td>16.22</td>
<td>20.15</td>
<td>16.68</td>
<td>14.78</td>
</tr>
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that incorporates the possibility of “flow” (Csikszentmihalyi, 1975; Pace, 2004) and therefore usability inferences. Information regarding the number of orders placed \( (N) \) was obtained directly from the grocers’ databases.

Regression analysis

In order to test the \( H1 \) hypotheses, variables from each hypothesis were entered in sequence using hierarchical regression techniques. The order of entry followed the numerical sequence of hypotheses, assuring that first order variables were entered prior to second-order, or interaction, variables. The ordering of hypotheses was chosen to mimic theoretical descending coefficient strength.

Each nonlinear model was fitted using a sequential quadratic programming algorithm for nonlinear regression in SPSS 12.0 (Spss, 2004). This method seeks to minimize the sum of squared residuals while allowing constraints to be placed on parameters, including a requirement for the incompressibility factor \( (0 < M < 1) \) and the learning index \( (\alpha < 0) \). There are cautionary issues to observe in comparing linear to nonlinear models (Neter et al., 1996b). Specifically, in nonlinear regression, if the parameters are not directly related to the number of independent variables, the estimation procedure requires a numerical search, and the traditional \( R^2 \) “goodness of fit” measure is misleading (Healy, 1984). Therefore, in order to test the \( H2 \) hypotheses, five model “fitness” criteria were used:

1. Efficiency;
2. Parsimony;
3. Healy’s modified \( R^2 \) (Healy, 1984);
4. Anderson-Sprecher’s \( GR^2_{adj} \) (Anderson-Sprecher, 1994); and

Efficiency is defined as the model’s absolute mean square error (MSE) and parsimony is the number of parameters (Nembhard and Uzumeri, 2000). Healy’s modified \( R^2 \) is given as \( 1 - \) (residual mean square/total mean square). Anderson-Sprecher’s \( GR^2_{adj} \) calculates a percent improvement from a common theoretical base model for predicting the dependent variable, given in this study as \( T_N = T_1 \). Finally, parameters should possess readily understood interpretations and practical usefulness (Ratkowsky, 1990). This is to be measured by the percentage and number of strong learnability inference parameters.

Findings

General statistics for the number of orders \( (N) \) and order times \( (T_1 \text{ and } T_N) \) are given in Table II. Important details revealed in the overall statistics are the disagreement between mean and median in values for \( N \), and the non-normal shape parameters for all three variables’ distributions. As described earlier, the grocer \( (G_i) \) should be a significant variable determining \( T_N \), therefore descriptive statistics by grocer are also given in Table II. Important to note regarding these grocer statistics is the variation in sample size and the general non-normality among the variables. The correlations among the variables were examined to detect issues of multicollinearity (Table III), of which most correlations were found significant but less than 0.2.
The hierarchical linear regression results demonstrate a significant ($p < 0.01$) positive coefficient for $T_1$ indicating first order times are similar to the most recent order times (Table IV – step 1). Further examination of the data indicates that customer orders are relatively consistent in terms of item variety and order size (e.g. if a customer’s first order contains 50 items they generally order similarly with later orders). Any decrease in order time should be due to learning rather than a change in order size. These findings lend support for $H1a$. Likewise in step 2, a negative association was found with respect to $N$ with a significant ($p < 0.01$) change in $R^2$ ($\Delta R^2$), thereby validating $H1b$. However, entering the indicator variable $G_i$ in step 3 resulted in only one grocer
### Hierarchical Linear Regression for TN (most recent order time)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model A₁</th>
<th>Model A₂</th>
<th>Model A₃</th>
<th>Model A₄</th>
<th>Model A₅</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>t</td>
<td>β</td>
<td>t</td>
<td>β</td>
</tr>
<tr>
<td><strong>Step 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>0.550*</td>
<td>38.95</td>
<td>0.553*</td>
<td>39.39</td>
<td>0.542*</td>
</tr>
<tr>
<td>N</td>
<td>-0.099*</td>
<td>-7.02</td>
<td>-0.133*</td>
<td>-8.26</td>
<td>-0.085*</td>
</tr>
<tr>
<td><strong>Step 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G1</td>
<td>0.114*</td>
<td>6.27</td>
<td>-0.017</td>
<td>-0.64</td>
<td>-0.010</td>
</tr>
<tr>
<td>G2</td>
<td>0.031**</td>
<td>1.81</td>
<td>-0.074*</td>
<td>-2.68</td>
<td>-0.069**</td>
</tr>
<tr>
<td>G3</td>
<td>0.018</td>
<td>1.12</td>
<td>-0.004</td>
<td>-0.15</td>
<td>-0.001</td>
</tr>
<tr>
<td>G4</td>
<td>0.024</td>
<td>1.40</td>
<td>-0.066*</td>
<td>-2.68</td>
<td>-0.057**</td>
</tr>
<tr>
<td>G5</td>
<td>0.013</td>
<td>0.80</td>
<td>-0.022</td>
<td>-0.79</td>
<td>-0.024</td>
</tr>
<tr>
<td>G6</td>
<td>-0.023</td>
<td>-1.38</td>
<td>-0.091*</td>
<td>-3.61</td>
<td>-0.080*</td>
</tr>
<tr>
<td>G7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Step 3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G1 × N</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G2 × N</td>
<td>-0.007</td>
<td>-0.26</td>
<td>-0.005</td>
<td>-0.18</td>
<td></td>
</tr>
<tr>
<td>G3 × N</td>
<td>-0.082*</td>
<td>-3.78</td>
<td>-0.081*</td>
<td>-3.74</td>
<td></td>
</tr>
<tr>
<td>G4 × N</td>
<td>-0.046*</td>
<td>-2.58</td>
<td>-0.053*</td>
<td>-2.92</td>
<td></td>
</tr>
<tr>
<td>G5 × N</td>
<td>-0.053**</td>
<td>-1.94</td>
<td>-0.047**</td>
<td>-1.69</td>
<td></td>
</tr>
<tr>
<td>G6 × N</td>
<td>-0.034**</td>
<td>-1.73</td>
<td>-0.039**</td>
<td>-2.01</td>
<td></td>
</tr>
<tr>
<td>G7 × N</td>
<td>-0.146b</td>
<td>-6.21b</td>
<td>-0.144b</td>
<td>-6.15b</td>
<td></td>
</tr>
<tr>
<td><strong>Step 4</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1 × N</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.303</td>
<td></td>
<td>0.312</td>
<td></td>
<td>0.324</td>
</tr>
<tr>
<td>ΔR²</td>
<td>0.010*</td>
<td></td>
<td>0.011*</td>
<td></td>
<td>0.012*</td>
</tr>
<tr>
<td>F-value of ΔR²</td>
<td>49.3</td>
<td>9.72</td>
<td>10.18</td>
<td>19.49</td>
<td></td>
</tr>
<tr>
<td>VIF</td>
<td>1.00</td>
<td>1.001</td>
<td>1.397</td>
<td>299</td>
<td>3.24</td>
</tr>
</tbody>
</table>

**Notes:** *p < 0.01, **p < 0.1, *reciprocal VIF < 0.0001 indicating excessive interdependence with other variables – variable not allowed to enter into model (Neter et al., 1996a), bnot interpretable since the main effect G7 is not included in the model.
displaying a significant \((p < 0.01)\) impact on order completion times. Also problematic with this step was the multicollinearity experienced with the variable \(G7\) as indicated by the reciprocal variance inflation factor (VIF) being less than 0.0001 (Neter et al., 1996a). Even though the \(\Delta R^2\) was significant, we concluded that only limited support was found for \(H1c\). In step 4, partial support was given for \(H1d\) because although \(\Delta R^2\) was significant, only two interaction terms \((G3N\) and \(G4N)\) revealed significant \((p < 0.01)\) associations with \(TN\). Interestingly, the standardized coefficients \((b)\) for the main effects \(N\) and \(Gi\) reversed sign upon entering the \(G_iN\) term, lending more evidence that the time-grocer interaction impacts the model. Finally, \(H1e\) was accepted because both the negative \(T1N\) coefficient and step 5 \(\Delta R^2\) were significant \((p < 0.01)\) in model A.

**Nonlinear model results**

The parameter, learning index \((\alpha)\), from model B was estimated for the entire data set to be \(-0.488\) with a standard error of 0.010 (Table V), which equates to a 71 percent learning rate (that is, \(\phi = 2^{-0.488} \times 100 = 71.3\) percent). In other words, a typical first order time \((T_1)\) may be around 70 minutes, while the second order time would be about 50 minutes, and the fourth order time would be near 35 minutes, and so on.

Conducting nonlinear regression further using model C, learning parameters \((\alpha_i)\) for each web site were estimated and some differences were found. Specifically, grocers one, two and five were estimated to possess insignificantly different learning indices of \(-0.336\), \(-0.346\) and \(-0.324\), respectively. These amounts equate to about a 79 percent learning rate, slower than the estimate for overall model B, and assuming a 70-minute first order attempt \((T_1)\) would equal a 44-minute fourth order attempt (9 minutes more than model B). Additionally, grocers three and six were estimated to have equivalent indexes of \(-0.506\) and \(-0.520\), respectively, or about a 70 percent learning rate – near typical. Finally, grocers four and seven seemed to possess the fastest learning rates of 64 and 49 percent, respectively, which in the case of grocer seven would result in an estimated fourth attempt order time of 17 minutes, given \(T_1\) of 70.

Lastly model D's two parameters – an overall learning index \((\alpha)\) and an incompressibility factor \((M)\) – were estimated to be \(-3.064\) and 0.374, respectively. The estimate for \(\alpha\) was much higher than in earlier models, equating to a 12 percent learning rate, but because \(M\) prevents users from processing orders less than 37.4 percent of their initial order time \((T_1)\), the fourth order would be about 27 minutes given a \(T_1\) of 70. In other words, model D characterized initial rapid learning to a lower efficiency bound and then near constant order times thereafter.

**Model comparison**

Each model was compared along the five fitness dimensions outlined in the methodology section, with the values presented in Table VI, the rankings shown in Table VII, and the curves shown in Figure 1. First, model A demonstrated the highest efficiency as measured by absolute MSE, followed by models D, C and lastly B. The second fitness dimension was parsimony, with model B having the simplest form, while models D, C and A followed in respective order. In regard to the third criterion, Healy’s (1984) modified \(R^2\), model C resulted in the highest proportion of variance accounted for, followed by models D, B and A. The fourth criterion demonstrates a relative improvement over a common base model, and the model fitness order followed...
<table>
<thead>
<tr>
<th>Overall learning index ($\alpha$)</th>
<th>Model B</th>
<th></th>
<th>Model C</th>
<th></th>
<th>Model D</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Est.</td>
<td>Std. error</td>
<td>Calc. learn rate</td>
<td>Est.</td>
<td>Std. error</td>
<td>Calc. learn rate (percent)</td>
<td>Est.</td>
</tr>
<tr>
<td>Overall learning index ($\alpha$)</td>
<td>-0.488</td>
<td>0.010</td>
<td>71 percent</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.336$^b$</td>
<td>0.012</td>
<td>79</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.346$^b$</td>
<td>0.014</td>
<td>79</td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.506$^b$</td>
<td>0.028</td>
<td>70</td>
</tr>
<tr>
<td>$\alpha_4$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.644$^b$</td>
<td>0.037</td>
<td>64</td>
</tr>
<tr>
<td>$\alpha_5$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.324$^b$</td>
<td>0.025</td>
<td>80</td>
</tr>
<tr>
<td>$\alpha_6$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.520$^b$</td>
<td>0.049</td>
<td>70</td>
</tr>
<tr>
<td>$\alpha_7$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-1.035$^b$</td>
<td>0.040</td>
<td>49</td>
</tr>
<tr>
<td>$M$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.374</td>
</tr>
</tbody>
</table>

Notes: $^a$Calculated as $2^a$, $^b$student's t-test shows $\alpha_1 = \alpha_2 = \alpha_5 < \alpha_3 = \alpha_6 < \alpha_4 < \alpha_7$
### Table VI. Fitness of online learning models

<table>
<thead>
<tr>
<th></th>
<th>I. Efficiency, MSE</th>
<th>II. Parsimony, number of parameters</th>
<th>III. Healy’s $R^2$ a</th>
<th>IV. Anderson-Sprecher $R^2$ improvement b (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model A</td>
<td>397</td>
<td>18c</td>
<td>0.336</td>
<td>86.7</td>
</tr>
<tr>
<td>Model B</td>
<td>947</td>
<td>1</td>
<td>0.421</td>
<td>68.3</td>
</tr>
<tr>
<td>Model C</td>
<td>824</td>
<td>7</td>
<td>0.496</td>
<td>72.4</td>
</tr>
<tr>
<td>Model D</td>
<td>785</td>
<td>2</td>
<td>0.479</td>
<td>73.8</td>
</tr>
</tbody>
</table>

**Notes:**
- $R^2 = 1 - (\text{MSE}_{\text{resid}}/\text{MSE}_{\text{total}})$
- $\text{GR}^2_{\text{adj}} = 1 - (\text{MSE}_{\text{full}}/\text{MSE}_{\text{reduced}})$
- c includes intercept
the same ranking as criterion one – A, D, C, B; albeit the improvement of model A (86.7 percent) was only somewhat better than D and C (73.8 and 72.4 percent, respectively).

The models were also ranked according to the fifth criterion in order of descending parameter interpretability as follows: C, B, D and A. All of model C’s parameters were learning indexes that have the utility of both predicting future order times and contrasting learning across web sites. Additionally, learning indexes are well known

<table>
<thead>
<tr>
<th>Model</th>
<th>I</th>
<th>II</th>
<th>Criteria</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>4</td>
<td></td>
<td>4</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>B</td>
<td>4</td>
<td>1</td>
<td></td>
<td>3</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>C</td>
<td>3</td>
<td>3</td>
<td></td>
<td>1</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>D</td>
<td>2</td>
<td>2</td>
<td></td>
<td>2</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

Table VII.
Overview of model ranking

![Figure 1. Model comparisons](Continued)
Learning models compared with actual
Grocer 2

Learning models compared with actual
Grocer 3

Learning models compared with actual
Grocer 4

(Continued)
Learning models compared with actual
Grocer 5

Number of orders

Mean time to order

Grocer 6

Number of orders

Mean time to order

Grocer 7

Number of orders

Mean time to order

Figure 1.
from learning theory literature, which allows web site learning rates to be compared to other contextual learning, like reading comprehension and hand-eye coordination (Newell and Rosenbloom, 1981). Model B lost the ability to distinguish between web sites, but maintained a reasonable learning rate estimate. Model D was nearly equal to model B; it included a useful parameter $M$ that may be helpful in understanding a user’s best possible time, but its estimate of learning seemed unrealistic as judged by previous learning studies. Lastly, model A contained many parameters that have mixed learning interpretability. For example, the parameters in step 4 ($b_4$) can be used to compare web site differences, but step 1 parameters ($b_1$) seemed to imply initial ability mattered most and the intercept $b_0$ has no rational meaning.

Finally, a graphical comparison of each model’s computed order time and actual mean order time for each grocer was performed (Figure 1). Qualitatively, it was noted that order times declined in an exponential manner to a threshold which seemed to be stable for some grocers while unstable (i.e. fluctuating up and down) for others. Because a few grocers experienced initial rapid learning, model D most frequently represented actual learning behavior (Figure 1, grocer 3). However, not all grocers’ actual times possessed this behavioral feature, therefore model C and then B seemed appropriate. The linear model A did characterize the gradual order time decline for $N > 7$, but it was not congruent with actual mean order time behavior for $N < 7$.

Upon review of the above results, hypothesis $H2a$ did not receive adequate support to reject its null, namely that model B was equal in fitness to model A. Specifically, what model A lacked in parsimony and interpretability, it made up for in efficiency, which was the opposite for model B. However, hypotheses $H2b$ and $H2c$ do have adequate support to be accepted, primarily because of model C’s interpretability, model D’s parsimony, and both of their adequate “goodness-of-fit” performances. Interestingly, model B and C tend to describe how order times diminish in the early stages of repetition ($N < 10$), but model D explains rather well the eventual (i.e. end-state) time to order.

**Discussion**

This research integrated three distinct research areas in order to investigate and model the factors that describe the nature of customer online learning within an extended supply chain. By revealing that e-commerce learnability is an integral part of usable firm-customer interfaces, it was argued that efficient and successful supply chain extensions require knowledge of customer online learning. Furthermore, any discussion of learning without the incorporation of learning-curve theory ignores a useful body of knowledge. Because consumer order time is important in an e-commerce environment for both customer satisfaction and interface efficiency, the time for ordering was selected as the unit of analysis. For these reasons, an integration of extended supply chains, e-commerce, and learning-curve theory was required.

After the background was presented, general factors influencing customer order time were hypothesized and tested using hierarchical linear regression. Each of the hypotheses were supported in general, with an exception of the grocer main effect proposed in $H1c$ and tested in step 3. Somewhat problematic in the step 3 results were the positive values for the $b_{3j}$ coefficients, which later reversed direction in step 4. This could be a statistical artifact, but another interpretation could be that web site differences in efficiency or usability are only truly revealed over time, which may be
an entry barrier for new grocers seeking to capitalize on their web site usability. All in all, the linear tests validated the general factors chosen and allowed the analysis to proceed.

Finally, nonlinear learning-curve theory based models were proposed and tested against each other, as well as the linear model. Acceptance of hypotheses $H_{2b}$ and $H_{2c}$ provided evidence for the claim that power-law web site learning exists and is more suitable for understanding the usability of web sites. Model C, which allowed a differentiation in learning index ($a_i$) by grocer, revealed that significantly different learning rates are likely. An inference could be made that usability is better for those web sites with higher $a_i$. However, learnability is one dimension of usability and other specific factors, like “memorability” and satisfaction, need to be examined before the full effects of learning rates can be understood. Model D proposed that an incompressible portion of order time might be near one-third of a customer’s original order time. An implication for this estimate is that users are not completely responsible for improving the firm-customer interface efficiency and organizations may need to identify web site processes beyond the user’s ability to improve upon. In sum, the nonlinear learning-curve theory models provided insightful parameters that can be used to enhance the interface between a supply chain and its customer.

Managerial implications

It is not surprising that there are substantial amounts of learning as customers repeatedly visit a web site as an ordering interface for last-mile supply chains. What is more surprising and useful to managers, are the insights unearthed as to the rate of learning and the differences between web sites/companies.

The first important insight has to do with the initial ordering experiences. As shown in Figure 1, all of the grocers see very rapid decreases in ordering time from the first to about the fifth order. This implies that there is an important threshold, after which customers have quickly reduced their order times and have become comfortable with online ordering. This implies that managers of businesses that involve repeated online ordering should offer incentives to get customers past this threshold. This fits well with out experience, since in our talks with ten or more online grocers, every single one had a strong incentive to get customers to order three to five times. As one manager put it, “we must change the food shopping habits of a lifetime.”

The second important insight involves the rate of learning. As shown in Table V, the estimated learning rate for the overall sample of customers was 71 percent, but the rate for customers of particular grocers ranged from a low of 49 percent to a high of 80 percent. This has two critical implications for managers. First, the web site or ordering interface can be improved to facilitate faster learning and quicker ordering. Just as physical stores place a premium on keeping the front of the store attractive and uncluttered, the web site for an internet retailer must be appealing and easy to learn/use. Similarly, just as physical grocers often place items at the store entrance that might logically be located elsewhere if based on logistical considerations, internet retailers may be tempted to put items or features that grab customers’ attention. As an example, consider fruit and vegetables at the front of the store. Why is this done? – Primarily because stores get a higher premium for these items, not because it is convenient for customers. The same holds true for web sites. Second, an understanding of learning rates should help managers forecast the need for server capacity and
maintenance more accurately. As supply chains increasingly utilize IT, it is important to remember that capacity is a constraint even for such “virtual” systems.

Limitations and future research
The data source for order time in this study was inherently subjective. Our survey requested users to recall both the ordering time for their most recent order and their first order. Although recent ordering times may be fairly accurate, the first order time likely has some inaccuracies — particularly if many orders have since taken place. The authors place confidence in the chosen approach, however, since smaller sample comparative studies between perceptual and actual data showed sufficient agreement (analysis available upon request). Although perceptions of order times may capture usability better than objective measures (Travis, 2003, p. 75), a worthwhile future study could be a comparison with objective order times as found in “clickstream” data (Montgomery et al., 2004). Obtaining true order time data is problematic because customers may remain logged on to a web site while performing some other household chore, therefore controlled experimentation may be warranted. Another limitation in this study was the lack of specific usability factors in the analysis, primarily because past learning curve theory did not include process usability. This study intended to bridge e-commerce usability to traditional learning-curve theory, therefore incorporation of non-traditional learning factors was not appropriate. However, with the bridge being made by this study, more specific design and perceptual factors may be incorporated to develop an even better picture of what mechanisms are at play with online learning — such as how the effects of “saved lists,” intuitive “interface metaphors” (Travis, 2003), and efficient navigation paths interact to enhance learnability. We also see benefit in testing other hybrid learning models in the future — such as combining models C, D and other learning parameters (Belkaoui, 1986). Finally, creating a learnability index utilizing learning rate metrics can be helpful for firms wishing to benchmark their supply chain’s customer interface effectiveness.

References


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