An empirical analysis of the antecedents of electronic commerce service continuance

Anol Bhattacherjee*

School of Accounting and Information Management, College of Business, BA-297N, Arizona State University, Tempe, AZ 85287-3606, USA

Abstract

This paper examines key drivers of consumers’ intention to continue using business-to-consumer e-commerce services. Multiple theoretical perspectives are synthesized to hypothesize a model of continuance behavior, which is then empirically tested using a field survey of online brokerage (OLB) users. Salient results include: (1) consumers’ continuance intention is determined by their satisfaction with initial service use, their perceived usefulness of service use, and the interaction between perceived usefulness and loyalty incentives for service use, and (2) satisfaction and perceived usefulness are both predicted by consumers’ confirmation of expectations from initial service use. Implications of these findings for e-commerce firms contemplating customer relationship management (CRM) initiatives are discussed. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: IS use; Continuance; Customer satisfaction; Customer relationship management; Expectation–confirmation theory; Technology acceptance model

1. Introduction

As the Internet continues to redefine the rules of doing business by eliminating transaction inefficiencies, reducing costs, and lowering barriers to entry, more and more online firms are turning to customer relationship management (CRM) as a means of ensuring their survival in the Internet economy. CRM is a new customer-centric business model that reorients firm operations around customer needs (as opposed to products, resources, or processes) in order to improve customer satisfaction, loyalty, and retention [22]. Despite the fact the average investment in a CRM project is US$3.1 million and the expected payback period is 28 months, a recent survey of 300 large US firms found that 65% of responding firms demonstrated corporate awareness of CRM, 28% are currently planning or implementing CRM, and 12% have completed CRM implementation [22].

A customer-centric orientation is important for e-commerce firms for several reasons. First, as the online marketplace becomes increasingly fragmented and competitors are just a mouse-click away, retaining a firm’s customer base (in addition to attracting new ones) is critical for sustaining revenue base, profitability, and market share. Second, superior customer experience is a more effective and less replicable differentiation strategy in the online marketplace than the more common cost leadership strategy...
(which has already led to margin erosion, reduced profitability, and subsequent demise of many online firms). Third, satisfied customers are a less expensive and more effective advertising channel (via word-of-mouth) than the print or mass media, due to the greater believability associated with personal experiences. Fourth, customer retention provides additional revenue opportunities via cross-selling (selling new products or services to existing customers) or upselling (enhancing customers’ use of existing products or services). Fifth, acquiring new customers may cost as much as five times compared to generating repeat business from existing customers, due to the costs of searching for new customers, setting up new accounts, and initiating new customers to firm services [8, 22]. As an example, a 5% increase in customer retention in the insurance industry typically translates into 18% reduction in operating costs [8].

However, a recent survey of 10,000 Internet customers of 16 leading US firms (including American Express, Ford Motor Credit, Hewlett-Packard, Nextel Communications, and Proctor & Gamble) found that only 36% of the respondents were satisfied with their online interactions, over 50% required phone calls or other offline means to resolve their problem, and 42% waited more than 24 h before receive any acknowledgement of their contact with the firm [14]. Such dissatisfaction often translates into lost customers and lost revenues. For instance, Carl [7] found that the number of subscription cancellations (discontinuance) for the top five internet service providers (ISP) in North America exceeded that of new subscriptions during certain months of 1995. In general, it appears that users of e-commerce services demonstrate little loyalty toward their service providers, forcing service firms to deploy loyalty programs (e.g., frequent flyer miles) to motivate customer retention. However, the efficacy of such programs has not yet been examined.

Improving customer satisfaction and retention may be more challenging in the Internet economy than in the traditional economy. Customers today are more demanding than ever before, are more information empowered to make their own decisions, and want their needs met immediately, perfectly, and for free [8]. Additionally, they have several online and offline options to choose from, and unless there is a compelling reason for choosing one particular firm over another, they tend to experiment or rotate purchases among multiple firms [8]. The nature of online firms’ interaction with customers is also transforming from traditional communication channels such as telephone and mail to electronic mail and web-based forms, from full-service to self-service, and from mass marketing to personalized marketing. It can therefore be expected that key drivers of customer satisfaction and retention in the Internet economy may be fundamentally different from that in the traditional economy. Until firms have a clear understanding of these drivers and implement a corresponding action plan, CRM programs initiated by these firms will only yield limited returns.

This paper examines the key motivations underlying consumers’ intention to continue using e-commerce services and associations between these variables. Based on a synthesis of consumer behavior, information systems (IS) use, and several other literatures, customers’ continuance intention is theorized as a function of their satisfaction with the service, perceived usefulness of that service, and loyalty incentives intended to enhance continuance. Both satisfaction and perceived usefulness are hypothesized as being predicted by consumers’ confirmation of sales, service, and marketing expectations. The hypothesized research model is then tested via a field survey of online brokerage users, and appropriate modifications to the initial model proposed.

Results of the study offer unique insights for online firm managers on how to manage customer satisfaction and retention. The proposed model can help managers identify potential discontinuers before they actually discontinue, so that these individuals may then be targeted with corrective actions (e.g., incentives, training) to improve their chances of retention. It also contributes to the nascent body of work in CRM and the IS use literature by providing insights into salient relationships underlying post-acceptance decision processes.

The paper proceeds as follows. Section 2 proposes a theoretical model of customer satisfaction and retention in the CRM context. Section 3 describes the field survey used for testing the above model. Section 4 presents the results of statistical data analysis, and proposes a modified model based on the observed results. Section 5 discusses the study’s implications for research and practice. The
2. Theoretical model

B2C e-commerce can be viewed by consumers as innovative IS services [21], and hence the IS use literature, based primarily on attitude theories from social psychology, is relevant to understanding consumer behavior related to B2C services. Attitude theories such as the technology acceptance model (TAM) and the theory of planned behavior (TPB) present intention as the strongest and most immediate predictor of individual behavior [1,9]. Theoretical justification for this association comes from cognitive dissonance theory [11], which argues that perceived discrepancies between intentions and behavior create a psychological tension (cognitive dissonance) that individuals attempt to relieve by adjusting their behavior to be consistent with their intentions. A strong correlation between intentions and behaviors is empirically validated in IS use contexts by Davis et al. [9], Taylor and Todd [27], and others. Consequently, much of the IS use literature (e.g., Refs. [10,17]) have taken intention–behavior association as granted and instead focused on understanding the predictors of user intention. Following this tradition, consumer's intention to continue using e-commerce services is employed as the dependent variable in this study, and salient determinants of intention are examined next.

2.1. Determinants of continuance intention

Based on expectation–confirmation theory (ECT) in the consumer behavior literature, TAM in the IS use literature, and agency theory in the organizational economics literature, three key factors are hypothesized as influencing consumers’ decision to continue using e-commerce services: satisfaction, perceived usefulness, and loyalty incentives (see Fig. 1).

ECT posits that satisfaction with a product or service is the primary motivation for its continuance [20]. Satisfied consumers continue using B2C services, while dissatisfied users discontinue it and/or switch to alternative services. Satisfaction is defined as an ex post evaluation of consumers’ initial (trial) experience with the service, and is captured as a positive feeling (satisfaction), indifference, or negative feeling (dissatisfaction) [2]. This evaluative response or affect is identical to the notion of attitude in the IS use literature [17], and hence, the attitude–intention association validated in IS use research (e.g., Refs. [9,16,27]) provides additional support for the hypothesized link between satisfaction and continuance intention. The centrality of dissatisfaction in triggering B2C discontinuance is observed in an Inteco [12] study, where Internet Service Provider (ISP) users cited negative experiences and dissatisfaction resulting from slow access or engaged lines, poor help lines, and other technical problems as their primary reason for service termination. Dissatisfaction is also evident in other B2C sectors such as e-brokerage, where users constantly complain of server outages, increased margin requirements, and late order fulfillment [23], and e-retailing, where many consumers are disillusioned with late deliveries, phantom purchases, and out-of-stock items on online catalogs [25].

TAM [9], an application of attitude theories to IS use contexts, presents usefulness of an IS, as perceived by potential users, as an important determinant of their intentions regarding IS use. Perceived usefulness refers to users’ subjective probability that IS use will improve their performance [9], and therefore captures the instrumentality or rational component of their usage decision. This is in contrast to the affective component embodied in satisfaction. In case
The rational and affective components oppose each other, relative strengths of the two components determine the outcome of the continuance decision process. For instance, users may continue using an e-commerce service if they consider it useful, even if they are dissatisfied with its prior use. Attitude theories hold that human behaviors are influenced by their subjective perceptions, even if such perceptions are biased or inaccurate [1]; hence perceived rather than objective assessment (e.g., third party or expert opinions) usefulness is relevant. Empirical support for the positive association between perceived usefulness and IS use intention is provided by Davis et al. [9], Matheison [16], and Taylor and Todd [27], among others.

The third determinant of continuance intention in our model is loyalty incentives. As B2C firms are realizing the importance and difficulties of retaining customers, many are actively instituting customer loyalty programs, such as frequent flyer miles (e.g., ClickMiles), loyalty points (redeemable toward future purchases), and incentives (e.g., cash, sweepstakes), to motivate continued use of their services. In fact, a new category of CRM vendors (e.g., Netcentives, MyPoints.com) has emerged that specialize in administering such loyalty programs for other online firms on an outsourced basis. Given their recency, the efficacy of loyalty incentives in improving online customer retention is largely unknown. However, agency theory [10] provides theoretical support for a positive association between loyalty incentives and continuance intentions. According to this theory, B2C firms can be viewed as principals and consumers as agents, engaged in a relationship characterized by incongruent goals. Incentives provided by firms can enhance consumers’ utilities, thereby aligning their goals with that of the firms and motivating them to behave in the firms’ best interests (i.e., continue using firm services).

2.2. Relationships among the determinants of intention

The next step is building a model of e-commerce continuance intentions is to explore the relationships among the three predictors of intention proposed earlier. According to ECT, satisfaction depends on the extent to which consumers perceive their initial expectations of a service to be confirmed or disconfirmed during actual use [20]. Confirmation of initial expectations of a B2C service lead to subsequent satisfaction and continuance intentions, while the reverse leads to dissatisfaction and discontinuance intentions. Recall that satisfaction is the outcome of an evaluative process, where consumers examine the results of their prior service use and decide whether or not to continue using the service. Confirmation, a cognitive belief representing the extent to consumers’ ex ante expectations of service use were met in reality, refers to this evaluation process. In other words, the affect in satisfaction is the outcome of a rational process of comparing initial expectations with actual experience or the confirmation belief. Such causality between cognitive beliefs and affect is well established in the social psychology literature [1], and has been validated across a wide range of IS use behaviors (e.g., Refs. [9,16,27]). Hence, the research model in Fig. 1 theorizes a positive association between confirmation and satisfaction.

Expectations in ECT refer to consumers’ beliefs about the potential utility that can be derived from a B2C service, which is akin to the notion of perceived usefulness. The extent to which these expectations are confirmed (during initial use experience) may also change their expectations of a service [20]. This is so because consumers often have unrealistically low or high initial expectations of new innovative services (e.g., most B2C e-commerce services) because they are unsure what to expect from it. They may still accept a service with low initial expectations with the intent of using their usage experience as a basis for forming more concrete expectations. Although low initial expectations are easily confirmed, these expectations themselves may be adjusted higher as a result of their usage experience, if customers realize that their initial expectations were unrealistically low. Likewise, unreasonably high initial expectations (often a result of overly positive advertising) may be lowered over the course of a service’s initial use, as some of those expectations are disconfirmed. The new level of expectations (higher or lower) may then serve to motivate or demotivate further usage (continuance) intentions. Since expectations are denoted in the research model
as perceived usefulness, a positive effect can be theorized from confirmation to perceived usefulness.

Conceptualizing confirmation in a B2C context is however not an easy task. The limited CRM literature suggests that B2C firms typically have three customer “touch points”: marketing, sales, and service, respectively referring to pre-transaction, transaction, and post-transaction experience [15]. Consumers are therefore likely to have three sets of expectations related to these three touch points, and their level of confirmation depends on the extent to which these expectations are met during initial service experience. Sales expectations for B2C firms refer to whether the consumer has his/her choice of selections (e.g., catalog items, payment options), whether a particular transaction is relatively effort-free, or whether the order is fulfilled in a timely manner. In more complex B2C contexts, these expectations may include whether the sales interface is personalized to consumers’ specific interests, whether the lack of physical presence is compensated by a rich multimedia setting (e.g., using animations, graphics, and audio/video), or whether all relevant information (e.g., comparative prices) are available to the consumer for making an informed decision. Service expectations typically refer to availability of multiple communication mechanisms for accepting consumer complaints (e.g., web-based forms, e-mail, telephone, fax) and timely resolution of complaints, but may also include assisting consumers in using a product/service effectively, suggesting complementary products or service, and joint problem-solving (e.g., product design or improvement). Customer self-service is another growing trend; this requires providing customers with real-time, online access to relevant data (e.g., their personal profiles, prior transactions, past invoices) and decision making tools (e.g., data mining capabilities). Online marketing refer to personalized, direct, one-on-one marketing based on consumer preferences, as opposed to advertisements, telemarketing and other forms of traditional offline mass marketing. Consumer expectations may therefore depend on issues such as whether the right products or services are recommended for cross selling or up selling, whether right promotions are run at the right time, whether customized products/services are available, and so forth. From a CRM perspective, the confirmation process for B2C consumers is therefore multidimensional in nature, based on their fulfillment of sales, service, and marketing expectations.

3. Research methodology

This section describes the research methodology employed to test the hypothesized model presented in Fig. 1. The background for the empirical study is first described, followed by a description of the research instrument used for data collection.

3.1. Study background

Empirical data for testing the research model was collected via a field survey of online brokerage (OLB) users. An OLB (e.g., Charles Schwab, E Trade) is a B2C e-commerce service that allows individual investors buy or sell securities (common stocks and options) over the Internet at commissions substantially lower than that of full service brokerages (e.g., Merrill Lynch). OLBs leverage universal access to the Internet, easy to use web interface, and online content from diverse sources to empower investors with tools and information they need for making independent investment decisions and executing those decisions (thereby eliminating the need for human brokers). Typical OLB services include stocks and options trading, real time quotes, e mail notification of trade execution, and portfolio tracking, while some OLBs may provide additional value added services such as mutual funds, after market trading, access to initial public offerings (IPO), analyst research, real time news feeds, and margin privileges for borrowing funds. The number of OLB users in the US has increased from 3 million in 1997 to 5.2 million in 1998, percentage of OLB adopters as a fraction of total investor population increased from 11% to 16%, and online trading activity increased by 18% during that time [6]. These numbers are expected to increase further as OLBs, by virtue of their economics and convenience, displace traditional brokerages as the preferred investment vehicle for small investors.

Subjects were self-selected for this study via messages placed on over 100 heavily trafficked online message boards on four popular investment-related
web sites: Yahoo Finance, Silicon Investor, Motley Fool, and Raging Bull. Message boards are online forums for discussing investment ideas, learning or disseminating “market rumors,” and identifying with a community with shared investment goals, and are hence frequently visited by online investors. The selected message boards represented companies across a wide range of industries trading on NYSE and NASDAQ stock exchanges. The posted message outlined the purpose of our study, solicited investors’ participation in an online survey of OLB use (via a hyperlink to the survey form), and as incentive, offered them an opportunity to register in a drawing for small cash prizes.

Online surveys have several advantages over traditional paper-based mail-in surveys: (1) the sample is not restricted to a geographical location (hence, large samples are possible), (2) lower costs, and (3) faster responses. Such surveys are routinely employed by consulting firms for data collection purposes, by business firms for soliciting employee opinions on issues of corporate interest, and by news organizations (e.g., http://www.CNN.com) for conducting online polls. Although novel in IS research, the online approach was appropriate since consumers’ online behavior was the focus of the study. Ninety-nine percent of respondents indicated that they were comfortable with filling out online forms (reasonably so, since online trading is itself a process of completing online forms), and hence the data collection method did not introduce any novelty bias on survey responses.

The online survey led to 172 usable responses. About 73% of the respondents were from the Yahoo boards, 24% from Silicon Investor, and 4% from Motley Fool and Raging Bull sites combined, which is somewhat representative of the number of online investors visiting these web sites on a regular basis. Subjects represented a wide range of OLBs, as listed in Table 1.

<table>
<thead>
<tr>
<th>OLB name</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E’Trade</td>
<td>12.2</td>
</tr>
<tr>
<td>Waterhouse (Toronto Dominion)</td>
<td>11.0</td>
</tr>
<tr>
<td>Datek</td>
<td>10.5</td>
</tr>
<tr>
<td>Charles Schwab</td>
<td>9.3</td>
</tr>
<tr>
<td>Discover (Morgan Stanley)</td>
<td>8.1</td>
</tr>
<tr>
<td>Ameritrade</td>
<td>8.1</td>
</tr>
<tr>
<td>Suretrade</td>
<td>8.1</td>
</tr>
<tr>
<td>DLJ Direct</td>
<td>6.4</td>
</tr>
<tr>
<td>National Discount Brokers</td>
<td>5.2</td>
</tr>
<tr>
<td>Scottrade</td>
<td>5.2</td>
</tr>
<tr>
<td>Others</td>
<td>8.1</td>
</tr>
<tr>
<td>Unspecified</td>
<td>8.7</td>
</tr>
</tbody>
</table>

The respondent group ranged in age from 19 to 54 (mean of 32.4 years), were 69% male and 31% female, had annual incomes between US$24,000 and 200,000 (mean income of US$75,000), had portfolio sizes between US$5000 and US$500,000 (mean of US$40,000), were employed in a wide range of professions (IS professionals, sales/marketing, banking/finance, law, and education), and had diverse educational levels (from college freshmen to doctoral degrees). While many respondents were relatively new to online trading, some had used OLBs as early as 1994. Thirty-four percent of respondents had transitioned from a traditional full-service brokerage to an OLB, while OLBs were the first brokerage for the remainder of the sample. Eleven percent of the sample had switched from a different OLB to their current one, citing dissatisfaction with service and higher commissions as primary reasons for discontinuing their prior OLB.

3.2. Instrument construction

Five constructs were measured in this study: continuance intention, satisfaction, perceived usefulness, loyalty incentives, and confirmation. All constructs were measured using multiple item, fully anchored, seven-point, Likert scales ranging from “strongly disagree” to “strongly agree.” Wherever possible, initial scale items were taken from previously validated measures in IS use or ECT literatures and reworded to relate to the OLB continuance context. At least three items were included per construct for adequate reliability, as recommended by Nunnally [19].

The continuance intention scale was adapted from Mathieson’s [16] two-item measure of IS use intention, with a third item (adopters’ overall intention to continue using their current OLB) added to improve reliability. The satisfaction scale consisted of six items taken from Oliver [20], and appropriately
reworded to fit the OLB use context. Prior user satisfaction scales in IS research were not considered because of their unwieldy size (e.g., Ref. [13]) or overlap with other dimensions of behavior such as attitudes and beliefs [17]. Perceived usefulness items were taken from Davis et al.’s [9] scale, which had four items measuring user perceptions related to word processing package use. No predefined scale was found for the loyalty incentives measure, and hence, a new three-item scale was constructed for this study and validated as described below. Finally, confirmation was assessed via a nine-item scale, with three items for each of the three dimensions of confirmation: sales, service, and marketing. Prior confirmation scales (e.g., Ref. [26]) were not applicable to the current CRM context and had significant confounding with other measures such as satisfaction and intention, and were therefore not used. All scale items are provided in Appendix A.

The initial version of this instrument was pretested for content validity using a convenience sample of six investors. Five of these investors used OLBS for managing personal investments, while the sixth person used a full-service brokerage. Participants were asked to examine the survey instrument and comment on its format and length as well as the wording of each individual item. Ambiguous items were reworded based on participant feedback. The revised scales were validated and refined further based on confirmatory factor analysis, as described in the next section.

4. Data analysis and results

Data analysis for this study was performed using EQS for Windows Version 5.4 [3]. EQS is a structural equation modeling approach similar to LISREL, where the covariance structure derived from observed data is used to simultaneously fit measurement equations and structural equations specified in the model. Such covariance-based approaches are appropriate for areas with strong a priori theory, where theory testing and refinement are the research goals [4], as was the case in this study. Each scale item was modeled as a reflective indicator of the underlying latent variable (construct). Model estimation was done in EQS using the maximum likelihood (ML) approach. Data analysis proceeded in two stages: the measurement model was first examined for validating and refining the research instrument, followed by an analysis of the structural equation model for testing the associations hypothesized in our research model.

4.1. Measurement model

The research instrument was validated using confirmatory factor analysis (CFA), performed via EQS’s measurement model. Results of the analysis, along with descriptive statistics (item means and standard deviations), are presented in Table 2.

Construct validity for each scale was assessed by examining the standardized CFA factor loadings of its hypothesized items, as derived from EQS measurement model. For acceptable construct validity, it is proposed that each item should have a minimum factor loading of 0.60 on its hypothesized construct [19]. This norm was met for 17 out of 25 items for the five constructs (see Table 2). Two items (in the loyalty incentive and confirmation scales) had loadings of 0.58, but were both significant at $p < 0.01$ and were therefore retained in the measurement model. Four items (in the satisfaction and confirmation scales) had loadings in the 0.3–0.5 range with marginal or no significance, and two others (in the confirmation scale) had loadings lower than 0.3 with no significance at $p = 0.05$. These items were dropped from subsequent analysis, by virtue of failing to meet the construct validity criterion and having poor correlations (less than 0.4) with remaining items within the same construct.

A closer examination of the two dropped satisfaction items revealed that one item (ST6, see Appendix A) was actually measuring post-hoc acceptance intention (as opposed to satisfaction), while the reference to affect a characteristic of satisfaction was very unclear in the other one (ST5). Of the four dropped confirmation items, CN4 attempted to measure service confirmation, while CN6, CN7, and CN8 measured marketing confirmation. CN4 examined perceptions of OLB’s handling of questions or complaints, an attribute that is generally rated by consumers as being poor across most OLBS (as observed during our pretest) and did not load well.
Table 2
Instrument reliabilities and validities

<table>
<thead>
<tr>
<th>Likert-scaled construct</th>
<th>Number of items</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Cronbach alpha</th>
<th>Standardized factor loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuance intention</td>
<td>3</td>
<td>5.11</td>
<td>1.59</td>
<td>0.887</td>
<td>0.882* (0.883*)</td>
</tr>
<tr>
<td></td>
<td>4.81</td>
<td>1.37</td>
<td></td>
<td>0.806*</td>
<td>(0.806*)</td>
</tr>
<tr>
<td></td>
<td>4.53</td>
<td>1.43</td>
<td></td>
<td>0.785*</td>
<td>(0.784*)</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>6 (4)</td>
<td>5.37</td>
<td>1.41</td>
<td>0.779 (0.807)</td>
<td>0.846* (0.849*)</td>
</tr>
<tr>
<td></td>
<td>5.20</td>
<td>1.25</td>
<td></td>
<td>0.752*</td>
<td>(0.760*)</td>
</tr>
<tr>
<td></td>
<td>4.92</td>
<td>1.12</td>
<td></td>
<td>0.659*</td>
<td>(0.677*)</td>
</tr>
<tr>
<td></td>
<td>4.93</td>
<td>1.24</td>
<td></td>
<td>0.692*</td>
<td>(0.702*)</td>
</tr>
<tr>
<td></td>
<td>5.09</td>
<td>0.93</td>
<td></td>
<td></td>
<td>0.401†</td>
</tr>
<tr>
<td></td>
<td>4.63</td>
<td>1.26</td>
<td></td>
<td></td>
<td>0.495†</td>
</tr>
<tr>
<td>Perceived Usefulness</td>
<td>4</td>
<td>5.12</td>
<td>1.46</td>
<td>0.880</td>
<td>0.866* (0.866*)</td>
</tr>
<tr>
<td></td>
<td>4.86</td>
<td>1.24</td>
<td></td>
<td>0.809*</td>
<td>(0.809*)</td>
</tr>
<tr>
<td></td>
<td>4.81</td>
<td>1.27</td>
<td></td>
<td>0.773*</td>
<td>(0.773*)</td>
</tr>
<tr>
<td></td>
<td>4.82</td>
<td>1.28</td>
<td></td>
<td>0.738*</td>
<td>(0.739*)</td>
</tr>
<tr>
<td>Loyalty incentives</td>
<td>3</td>
<td>2.33</td>
<td>1.46</td>
<td>0.811</td>
<td>0.631* (0.621*)</td>
</tr>
<tr>
<td></td>
<td>1.71</td>
<td>0.97</td>
<td></td>
<td>0.579*</td>
<td>(0.578*)</td>
</tr>
<tr>
<td></td>
<td>1.98</td>
<td>1.01</td>
<td></td>
<td>0.642*</td>
<td>(0.642*)</td>
</tr>
<tr>
<td>Confirmation</td>
<td>9 (5)</td>
<td>4.98</td>
<td>1.98</td>
<td>0.675 (0.756)</td>
<td>0.749* (0.767*)</td>
</tr>
<tr>
<td></td>
<td>5.21</td>
<td>1.71</td>
<td></td>
<td>0.646*</td>
<td>(0.658*)</td>
</tr>
<tr>
<td></td>
<td>5.19</td>
<td>2.21</td>
<td></td>
<td>0.742*</td>
<td>(0.759*)</td>
</tr>
<tr>
<td></td>
<td>1.85</td>
<td>0.95</td>
<td></td>
<td></td>
<td>0.421†</td>
</tr>
<tr>
<td></td>
<td>4.23</td>
<td>1.69</td>
<td></td>
<td>0.581*</td>
<td>(0.596*)</td>
</tr>
<tr>
<td></td>
<td>4.77</td>
<td>1.86</td>
<td></td>
<td>0.607*</td>
<td>(0.618*)</td>
</tr>
<tr>
<td></td>
<td>1.21</td>
<td>0.56</td>
<td></td>
<td>0.231†</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.03</td>
<td>0.69</td>
<td></td>
<td>0.391†</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.79</td>
<td>0.77</td>
<td></td>
<td></td>
<td>0.208†</td>
</tr>
</tbody>
</table>

*Factor significance: $p < 0.001$.
†Factor significance: $p < 0.05$.
+Factor significance: $p < 0.1$.
*Factor significance: non-significant at $p = 0.05$.
Parentheses indicate parameters after scale revision.
These items were dropped from the final scales.

with other confirmation items. In general, consumers have come to expect low service levels from OLBs in lieu of low commissions, and such expectations are easily met. However, personalized one-on-one marketing, though expected in the Internet economy, is far from reality at least in the OLB sector. Hence, all three items for marketing confirmation (CN6, CN7, and CN8) had low, non-significant loadings on the confirmation scale, and were dropped from analysis.

This scale refinement process shortened the confirmation scale to five items and the satisfaction scale to four items, while the other three scales (continuance intention, loyalty incentives, and perceived usefulness) remained unchanged for the remainder of the analysis. A rerun of the CFA model on the shortened scales found that 18 of the remaining 19 items had factor loadings exceeding 0.6. LI2 had a loading just under the 0.6 norm, and was considered acceptable. Scale reliabilities were estimated using Cronbach alpha for both initial and shortened scales. Three of the five initial scales (continuance intention, satisfaction, and perceived usefulness) had Cronbach alpha exceeding the standard acceptance norm of 0.80. Cronbach alpha for the initial six-item satisfaction scale was 0.78; this improved to 0.81 after the two items with poor factor loadings were dropped. Likewise, the nine-item initial confirmation scale had a Cronbach alpha of 0.68, which improved to 0.76 (reasonably close to the acceptance norm) after dropping the four non-confirming items.
4.2. Structural equation model

The first step in model testing was to estimate the goodness-of-fit of the hypothesized research model (Fig. 1). This is typically done using a chi square ($\chi^2$) test; however such tests are sensitive to sample sizes and the probability of rejecting any model increases as sample size increases, even when the model is minimally false. Hence, Bentler and Bonnett [4] suggest $\chi^2/df$ ratio ($df$: degrees of freedom) as a more appropriate measure of model fit. This ratio should not exceed 5 for models with good fit [3], and was estimated as 1.73 in our hypothesized model ($\chi^2 = 245.6, df = 142$).

EQS also provides additional goodness-of-fit measures such as Bentler–Bonett Normed Fit Index (NFI), Bentler–Bonett Non-Normed Fit Index (NNFI), and Comparative Fit Index (CFI). NFI is sensitive to sample size and may indicate poor fit with small samples even when the model is accurate. This is corrected in NNFI via appropriate normalization. Both NFI and NNFI assume the goodness-of-fit statistic to follow a central $\chi^2$ distribution or at least approximate to a non-central $\chi^2$ distribution in large samples (this may not hold true with models having large misspecifications); CFI is robust to this assumption. Though each fit metric is limited in its own way, the three measures collectively provide a reasonable estimation of overall model fit. In general, NFI, NNFI, and CFI greater than 0.90 are indicative of good model fit [3]. This norm was met in the hypothesized research model for NNFI and CFI (0.911 and 0.926, respectively), while NFI had a value of 0.887 (see Fig. 2). Hence, this model fit reasonably well with the observed data.

The second step in model estimation was to examine the path significance of each association in our research model and variance explained ($R^2$ value) by each path. EQS reports raw and standardized estimates for all specified paths, along with standard errors and test statistics for each path. Standardized path coefficients and path significances are shown in Fig. 2 (the measurement model is left out for purposes of clarity). All of our hypothesized associations were strongly significant at $p = 0.001$, except the link between loyalty incentives and continuance intention which was non-significant at $p = 0.05$.

As expected, satisfaction was the strongest predictor of continuance intention ($\beta = 0.76$), explaining 58% of the variance in continuance, followed by perceived usefulness ($\beta = 0.44$), which explained another 19% of the variance in the dependent variable. Confirmation predicted 43% of the variance in satisfaction ($\beta = 0.66$) and 24% of the perceived usefulness variance ($\beta = 0.49$). About 24% of the continuance intention variance, 56% of the satisfaction variance, and 76% of the perceived usefulness variance remained unexplained.

![Fig. 2. EQS analysis of research model.](image)
The lack of any significant effect of loyalty incentives on continuance intention was particularly intriguing, since it runs counter to the common logic that incentives drive behavior and a common business practice for many online firms. A closer examination of this unexpected finding suggested that although incentives may not motivate behaviors that are less useful or relevant to the individual, they could still motivate behaviors that contribute positively to consumers’ utility. In other words, loyalty incentives alone are inadequate to motivate consumers’ continuance of B2C services, but consumers would be motivated by incentives if the service in question was perceived as being useful. If this is indeed the case, then one would expect a significant interaction effect between loyalty incentives and perceived usefulness on continuance intention, but no significant main effect of incentives alone.

To test for the above proposition, the loyalty incentives construct was dropped from the initial research model (Fig. 2) and replaced with a construct representing the interaction between loyalty incentives and perceived usefulness. This new construct (interaction term) was modeled as a reflective combination of 12 items, representing the products of the three loyalty incentive items and four perceived usefulness items. The new model was tested for goodness-of-fit and path significance using EQS. The revised model (see Fig. 3) demonstrated better fit compared to the initial model on all four goodness-of-fit metrics: \( \chi^2 / df = 1.435 \) (improved from 1.730), NFI = 0.901 (improved from 0.887), NNFI = 0.924 (improved from 0.911), CFI = 0.936 (improved from 0.926). Paths unchanged from the initial research model retained their original significance levels. In addition, the new path denoting the interaction new effect was significant at \( p = 0.01 \), and explained about 15% of the continuance intention variance. About 17% of continuance intention variance still remained unexplained. Implications of these findings for CRM and B2C e-commerce are discussed in the next section.

5. Discussion and implications

The goal of this paper was to identify the antecedents of consumers’ continuance intentions from a CRM standpoint, and the interrelationships among these antecedents. Toward that goal, multiple theories from diverse referent disciplines were synthesized to propose a theoretical model of continuance intention (Fig. 1). A field survey of online brokerage (OLB) users validated much of the hypothesized model, and suggested additional modifications. Implications of these findings are discussed next.

5.1. Understanding continuance intention

Results of the study supported the study’s expectation that satisfaction and perceived usefulness are
strong predictors of consumers’ intention to continue B2C services. The satisfaction–intention link has previously been validated in consumer behavior research over a wide range of product and service contexts (e.g., Refs. [2,27]); its revalidation in the B2C context further attests to the robustness of this association. Coupled with the intention–behavior association that has been validated extensively in the IS use literature (e.g., Refs. [9,28]), this finding suggests that satisfaction is an important (though indirect) predictor of continuance behavior.

Consequently, B2C firms concerned with minimizing the effects of customer churn (discontinuance) and establishing a loyal customer base, must consciously seek to identify dissatisfied consumers and redress their dissatisfaction concerns before they actually discontinue. Minimizing churn is of utmost importance because: (1) churn reduces a firm’s customer base and revenues, (2) negative word-of-mouth initiated by discontinuers is generally more persuasive than most positive influences and may trigger further discontinuance among other consumers, and (3) firms may incur substantial costs in winning back prior consumers lost to competitors [21]. Customer satisfaction should therefore be a key business metric for B2C firms attempting to transform from being “customer-aware” to “customer-centered,” and should be consciously measured, monitored, and improved upon. This metric can be easily assessed using a short satisfaction scale similar to the one employed in this study.

Perceived usefulness was identified in this study as a secondary determinant of continuance intention. Rationally speaking, service consumers would want to continue subscribing to a service only if they find it useful. Given the innovative and intangible nature of most B2C services, many consumers realize the potential benefits of a service only after using it. Even so, many consumers may not recognize all of the service’s benefits due to limited prior experience with e-commerce services, fear of computers and the Internet, and other reasons. To ensure customer retention, the onus is on B2C service providers to “educate” their subscribers on the potential benefits of their service and how to realize such benefits. B2C business models that emphasize customer education/mentoring are likely to be more successful in customer retention than those than do not. Some B2C firms (e.g., Charles Schwab) are beginning to employ this strategy to build a “sticky” base of loyal customers. However, given the higher effect size of satisfaction compared to perceived usefulness in explaining continuance intentions, B2C firms having limited resources to deploy should focus first at improving consumers’ satisfaction with their service and then on consumer education/mentoring programs.

Loyalty incentives did not have any significant effect on continuance intention, but its interaction effect with perceived usefulness was significant. This suggests that incentive programs such as frequent flier miles, loyalty points, and cash-back plans are not universally effective customer retention strategies [5], but are effective only when consumers find the service useful. To maximize the effect of loyalty incentives, B2C e-commerce firms must not rely solely on these programs for improving consumer retention, but must exercise a judicious mix of consumer training/education and loyalty programs. Coupled with prior studies on the impact of loyalty programs on consumer switching behavior (e.g., Ref. [5]), the above finding calls for greater caution on the part of e-commerce firms in interpreting the effects of loyalty incentives and exercising its use in consumer settings.

5.2. Understanding associations between antecedent constructs

Confirmation was a significant predictor of satisfaction and perceived usefulness in the proposed model. Hence, confirmation influences continuance intentions in two (indirect) ways: by influencing consumer satisfaction toward the service and by impacting consumers’ perceptions of service usefulness. Confirmation is the rational decision process B2C service users go through prior to setting up an affect (satisfaction) and subsequent intentions. Though some of the affect could be beyond the control of B2C firms, firms can influence consumers’ decision process (confirmation) by building appropriate levels of B2C expectations among consumers and being able to meet those expectations. Understanding the optimal level of consumer expectation is a complex and challenging task, since high
expectation may lead to disconfirmation and low expectation (or low perceived usefulness) may reduce the motivation to continue using the service. Further, expectation can vary greatly across a population of consumers. A segmentation strategy may be useful, whereby B2C firms can segment their consumer base based on their service needs and capabilities and design separate marketing programs for each segment. Nevertheless, expectation management remains a crucial yet less understood aspects of B2C services.

From a CRM perspective, confirmation was operationalized in this study in terms of sales, service, and marketing expectations. However, significant measurement problems were encountered during empirical analysis, due to dissociation of marketing confirmation from sales and service confirmation. Marketing confirmation relates to personalized, one-on-one, direct marketing by B2C firms based on customer preferences. Though this concept has significant relevance in the new Internet economy, it is unclear to what extent individual consumers are aware of such expectations, and hence, confirming these expectations is problematic. In contrast, consumers typically have more well-defined sales and service expectations, by virtue of their prior experience with traditional “brick-and-mortar” firms, and can more readily assess whether a B2C firm is meeting at least expectations typical of these traditional firms. Additional research is required to understand the underlying constituents of the confirmation construct and design appropriate scales to measure this construct.

Finally, while consumer satisfaction is certainly a preferred outcome for most B2C firms, such satisfaction can only come at a cost. For instance, a “satisfaction guaranteed” policy may require remunerating dissatisfied adopters with partial or full refund, providing additional service at no cost, and even additional manpower costs in accepting, verifying, and resolving adopter dissatisfaction. B2C firms also need to understand whether such costs are justified in lieu of retaining a dissatisfied consumer’s business. This requires mining historical data on consumers’ preferences, expectations, and service use, and is the topic of a new segment of CRM application called “customer profitability analysis” [18]. Also, there is no assurance that dissatisfied consumers will return once their reason for dissatisfaction is resolved. These issues, though perplexing, suggest interesting opportunities for future research.

6. Limitations

This study suffers from methodological limitations typical of most field surveys. An attempt was made to systematically identify and test for some of these biases. First, given the novelty associated with online surveys, the empirical data may be biased by novelty effect. A single-item measure assessing subjects’ degree of comfort with filling out online forms indicated that 99% of the respondents were comfortable with online surveys. This suggested that novelty effect was not a serious concern in this study.

Second, the survey of OLB users may have had a non-response bias because data was collected from 172 self-selected respondents recruited via online message boards from among a population of several million online investors. It is possible that investors visiting message boards may differ systematically from the general population, and hence their survey responses may be different. Though there is no systematic way to test for all such differences, two demographic variables (age and income level) and one contextual variable (portfolio size) were compared between this study’s sample and a larger sample of 1015 online and offline investors [24] as a surrogate for the population. A difference of means test on age between the two groups was weakly significant \( p = 0.05 \), while those on income levels and portfolio size were non-significant. This suggested that the subject sample was fairly representative of the target population, and hence their responses are not likely to be substantively different.

Third, about 40% of the respondents thought that discontinuing their current OLB and moving investment assets to a different OLB or a full-service brokerage firm was a complicated and expensive process. It is possible that these individuals did not view OLB discontinuance as a viable option, which in turn, may have biased their responses to items requesting their continuance intentions. To test for this bias, discontinuance-aware respondents were separated from discontinuance-unaware respondents,
and the research model was rerun separately for each group. Despite minor differences in model fits and path coefficients, the overall pattern of path significance and the relative influence of determinants were unchanged between the two groups. This suggested that even if some subjects were biased in their perceptions of continuance behaviors, such bias did not affect their responses to this survey.

Finally, this study employed only a few of several possible theoretical “lenses” that can explain causative relationships among the antecedents of continuance intentions. Application of any theory to a research problem automatically places constraints on variables, relationships, assumptions, and boundary conditions that can be examined, which then leads to a “colored” or biased interpretation of the problem domain and solution space. There may be additional determinants of continuance intention (or associations between them) that were not examined in this study. Further examination of this topic, using diverse theoretical perspectives from other disciplines, is required to validate the study’s model or propose a more comprehensive explanation of continuance behavior.

Appendix A. Questionnaire items

Continuance intention:
IN1. I want to continue using my OLB rather than discontinue its use.
IN2. My intentions are to continue using my OLB rather than any alternative means.
IN3. If I could, I would like to discontinue use of my OLB.

Satisfaction:
ST1. I am satisfied with my decision my OLB use.
ST2. My choice to use this OLB was a wise one.
ST3. I am not happy with my earlier decision to use my OLB.
ST4. My experience with using this OLB was very unsatisfactory.
ST5. I think I did the right thing by deciding to use my OLB.
ST6. If I were to do it again, I would feel differently about using my OLB.

Perceived usefulness:
US2. I think that my OLB use improves my productivity in managing personal investments.
US3. In my opinion, using my OLB increases my effectiveness in managing personal investments.
US4. I find my OLB useful in managing personal investments.

Loyalty incentives:
LI1. My OLB offers incentives for its continued use, such as frequent flier miles or bonus points.
LI2. I get rewarded for my continued patronage of my OLB.
LI3. My OLB generally does not give me any loyalty incentives for my continued use of its service.

Confirmation:
CN1. My OLB’s execution of online trades meets my expectations.
CN2. My OLB gives me all the information and tools needed to place and execute trades.
CN3. My online trading experience via my OLB falls short of my expectations.
CN4. My OLB is generally good at handling questions or complaints before or after a trade.
CN5. After-sales service provided by my OLB meets my expectations.
CN6. I generally get the level of service I expect from my OLB.
CN7. My OLB provides me with customized one-on-one marketing as I would expect.
CN8. Products and services recommended to me by my OLB meet my expectations.
CN9. My OLB’s direct marketing activities meet my expectations.
† Reverse coded items.
† Items dropped from final analysis due to poor factor loadings.

References


Anol Bhattacharjee is an Assistant Professor of Information Management at Arizona State University. He received his PhD and MBA degrees from the University of Houston, Texas, and prior to that, he earned BS and MS degrees from Indian Institute of Technology, Kharagpur (India). His research interests include behavioral issues in electronic commerce, information technology (IT) acceptance and use, and IT-enabled organizational transformation. His prior research has been published in several refereed journals, including Information Systems Research, Decision Sciences, Journal of MIS, IEEE Transactions on Systems, Man, and Cybernetics, Data Base, and Information & Management.