

# Acceptance of E-Commerce Services: The Case of Electronic Brokerages

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**Abstract**—This paper examines human motivations underlying individual acceptance of business-to-consumer (B2C) electronic commerce services. Such acceptance is the key to the survival of firms in this intensely competitive industry. A modified theory of planned behavior (TPB) is used to hypothesize a model of e-commerce service acceptance, which is then tested using a field survey of 172 e-brokerage users. We found TPB useful in explaining e-commerce service acceptance; however acceptance motivations are significantly different from that of typical IS products. Based on a broader conceptualization of TPB's subjective norm to include both external (mass-media) and interpersonal influences, we report that subjective norm is an important predictor of e-commerce acceptance, behavioral control has minimal impact on e-commerce acceptance, and external influence is a significant determinant of subjective norm. Implications of these findings in light of e-commerce research and practice are discussed.

**Index Terms**—Electronic brokerage, electronic commerce, IS acceptance, IS adoption, IS services, theory of planned behavior.

## I. INTRODUCTION

THE increasing popularity of the Internet has led to the emergence of a new genre of information systems (IS) services. Such services span the entire gamut of business-to-consumer (e.g., Internet service providers, online banking, electronic brokerages, online retailing, online auctions) and business-to-business (e.g., web site hosting, traffic load balancing, online payment processing, online procurement, customer resource management) electronic commerce. In fact, the need for such services has created a new class of service firms ("cybermediaries"): middlemen linking suppliers to customers (e.g., auctioneers, brokers), outsourcing vendors supporting mission-critical business processes (e.g., procurement, payment processing), and firms offering entirely new services never conceived before (e.g., customer profiling, load balancing).

Understanding what motivates individuals and/or firms to accept e-commerce services is important because such acceptance is key to survival in this fast-paced and hypercompetitive industry. Establishing a "critical mass" of adopters is a necessary precondition for generating revenues, growth, and market share, and ultimately for achieving scale efficiencies and profitability. Attracting customers in an online environment is far more challenging than in a traditional business environment because of substantive behavioral changes required by adopters

in learning how to use e-commerce technologies, trusting such technologies, and making informed decisions using these technologies. As e-commerce firms rush in to establish "footprints" in this emerging industry, a good understanding of potential customers' decision processes can help them design effective marketing techniques for attracting and retaining customers and provide them with substantial competitive advantages.

This paper takes a first step toward building a knowledge base of e-commerce acceptance at the individual level, by examining human motivations underlying adoption of business-to-consumer (B2C) e-commerce services. Our focus on the B2C segment is motivated by the dramatic growth of this segment from \$10 billion in 1997 to \$220 billion in 2001 [20] and its profound impact on our personal and social lives (e.g., buying behaviors, socialization patterns, decision making). The deductive approach of scientific inquiry is employed by first hypothesizing a theoretical model of e-commerce acceptance and then testing that model via a field survey of e-brokerage users.

Our search for an e-commerce acceptance model takes us to the existing research on IS acceptance and service adoption research in the marketing literature. The last decade has seen a growing body of theoretical and empirical research on acceptance of IS *products*, including hardware such as microcomputers and networking devices and software such as spreadsheets and word processing packages (e.g., [5], [7], [8], [13], [14], [19]). However, it is questionable to what extent such research can be applied to IS *services* such as B2C e-commerce (e.g., ISP, e-brokerage, e-banking), given salient differences underlying IS product and service adoption, which will be described later.

Our proposed model of e-commerce service acceptance is an adaptation of the theory of planned behavior (TPB) [2], a widely accepted theoretical referent for understanding individual acceptance of IS products. Specifically, we model TPB's subjective norm construct as being determined by interpersonal influence (e.g., word of mouth) and external influence (e.g., mass media), based on theoretical arguments and empirical findings from the innovation diffusion literature [17]. Our primary findings are:

- 1) subjective norm plays a very significant role in explaining intentions to accept e-commerce services;
- 2) behavioral control has minimal influence on acceptance intentions;
- 3) external influence is an important predictor of subjective norms.

Though these findings run contrary to the existing literature on IS product acceptance, they have interesting implications in explaining the unique aspects of e-commerce service acceptance.

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While advancing our limited knowledge in this area, the findings also provide practitioners with valuable insights on how to influence potential adopters' decisions.

The rest of the paper proceeds as follows. Section II reconceptualizes TPB to hypothesize a model of e-commerce service acceptance. Section III describes a field survey of e-brokerage users employed for testing the proposed model. Section IV presents data analysis techniques and results. Section V discusses the implications of our findings for B2C e-commerce acceptance. The final section outlines the study's contributions for IS research and practice and suggests avenues for further research.

## II. A THEORETICAL MODEL OF E-COMMERCE ACCEPTANCE

IS acceptance research to date has been influenced by two predominant research streams: innovation diffusion theory (IDT) based in communication and marketing literatures (e.g., [1], [5], [13]) and intention-based models rooted in cognitive psychology (e.g., [7], [14], [19], [21]). IDT describes a rich set of innovation attributes and communication patterns influencing innovation acceptance among a population of potential adopters [17]. Individual adopters evaluate these influences, form attitudes toward the IS, and decide whether and how to accept it [2]. However, the adopter population is rarely homogeneous, adopters vary greatly in their ability and propensity to be influenced by external stimuli, and hence, their acceptance motivations and patterns are often vastly different. Though IDT acknowledges a behavioral process from awareness to acceptance, it does not explain how attitudes are formed, how it leads to the eventual acceptance or rejection decision, or how innovation attributes fit into the process [13].

Intention-based models such as TPB view individual behavior (e.g., e-commerce service acceptance) as being determined primarily by behavioral intention, which in turn, is predicted by multiple belief structures concerning the intended behavior [2]. Of the three intention-based models described in the literature (theory of reasoned action, technology acceptance model, and TPB), TPB is by far the most comprehensive and explains the most variance on intention and actual behavior [19], [21], and was therefore chosen as the theoretical basis for this study.

TPB defines intentions in terms of three belief structures: attitude (predisposition toward a particular object, event, or act, that is subsequently manifested in actual behavior), subjective norm (perceptions about social forces influencing a behavior), and behavioral control (perceptions of internal or external constraints affecting the behavior). These constructs are, in turn, determined by three sets of perceptual beliefs: attitudinal beliefs (cognitive beliefs regarding the instrumentality of the intended behavior), normative beliefs (beliefs about the social desirability of that behavior), and control beliefs (beliefs about behavioral constraints affecting behavioral performance). TPB includes an additional link from behavioral control to actual behavior to account for situations where individuals lack complete volitional control over their behavioral choice (e.g., in workplace settings) and may be forced to act against their intentions [2]. Empirical tests of TPB in IS acceptance contexts attest to its explanatory

power, though the link between subjective norm and intention has typically been nonsignificant (e.g., [7], [14], [21]).

It is important to note that TPB focuses on cognitive effort (e.g., learning costs) and social desirability related to a behavior, but not on its monetary costs. Therefore, TPB is applicable to those acceptance contexts, where adopters are not faced with significant monetary costs. This is true for most B2C e-commerce contexts where the service is free (e.g., online retailing, e-brokerages), but users must invest time and effort in learning how to utilize it properly (e.g., researching products or stocks, finding out prior buyers' or expert opinions, retrieving price or quote information, placing orders, verifying order fulfillment). The learning cost is further magnified by the automated nature of e-commerce service and the lack of human assistance (for helping adopters). The amount of cognitive effort required to use these services may vary from person to person, based on their prior training or expertise, and may even demotivate some technologically-challenged individuals from accepting, despite their apparent advantages (e.g., lower product prices or commissions, complete control over the behavior, and convenience). Certain B2C services (e.g., online banking) may charge a small monthly fee, but this fee is similar to that of comparable offline services (e.g., maintenance fee for checking accounts) and are waived under certain circumstances (e.g., if a minimum balance criterion is met), hence monetary cost is not a constraint on B2C e-commerce acceptance.

Fig. 1 represents our reconceptualization of TPB. We focused on intention as the dependent variable, thereby excluding TPB's intention-behavior link. This was done for three reasons. First, prior empirical studies overwhelmingly support a strong positive association between intention and IS acceptance (e.g., [7], [8], [14], [19], [21]); retesting this association will not serve any purpose beyond validating the obvious. Second, while individuals may be forced to act against their intentions in organizational settings due to management edicts and workplace norms, such influences are typically lacking in personal-use or home contexts typical of B2C e-commerce (e.g., online shopping, managing personal investments). Hence, we expected behavioral control to have little or no direct effect on e-commerce acceptance. Third, as described later, our subject sample consisted of individuals who had already accepted e-commerce services; lack of variance on behavior would have rendered the intention-behavior association meaningless.

Being a generic model of human behavior, TPB does not specify belief sets that are relevant to the specific behavior of IS acceptance. This makes it difficult to operationalize TPB or compare relevant beliefs across multiple acceptance contexts. Davis *et al.* [7] addressed this concern in their formulation of the technology acceptance model (TAM) by proposing perceived usefulness and ease of use as attitudinal beliefs influencing IS acceptance behaviors. Perceived usefulness refers to the expectation that IS acceptance will enhance task performance, and ease of use is the expectation that IS use will be relatively effortless. Theoretical support for these constructs comes from Porter and Lawler's [16] instrumentality model of job performance and IDT [17], while empirical support is provided by Davis *et al.* [7], Davis *et al.* [8], and Taylor and Todd [19], among others. Both constructs makes sense in e-commerce acceptance settings, as

individuals are likely to use e-retailing or e-brokerage if they perceive value in that service (i.e., find it useful) and find it easy to use. Additional constructs suggested by IDT, such as compatibility and trialability, lacks adequate explanatory power in IS acceptance contexts [13], and were therefore excluded from this study.

Given the relative nonsignificance of the link between subjective norm and intention reported in the empirical literature on IS acceptance, a careful examination of this construct and its determinants was in order. Subjective norm captures the social desirability of a behavior, which affect behavior in three ways: internalization, identification, and compliance [13]. Internalization results from accepting documented information from expert sources and integrating this information into one's cognitive system, identification results from the urge to be viewed as being similar to a desired person or referent group, while compliance is control exercised by a person or group via rewards or punishments. Karahanna [13] described two forms of social influence:

- 1) informational influence, when individuals accept information as evidence of reality; and
- 2) normative influence, when individuals conform to expectations of others [13].

Internalization can be viewed as informational influence, while identification and compliance are forms of normative influence.

The two forms of social influence (informational and normative) are in consonance with the communication network aspect of IDT [17]. This theory proposes that potential adopters may form opinions of an innovation based on information from two alternative sources: external and interpersonal. External influence refers to mass media reports, expert opinions, and other nonpersonal information considered by adopters in making a "rational" acceptance decision, while interpersonal influence refers to word-of-mouth influence by friends, colleagues, superiors, and other prior adopters known to the potential adopters. Evidence of both forms of influence are evident in the marketing literature (e.g., [10], [11]) and the IS product acceptance literature (e.g., [1], [5]). In B2C e-commerce contexts, industry surveys reveal that magazines and word of mouth are key variables considered by adopters in their ISP subscription decision [12].

Typical applications of TPB in IS acceptance contexts (e.g., [19], [21]) have viewed subjective norm as including only the normative influence (from peers and superiors influences). Informational influence is left out of this conceptualization, which may partially explain the nonsignificant relationship between subjective norm and intention in prior research (e.g., [7], [14], [19]). We overcome this limitation by broadening the scope of subjective norm construct to include both external (informational) and interpersonal (normative) influences, and combining peer and superior influences into a single interpersonal influence construct. The latter is justified since superiors at work typically have minimal influence on individual behavior outside of workplace settings (e.g., personal investment decisions), and even if such influence exists (by virtue of superiors' knowledge or experience), it is generally no stronger than that of peers with comparable knowledge or experience.

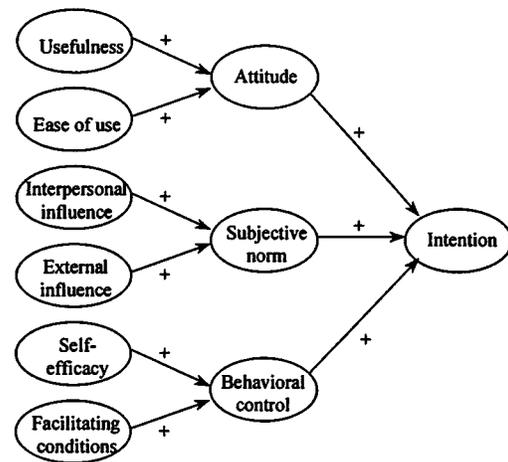


Fig. 1. Modified theory of planned behavior.

The determinants of behavioral control follows from Ajzen's [2] discussion of this construct. Self-efficacy (an individual's self-confidence in skills or ability to perform the intended behavior) is an internal constraint affecting e-commerce acceptance, while facilitating conditions (beliefs about availability of resources to facilitate that behavior) is an external constraint. Taylor and Todd [19] distinguished between two types of facilitating conditions: resources (e.g., time, money) and technology compatibility. Technology compatibility is not meaningful in this context, since e-commerce is based on open systems and TCP/IP protocols, which are compatible across diverse hardware, operating systems, and browser platforms. Also, Taylor and Todd [19] found technology compatibility to have a nonsignificant effect on behavioral control. Access to computers and the Internet, which may constrain e-commerce acceptance, are resource issues and can be subsumed under resource facilitating conditions. Hence, we drop technology facilitating conditions from our model, and define behavioral control solely in terms of self-efficacy and resource availability (resource facilitating conditions).

Several TPB-based studies have observed strong correlations among behavioral beliefs [19], [21]. TAM-based studies indicate strong correlations between ease of use and usefulness, leading Davis *et al.* [4] to propose a direct empirical link from ease of use to usefulness. Davis *et al.* [7] argued that ease of use of an IS, as perceived by adopters, are related to feelings about self-efficacy, which in turn may affect perceived usefulness of the IS. Xia and King [21] contended that "although behavioral and normative beliefs may be conceptually independent, they are not causally independent." Even Ajzen [2] admitted that "crossover effects" may be unavoidable between belief sets because these beliefs are intertwined to some extent. Given these assertions, the six behavioral beliefs are allowed to covary in our model (not shown in Fig. 1 for purposes of clarity).

Having justified salient constructs in our reconceptualization of TPB, we next examine the relative effects of these constructs on acceptance decisions for IS products and services. According to the services marketing literature, IS service (e.g., B2C e-commerce) acceptance may differ from IS product (hardware or software) acceptance because of four salient differences: intangi-

bility, simultaneity, perishability, and heterogeneity [20]. Unlike products, service acceptance does not result in ownership of the service (intangibility), services are produced and consumed at the same time (simultaneity), services perish if not consumed (perishability), and services may be perceived differently by different customers based on their personal expectations (heterogeneity).

Collectively, these four characteristics introduce significant uncertainties into service acceptance decisions. While IS products (e.g., software) have a predefined set of attributes (e.g., range of functionalities, data volume supported) that can be used for evaluation, intangibility of services makes their assessment much more complex and subjective. In other words, it is difficult to form positive or negative beliefs and attitudes about a service prior to experiencing it. Potential adopters typically attempt to minimize this uncertainty by soliciting opinions from prior adopters (interpersonal influence) or domain experts in the popular media (external influence). Hence, we can expect subjective norm to play a more significant role in service acceptance than in product acceptance, and attitudes to play a less significant role. The service marketing literature (e.g., [11]) justifies this shift in the locus of motivation by suggesting that information gathered from outside sources (word-of-mouth or mass-media) compensate for the lack of cognitive beliefs (e.g., usefulness) when it is difficult to form an attitudinal judgment about a service.

Further, IDT posits that external influences are generally more dominant in the initial stages of innovation adoption, since there are fewer prior adopters to drive word-of-mouth influence [17]. Early adopters are therefore motivated by mass media influences to try out a new service. With time, as the adopter population reaches “critical mass,” the adopter network self-sustains innovation adoption among later adopters via interpersonal influences. Since most e-commerce services are relatively recent, novel, and innovative, it is likely that external influences may play a dominant social force driving their acceptance. The IS product-service dichotomy does not have any implications for the behavioral control component of TPB.

### III. RESEARCH METHODOLOGY

A field survey of e-brokerage users was employed to empirically test the research model proposed earlier. We first describe the data collection process and then discuss the construction of research instrument used in this survey.

#### A. Data Collection

Data for this study was collected via an online survey of 172 electronic brokerage adopters. E-brokerages have experienced phenomenal growth in recent times, with the number of online investors in the U.S. increasing from 3 million in 1997 to over 5.2 million in 1998, percentage of online investors as a fraction of total investors increasing from 11% to 16%, and average trading levels among online investors increased by 18% during that time [6]. As such, e-brokerage is one of the fastest growing sectors of B2C e-commerce industry, as financial services firms reinvent the way they do operations in the emerging information economy.

TABLE I  
SAMPLE DISTRIBUTION BY E-BROKER

E-broker	Percentage
E-Trade	12.2%
Waterhouse (Toronto Dominion)	11.0%
Datek	10.5%
Charles Schwab	9.3%
Discover (Morgan Stanley)	8.1%
Ameritrade	8.1%
Suretrade	8.1%
DLJ Direct	6.4%
National Discount Brokers	5.2%
Scottrade	5.2%
Others	8.1%
Unspecified	8.7%

Subjects were self-selected for this study via messages placed on over 100 heavily-trafficked online message boards on Yahoo! Finance, Silicon Investor, Motley Fool, and Raging Bull web sites. These message boards are frequently visited by online investors, since they provide forums for online investors to share ideas or information on stocks of mutual interest. The posted message outlined the nature and purpose of the study and provided a hyperlink to an online survey form. As an incentive for completing the survey, respondents could sign up for small cash prizes. 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 fairly representative of the number of online investors visiting these boards on a regular basis). The subjects subscribed to a wide range of e-brokers (see Table I for adopter distribution by e-brokerage firm) for managing their personal investments (i.e., trading stocks, options, and mutual funds).

The online mode of data collection, though novel in the context of scientific research, was appropriate since we wanted to capture a cross section of online investors across multiple e-brokers (to eliminate any broker-specific bias). Such surveys are routinely employed by consulting firms for data collection purposes, by business firms for soliciting employee opinions on corporate issues, and by news organizations (e.g., CNN.com) for conducting online polls. Ninety-nine percent of the respondent group indicated that they were comfortable with the process of completing online forms (and reasonably so, since online trading itself involves filling out online forms), and hence the data collection method did not introduce any novelty bias on survey responses.

The respondent group of online investors ranged in age from 19 to 54 (mean 32.4 years), were 69% male and 31% female, had annual incomes between \$24 000 and 200 000 (mean \$75 000), had portfolio sizes between \$5000 and \$500 000 (mean \$40 000), and had a wide range of occupation (IS professionals, sales/marketing, banking/finance, law, and education) and educational levels (from college freshmen to doctoral degrees). While some subjects were relatively new to online trading, a few had used e-brokers since 1994. Thirty-four percent of respondents had transitioned from a traditional full-service brokerage (e.g., Merrill-Lynch) to e-brokerage, while e-brokerage was the first broker for the remainder of

the sample. Eleven percent of respondents indicated that they were currently using their second e-brokerage firm, citing dissatisfaction with service and higher commissions as primary reasons for discontinuing their prior e-brokers.

### B. Instrument Construction

Ten constructs were measured in this study using multiple-item, perceptual scales for each construct. Initial scale items were taken from previously validated measures in IS research (based on psychometric properties reported in the original studies) and reworded to relate specifically to the current context, i.e., acceptance of e-brokerage services for managing personal investments. All items were measured using fully anchored, 7-point Likert scales ranging from “strongly disagree” to “strongly agree.” Respondents were asked to recall back to the time prior to their *first* e-broker service (as opposed to their *current* service), and enter their perceptions on each item to the best of their recall.

Usefulness and ease of use were each measured using four-item scales taken from Davis *et al.* [7]. The self-efficacy, facilitating (resource) conditions, and interpersonal (peer/superior) influence scales were adapted from Taylor and Todd [19]. However, in order to meet the minimum three-item per scale guideline suggested in behavioral research, these three scales were expanded from their original two-item measure to include a third item assessing service adopters’ overall perceptions of the constructs [15]. Given the lack of an existing scale, external influence was measured using three items similar to interpersonal influence. Attitude and behavioral control were measured using scales adapted from Taylor and Todd [19], while the intention scales were taken from Mathieson [14]. The subjective norm scale was a variation of Mathieson’s [14] scale, adapted to fit the broader conceptualization of this construct. Initial scale items are reproduced in the Appendix, which were subsequently refined as described next.

## IV. DATA ANALYSIS AND RESULTS

Data analysis in this study was performed using EQS structural equation modeling approach using EQS for Windows (Version 5.4). EQS is a covariance-based 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 especially appropriate in areas with strong *a priori* theory [4], as was the case in this study. Model estimation was done in EQS using the maximum likelihood (ML) approach. ML was selected over more sophisticated approaches such as adjusted weighted least squares because it is less memory intensive and reaches solution convergence within fewer iterations. Data analysis proceeded in two stages: the measurement model was first examined for instrument validation and refinement, followed by an analysis of the structural equation model for testing associations hypothesized in Fig. 1. These results are described next.

### A. Measurement Model

The measurement model specified in EQS provided a convenient way of validating the research instrument via confirmatory

factor analysis (CFA). CFA was considered more appropriate than exploratory factor analysis, since we employed prevalidated scales. Results of the analysis, along with descriptive statistics (item means and standard deviations), are presented in Table II.

Construct validity for each scale was assessed by examining the standardized factor loadings obtained from the EQS measurement model. A commonly accepted norm for assessing construct validity is that each item should have a minimum factor loading of 0.60 on its hypothesized construct [15]. This condition was met for 25 out of the 33 items for the ten constructs (see Table II), while four others had factor loadings very close to the threshold value (i.e., in the 0.57–0.60 range). The remaining four items exhibited factor loadings less than 0.50 and had marginally significant or nonsignificant p-values. A closer examination of these items revealed that their semantics were somewhat different from that of the remaining scale items. For instance, IN3 (see Appendix) measured intention to accept e-brokerage “to the greatest extent possible,” while the remaining intention items were not concerned with the extent of acceptance, but simply with the intent to accept. Likewise, AT4 examined subjects’ expectations of the “experience” of using e-brokerage, in contrast to other attitude items that examined their overall affect with anticipated e-brokerage acceptance. These four items were thereby dropped from the model.

Cronbach alpha was calculated for each scale as a reliability metric. Six of the ten initial scales had Cronbach alpha exceeding the acceptance norm of 0.80. The four nonconforming scales were the same ones with poor factor loadings on at least one item. After dropping items with poor loadings, Cronbach alpha for three of the four revised scales (ease of use, attitude, and behavioral control) met the 0.80 threshold, while the intention scale had a reliability (0.78) very close to that norm.

This scale refinement process shortened the ease of use and attitude scales from four to three items per scale, and behavioral control and intention scales from three to two items per scale. A rerun of the CFA model (after dropping the four items) indicated that all remaining 29 items in the measurement model exhibited factor loadings of 0.59 or above, and were considered acceptable for the remainder of the analysis.

### B. Structural Equation Model

The first step in model estimation was to examine the goodness-of-fit of the hypothesized model (modified TPB) in Fig. 1. EQS estimates model fit using a chi-square test, in which the model  $\chi^2$  statistic is compared with  $\chi^2$  from a comparable model with uncorrelated variables [3]. Chi-square tests are especially sensitive to sample sizes, and the probability of rejecting a model increases with increasing sample sizes, even when the model is minimally false [4]. Consequently, in very large samples, virtually all models are rejected as statistically untenable. Hence, Bentler [3] recommended using the  $\chi^2/df$  ratio (*df*: degrees of freedom) as a more appropriate measure of model fit. This ratio should not exceed 5 for models exhibiting reasonable fit with observed data, as was the case with our research model ( $\chi^2/df = 1.87$ ).

EQS also provides additional goodness-of-fit measures such as Bentler-Bonett Normed Fit Index (NFI), Bentler-Bonett Non-

TABLE II  
INSTRUMENT RELIABILITIES AND VALIDITIES

<i>Likert-scaled construct</i>	<i>Number of items*</i>	<i>Mean</i>	<i>Standard deviation</i>	<i>Cronbach alpha*</i>	<i>Factor loadings (standardized)</i>
Usefulness	4	6.17	0.91	0.820	0.755 <sup>a</sup>
		5.59	0.87		0.609 <sup>a</sup>
		5.62	1.03		0.644 <sup>a</sup>
		5.52	1.02		0.585 <sup>b</sup>
Ease of use	4 (3)	4.69	1.10	0.721 (0.810)	0.800 <sup>a</sup>
		4.72	1.09		0.583 <sup>a</sup>
		4.67	1.51		0.491 <sup>c †</sup>
		4.40	1.27		0.662 <sup>a</sup>
Interpersonal influence	3	5.83	1.10	0.828	0.799 <sup>a</sup>
		5.05	1.20		0.853 <sup>a</sup>
		4.56	1.40		0.763 <sup>a</sup>
External influence	3	4.66	1.22	0.820	0.768 <sup>a</sup>
		4.52	1.69		0.723 <sup>a</sup>
		4.14	1.43		0.716 <sup>a</sup>
Self-efficacy	3	5.67	1.18	0.810	0.744 <sup>a</sup>
		5.38	1.15		0.665 <sup>a</sup>
		5.06	1.05		0.665 <sup>a</sup>
Facilitating conditions	3	5.13	1.09	0.803	0.716 <sup>a</sup>
		5.09	0.92		0.641 <sup>a</sup>
		4.62	1.25		0.657 <sup>a</sup>
Attitude	4 (3)	5.96	1.05	0.696 (0.802)	0.836 <sup>a</sup>
		5.74	0.96		0.613 <sup>a</sup>
		5.53	0.89		0.573 <sup>b</sup>
		5.48	1.52		0.396 ns †
Social influence	3	5.09	1.40	0.818	0.890 <sup>a</sup>
		5.01	1.48		0.863 <sup>a</sup>
		4.70	1.32		0.766 <sup>a</sup>
Behavioral control	3 (2)	5.14	1.20	0.724 (0.796)	0.674 <sup>a</sup>
		5.17	1.62		0.451 <sup>c †</sup>
		5.14	1.31		0.593 <sup>a</sup>
Intention	3 (2)	6.01	0.88	0.707 (0.782)	0.652 <sup>a</sup>
		5.53	0.96		0.654 <sup>a</sup>
		5.19	1.59		0.443 <sup>c †</sup>

Factor significance: <sup>a</sup>  $p < 0.001$ , <sup>b</sup>  $p < 0.01$ , <sup>c</sup>  $p < 0.05$ , ns = non-significant

† These items were dropped from the final scales.

\* Parenthesis indicate number of scale items and Cronbach alpha for revised scales (after dropping items).

Normed Fit Index (NNFI), and Comparative Fit Index (CFI). For models with good fit, NFI should have a value between 0 and 1, with higher values indicating better fit [3]. NFI is however affected by sample size and may not reach 1 with small samples, even if the model is correct. To overcome this problem, Bentler and Bonett [4] recommended a NNFI metric, which adjusts NFI for degrees of freedom. NNFI may fall outside the 0–1 range, but is invariant to sample sizes and incorporates model parsimony (via degrees of freedom) in fit estimation. Both NFI and NNFI are based on the assumption that the goodness-of-fit statistic follows a central  $\chi^2$  distribution, or at least can be approximated in large samples by a noncentral  $\chi^2$  distribution. This assumption is reasonable for true models or models with small misspecifications. If this assumption is not met, CFI is suggested as a third measure of model fit, which avoids underestimation of fit by NFI and NNFI in small samples [3]. In general, NFI, NNFI, and CFI greater than 0.90 are indicative of good fit [3]. This norm was met by our hypothesized model for the NNFI and CFI metric, while NFI had a value of 0.89. Overall, we were satisfied that our model demonstrated adequate levels of fit.

The second step in model estimation was to examine the significance of each hypothesized path 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. These data are provided in Fig. 2 (the measurement model and belief correlations are left out for purposes of clarity). All of our hypothesized paths were significant at .05 level. Attitude, subjective norm, and behavioral control collectively explained 52% of intention to use e-brokerage services, while usefulness and ease of use explained 60% of attitude, interpersonal and external influences explained 62% of subjective norm, and self-efficacy and facilitating conditions explained 25% of behavioral control.

Comparing the relative effects of each determinant on dependent variables, we found that subjective norm explained about the same variance (23%) in intention to use e-commerce services as did attitude and significantly higher than variance explained by behavioral control (5%). External influence explained 27% of the variance in subjective norm, compared to 35% explained by interpersonal influence. Usefulness ex-

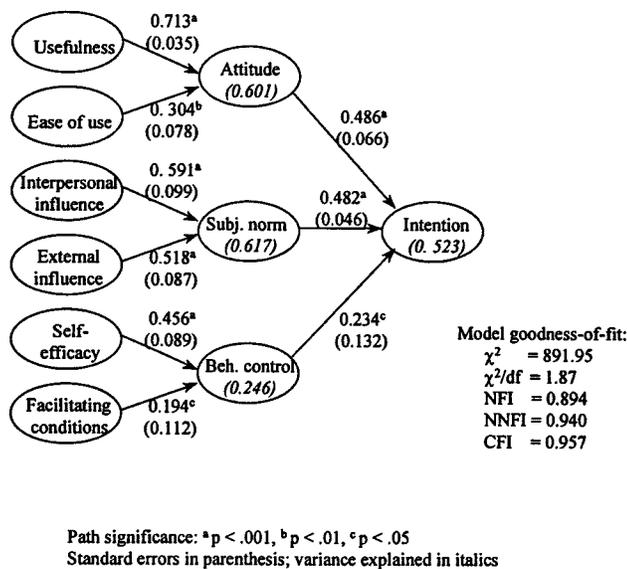


Fig. 2. Structural equation model results.

plained 51% of the attitude variance, compared to 9% explained by ease of use. However, facilitating conditions explained only 4% of the variance in behavioral control, compared to 20% explained by self-efficacy. While much of the path significance and variance explained are consistent with prior research (e.g., [7], [14], [19], [21]), significant differences include:

- 1) a large effect of subjective norm on intention (comparable to the effect size for attitude);
- 2) a relatively small effect of behavioral control on intention; and
- 3) a large effect of external influence on subjective norm (external influence was not tested in prior TPB-based research).

Implications of these differences in the context of e-commerce service acceptance are elaborated next.

## V. DISCUSSION

The goal of this paper was to examine to what extent TPB, a theoretical referent commonly used for explaining acceptance of IS *products*, could explain the acceptance of e-commerce *services*. Much of our current body of knowledge in IS acceptance is based on IS products, and salient differences in the nature and acceptance uncertainties of products versus services suggested that motivational forces driving their acceptance could be different. If resolved, the “anomalies” between IS product and service acceptance motivations can add valuable insights to our limited understanding of e-commerce service acceptance.

The total variance explained in intention to accept e-brokerage service (52%) is comparable to that in prior research in IS product contexts (62% in Matheson [14], 60% in Taylor and Todd [19], and 32% in Davis *et al.* [7] without behavioral control), but the relative contribution of attitudes, subjective norm, and behavioral control were remarkably different. In our study, subjective norm and attitudes had similar explanatory powers (23%), while behavioral control explained only 5%. This is in contrast to prior research on IS product acceptance,

where subjective norm had nonsignificant [7], [14], [21] or weakly significant [13], [19] effects on intention, and the explanatory power was shared between attitude and behavioral control.

Given the uncertainty associated with service acceptance (as opposed to product acceptance) and the ease of switching to alternative services, we expected that adopters would spend less effort in rationally evaluating a service prior to acceptance (low attitude-intention association) and instead rely on opinions communicated by prior adopters and the mass media (high subjective norm-intention association). This expectation was partially validated in our study, since attitude and subjective norm had similar effect sizes on intentions of e-commerce service acceptance. Marketing studies indicate that in the absence of first-hand experience with a product or service, individuals may rely on second-hand or vicarious experiences for deciding among behavioral choices [10]. Second-hand experience may be an effective, inexpensive, and convenient way of forming intentions about using new, unproven services such as e-commerce. At the same time, information obtained via second-hand experiences or the public press may be used to supplement attitudinal judgements for justifying behaviors with uncertain outcomes [10].

The smaller effect of behavioral control on intention suggests that behavioral control is an input to, but not a key motivational force behind, B2C e-commerce acceptance. E-commerce services are fairly simple to use (e.g., clicking hypertext links, completing online forms), widely available (by virtue of the omnipresence of the Internet), and fairly inexpensive (since microcomputers are today provided free with an ISP subscription and vice versa), resulting in higher levels of self-efficacy and facilitating conditions across the adopter population. High control beliefs imply that potential adopters may take these variables (and behavioral control, in general) for granted, so that presence of these variables is not factored into their behavioral choices, though their absence may hinder e-commerce adoption. In contrast, complex, proprietary software programs (e.g., data mining or enterprise resource planning packages), that require higher technical skills, analytical capability, or relevant business knowledge) for effective utilization, may impose greater cognitive (learning) burden on potential adopters, and would be reflected in their behavioral choice. An alternative explanation for the small effect of behavioral control on intention may come from high positive correlations between self-efficacy, facilitating conditions, and ease of use, as observed in our study (these beliefs were allowed to covary in our structural model). As suggested by Ajzen [2], it is possible that the effect of behavioral control beliefs on intention may be mediated by ease of use. Such linkage makes conceptual sense since lower self-efficacy and facilitating conditions would implicitly render e-commerce services less easy to use. If this is indeed the case, one can make a strong case for dropping the behavioral control construct (and its determinants) from TPB to make the model more parsimonious without substantive loss of explanatory content. This suggestion has been recently voiced in the marketing literature.

Attitude toward accepting e-commerce services was predicted primarily (51%) by usefulness and secondarily (9%) by ease of use. This is consistent with prior research on IS product

acceptance [14], [19]. The usefulness of using e-brokerage services is widely documented, namely lower commissions (than full-service brokerages), faster order placement and execution (via automated exchanges), convenient online access to information (e.g., company profiles, research reports), timely notification of relevant events (e.g., fulfillment of limit orders, increased trading activities), and borrowing privileges (via margin accounts). Recent volatility in stock markets (in part due to increased interest in Internet stocks) has further enhanced e-brokerages' perception as a way to quickly, conveniently, and economically execute trades without telephoning a broker [6]. The intuitive and easy to use web-based interfaces of e-brokerage services (which hides trade execution, security, and other complex technological issues from the user) may contribute to an underestimation of the effect of ease of use on attitude formation.

Interpersonal and external influences, respectively, explained 35% and 27% of the subjective norm variance in this study. These numbers are difficult to compare with prior research, given that no prior study to our knowledge has examined the joint effects of these influence sources. Few studies did not break down the normative components of subjective norm (e.g., [14], [21]), while others decomposed interpersonal influence into superior and peer influences, thereby ignoring external influence entirely (e.g., [19]). Our findings suggest that individual intentions about e-commerce service acceptance is shaped not only by the prior experience of earlier adopters (peers, superiors, family members, etc.), but also by the opinions of industry experts, as disseminated by the popular press. External influence may be particularly critical in generating awareness and trial in the initial stages of new technologies such as e-commerce services. For e-brokerage firms, external influence is generated via press releases of market research firms (e.g., Mediametrix, Gomez Advisors), trade journals (e.g., Computerworld, Datamation), advertisements in online and offline media, and promotional offers. However, the greater effect of interpersonal influence on subjective norm compared to external influence suggests that adopters may place more credence on personal experiences of prior adopters than on mass media coverage. Prior marketing studies (e.g., [10]) attests to the persuasive ability of word of mouth communication compared to print media communication. Hence e-commerce firms need to rethink how to tap into positive experiences of their existing customers as a means of driving future acceptance rather than relying solely on mass media.

Finally, self-efficacy explained 20% of the variance in behavioral control, while facilitating conditions explained only 4%. Taylor and Todd [19] found a significantly higher effect size for facilitating conditions, but this may have been an artifact of their study's context (use of a computer lab by undergraduate students), where inadequate access to specialized software may have imposed behavioral controls on subjects' behaviors. Such constraints generally do not exist with most e-commerce services, given its reliance on open standards, inexpensive hardware/software, and omnipresent Internet access. It is conceivable that under more restrictive conditions (e.g., use of a specialized software), facilitating conditions may play a larger role in determining IS acceptance behaviors. Also, the low overall

$R^2$  for behavioral control suggests that this construct may be more complex than previously thought and may have more underlying predictors than tested in this study. Additional research is required to explore the conceptual dimensions and measurement of this construct.

## VI. IMPLICATIONS AND LIMITATIONS

This study represented an initial attempt to extend our understanding of IS product acceptance to the case of e-commerce services. This was done by synthesizing elements of two distinct theories of product acceptance, TPB and IDT, reconceptualized the integrated framework within the context of e-commerce service acceptance, and tested the model using a field survey of e-brokerage acceptance.

From a research standpoint, our study observed that:

- 1) motivational forces impacting e-commerce service acceptance are different from those influencing IS product acceptance;
- 2) subjective norm is as important as attitudinal judgments in influencing service acceptance decisions, while behavioral control has a much smaller impact;
- 3) external influence is as important as interpersonal influence in individuals' formation of subjective norms toward e-commerce acceptance.

Studies of e-commerce acceptance should not underestimate the role of subjective norm, and should reconceptualize this construct to include external influence as a determinant. Segregating peer influences from superior influences may help explain IS acceptance in organizational contexts, but may not add much explanatory power in personal use B2C e-commerce contexts.

From a practitioner standpoint, our study suggests that the underlying dynamics driving consumer acceptance of B2C e-commerce services is different from that of IS products such as software. Understanding such differences is important because individual acceptance of such services is the key factor to firm survival and growth in this competitive industry. Our study underscores the importance of building public awareness of e-commerce services using both mass media exposure and positive testimonials from satisfied customers. Such testimonials should be backed by high quality service, because negative word-of-mouth can potentially inflict more damage to a firm's reputation and competitive position than the positive effects of positive word-of-mouth [10].

Finally, like most field surveys, our study suffers from some methodological limitations. First, respondents in our survey were asked to recall their perceptions at the time they first subscribed to an e-brokerage service, which may have been several years prior for some subjects. Subjects' ability to recall may have confounded their responses, thereby introducing a recall bias. To test for this bias, we divided our subject sample into two equal groups (earlier and later adopters) based on their date of initial adoption. Despite some minor differences among the two groups (e.g., earlier adopters' subjective norms were influenced more by external influence than interpersonal influence), the overall nature of path significance was unchanged.

This suggested that recall bias, even if it existed, did not greatly influence subjects' responses.

Second, the online approach to data collection may introduce some novelty effect on respondents. As stated before, this was not the case with our sample since 99% of the respondents indicated that they had previously filled out online forms and were fairly comfortable with online surveys.

Third, our subject pool consisted solely of e-brokerage acceptors. This was motivated by our goal to study service acceptance (as opposed to rejection); however, excluding eventual rejectors may have introduced some sampling bias in our survey. A carefully constructed sample, including both acceptors and rejectors, may be constructed to test for this bias, but such purposive sampling may compromise the randomization of the sample.

Fourth, our study may have suffered from a nonresponse bias in that our sample consisted of only 172 responses among a population of several million online and offline investors using e-brokerages and traditional full-service brokerages. Though there is no systematic way to cross-check our sample's perceptions against those of the entire population, we compared key demographic variables such as age, income level, and portfolio size between our sample and a larger sample (as a surrogate for the population) of 1015 online and offline investors as reported by Silicon Investor [18]. A difference of means test on age between the two groups was weakly significant ( $p = 0.05$ ), while those of income levels and portfolio size were nonsignificant. This suggests that our sample response was fairly representative of the target population.

Finally, the theories employed in this study (TPB and IDT) are only two "lenses" for viewing and interpreting causative relationships underlying e-commerce acceptance. As observed before, IDT focuses on innovation-specific characteristics and communication processes, while TPB is concerned with attitude formation via individual perceptions. Of particular interest to e-commerce firms would be an understanding of how they can optimize the service design or promotional features to appeal to specific adopter segments. To that end, neither TPB nor IDT offers a satisfactory answer, and future research may be diverted at building theories that provide a more complete explanation of e-commerce acceptance.

#### APPENDIX RESEARCH INSTRUMENT

This survey examines your perceptions of e-brokers in general, rather than your current e-broker. Please recall back to the time prior to your first e-broker, and answer the following questions to the best of your recollection.

Before subscribing to my *first* e-broker, I thought that ...

*Usefulness (adapted from Davis et al.1989):*

USS1. ... using e-brokers would improve my performance in managing investments.

USS2. ... using e-brokers would improve my productivity in managing investments.

USS3. ... using e-brokers would enhance my effectiveness in managing investments.

USS4. ... I would find e-brokers useful in managing investments.

*Ease of use (adapted from Davis et al.1989):*

EU1. ... learning to use e-brokers would be easy for me.

EU2. ... I would find it easy to manage investments using e-brokers.

†EU3. ... it would be easy for me to become skillful at using e-brokers.

EU4. ... I would find e-brokers easy to use.

*Interpersonal influence (expanded from "peer influence" scale by Taylor and Todd 1995):*

II1. ... my peers/colleagues/friends thought that I should use e-brokers for managing investments.

II2. ... people I knew thought that using e-brokers was a good idea.

II3. ... people I knew influenced me to try out e-brokers for managing investments.

*External influence (indigenously constructed):*

EI1. ... I read/saw news reports that using e-brokers was a good way of managing investments.

EI2. ... the popular press depicted a positive sentiment for using e-brokers.

EI3. ... mass media reports influenced me to try out e-brokers for managing investments.

*Self efficacy (adapted from Taylor and Todd 1995):*

SE1. ... I would feel comfortable using e-brokers on my own.

SE2. ... I would be able to use e-brokers reasonably well on my own.

SE3. ... I would be able to use e-brokers even if there was no one around to help me.

*Facilitating conditions (expanded from Taylor and Todd 1995):*

FC1. ... resources required to use e-brokers for managing investments were available to me.

FC2. ... I had access to hardware, software, and services needed to use e-brokers.

\*FC3. ... I was constrained by the lack of resources needed to use e-brokers.

*Attitude (adapted from Taylor and Todd 1995):*

AT1. ... using e-brokers for managing investments would be a good idea.

\*AT2. ... using e-brokers for implementing my investment plans would be a foolish idea.

AT3. ... I liked the idea of using e-brokers for managing personal investments.

†AT4. ... using e-brokers would be a pleasant experience.

*Subjective norm (adapted from Mathieson 1991):*

SN1. ... people (peers and financial experts) important to me supported my use of e-brokers.

SN2. ... people who influenced my behavior wanted me to use e-brokers instead of any alternative means.

SN3. ... people whose opinions I valued preferred that I use e-brokers for managing investments.

*Behavioral control (adapted from Taylor and Todd 1995):*

BC1. ... I would be able to use e-brokers well for managing personal investments.

†BC2. ... using e-brokers was entirely within my control.

BC3. . . I had the resources, knowledge, and ability to use e-brokers.

*Intention (adapted from Mathieson 1991):*

IN1. . . I wanted to use e-brokers rather than any full service broker for managing investments.

IN2. . . my intentions were to use e-brokers rather than any full service broker for managing investments.

†IN3. . . for managing my personal investments, I intended to use e-brokers as much as possible.

Note: All items were measured on 7-point Likert scales ranging from “strongly disagree” to “strongly agree.” Asterisk (\*) indicates reverse coded items. Items indicated by † were dropped from the final analysis based on poor loading on their hypothesized construct during confirmatory factor analysis.

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