System Design Features and Repeated Use of Electronic Data Exchanges

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ABSTRACT: Oftentimes researchers may not only generalize across a population, but may also extrapolate research findings across time. While either assumption can introduce difficulties, generalizing results in one time frame to another time frame may be especially perilous. We study a data exchange, and find that interventions designed to improve exchange features at two points in time have markedly varying effects, from an initial transaction use (time one) to a second transaction occurring two weeks later (time two). Our research objective is to test whether two system design features have the same effects on the intent to continue using an exchange in time two as they had in time one. The two features are control transparency (the availability of information cues) and interim shipping outcome feedback. These effects are mediated, in varying degrees, by perceived information quality. We use social exchange theory and social cognition theory to develop hypotheses regarding changes between time one (the first user transaction) and time two (the second transaction). These are tested using a combined experiment and survey. Supporting the theory, outcome feedback matters...
at time two even though it did not matter at time one. While control transparency has direct effects on a user’s intent to continue use of the exchange in time one, its effects are reduced in time two if negative outcome feedback is communicated to the user. Outcome feedback’s effects grow stronger from time one to time two vis-à-vis control transparency’s effects. This underscores how critical it is to examine such phenomena at more than one period of time. The study also suggests different strategies for managing data exchanges based on the time frame of use. At the initial transaction use, the exchange should make transparent high-quality information cues to its user. At the next transaction, it should provide feedback showing properly fulfilled orders. These findings have implications for both future research examining effective data exchange design and for professionals who wish to enrich electronic data exchange interactions.

**Key words and phrases:** control transparency, electronic data exchanges, outcome feedback, perceived information quality, system modifications, two-period model, usage continuance intention.

*After conducting a one-time experiment,* a researcher may feel rather secure that causality between variables has been established. Because of this, the researcher may next provide intervention advice for the practitioners in the situation, based on the experimental results. While random sampling can justify certain types of statistical generalization, we believe it does not justify recommending that the same advice used for time one (the initial system use) will always work for time two (repeated use). We believe that only studies that examine a phenomenon across time can justify recommending cross-time interventions.

A number of longitudinal studies have revealed that what works at time one may not work at later points in time. For example, Venkatesh et al. [83] found that effort expectancy, which predicted well in time one, quickly faded as a predictor of system use intention in later rounds. Gefen et al. [32] found that while perceived system usefulness did not predict purchase intentions for potential customers, it became a significant predictor for repeat customers. Venkatesh and Speier [82] found that at time one, both a positive and negative mood intervention significantly predicted behavioral intention to use a system; but at time two, only the negative mood intervention was significant.

Using a one time-period study to recommend a course of action across several time frames may result in wasted resources rather than good results. For example, the intervention from Venkatesh et al.’s [83] time one would have been to work on ways to reduce effort expectancy. While this may be effective in period one, such efforts would waste valuable effort in later periods. Based on Gefen et al.’s [32] results relating to potential customers, one might decide to ignore perceived usefulness. But this would have backfired, as usefulness was critical to repeat customers.

Because an electronic data exchange is a type of information system (IS), the same caveats apply. What works in the initial data exchange transaction may not work in the next transaction. This is especially applicable to our situation as we also study use
intention, which past studies have shown is affected by the timing of system use. For example, Venkatesh and Davis [81] find that subjective norm is an important predictor of perceived system usefulness and usage intention in earlier but not in later time periods. Similarly, Kim and Malhotra [46] report on the importance of intertemporal belief revision, and support their research model with four theory bases. In a two-wave study, they show that most constructs relating to use in time one predict the same construct in time two and that all four theory bases help explain such effects. This suggests that multiperiod phenomena are complex, and thus initial use predictors will not be adequate. Hence, we consider it important to examine electronic data exchange use across two time periods.

Cooperative electronic data exchanges play a major role in domestic and international commerce. For example, Greene [36] predicts that business-to-business (B2B) spending will double from $2.3 billion in 2009 to $4.8 billion by 2014, with emphasis on online customer interactions. Electronic data exchanges are often used in partnerships among firms, as reported by Vollmer [84]. Such exchanges are widely used by customer firms to order products and services, and by vendor firms to offer products and to coordinate inventory and supply chain issues. The data exchanges examined in this study are online ordering systems in which customers order on a spot market basis. Sharing information between firms enables faster and more cost-effective transactions [60, 63, 70, 86].

Our research objective is to test whether two system design features have the same effects on the intent to continue using an exchange in time two as they had in time one (when the initial transaction occurred). These two features are control transparency [72] and outcome feedback [21]. We chose these two system design features for a practical reason: because one can design these in ways that will enhance user experience with the exchange. We also selected these design features because they are both likely to positively affect user continuance intention.

Control transparency means the extent to which one provides information that allows the user to verify that a data exchange is operating properly. For example, whether or not the exchange validated and accepted an order should be transparent to the system user. Control transparency helps reduce uncertainty about the partner’s actions [72]. Outcome feedback means providing interim result data about the transaction. This concept is similar to Kirsch’s [47] outcome control concept. For example, outcome feedback includes receiving notice that one’s order has been shipped. We contrast the extent to which these two design features affect exchange use continuance intention in time one versus time two.

Some research has been done on data exchanges in the IS field. For example, Hart and Saunders [38] examined power and cooperation issues for electronic data interchange. Data exchanges are becoming increasingly critical among supply chain partners [15]. Hence, the study of design features in electronic data exchanges should enhance value in an exchange relationship.

Data exchanges typically pertain to relationships between buyers and sellers from two organizations. The broader phenomenon of interorganizational relationships (IORs) (e.g., [37]) enlightens data exchange studies. Data exchange relationships form a subset of IORs. Because data exchanges involve two organizations, research
on IORs helps us understand the factors that lead to IOR success and the importance of relationships [5, 37]. The IOR literature helps us understand some of the relationship constructs crucial to exchange success, such as risk, information sharing, trust, coordination, and similarity.

For IOR effectiveness, Gulati and Gargiulo [37] suggest that users need positive cues initially both to overcome “information hurdles” and to help strengthen the exchange relationship. Positive cues such as special site features help exchange users feel secure about the exchange even when uncertainty is high. Cues can include the features of exchange systems (e.g., control transparency), an area in need of more IS research attention.

We add to the literature by studying how two such system features affect use continuance intention. Studying system features answers the call to study the information technology (IT) artifact [65]. The IT artifact includes design features for Web exchanges. Further, we study the features over two time periods (i.e., the first and second transaction instances) instead of taking a static view. In particular, we address the following research question: How will exchange outcome feedback and control transparency features affect perceived information quality (PIQ) and user intent to use the exchange over the first two transactions? We also examine how PIQ mediates these relationships. These questions are examined by proposing and testing time-related hypotheses. This research contributes to the IT data exchange literature by showing how the exchange system’s design features affect PIQ and use intention differently at time two versus time one. The result is the ability to recommend different exchange management strategies for each time period.

Studying this phenomenon at two time periods is crucial to progress in this field of study. This is because prior studies of data exchanges have in general not examined how data exchanges work over time. Instead, they study the phenomenon at one point in time (e.g., [86]). However, the prediction of B2B data exchange system use is complex. How the parties interact is likely to change their perceptions over time. Understanding these changes requires studying data exchange use across the first two transactions rather than at one particular transaction.

Theory Development

A Dual Theoretical Framework

Most articles that predict use at one point in time employ a single overarching theory. For example, most technology acceptance model articles use either the theory of reasoned action or the theory of planned behavior (e.g., [17]). One theory can predict most phenomena at one point in time. However, changes in user perceptions across time are more complex and one simple theory may not explain everything that happens.

Using a two-theory strategy helps explain how data exchanges work over time. We primarily use social exchange theory (SET) to explain the data exchange phenomenon. SET is especially appropriate for data exchange research because it focuses on exchanges and because it explains perceptions about commerce. However, because the explanatory power of any theory is limited, we supplement SET with social cognition
principles. The latter helps us understand how data exchange features are evaluated in the user’s mind over time. Social cognition fits our research well because we study how the exchange user cognitively evaluates the exchange provider across two time periods. We next present a research model and evaluate how these two theories illuminate our study; we then develop research hypotheses.

Research Model

The research model (Figure 1) examines the effects of exchange system design manipulations (control transparency and outcome feedback) on PIQ and intent to continue using the exchange. The two time periods (T1 and T2) represent the two initial times a user transacts with the data exchange. We study a two-week time interval between the two exchange uses so that respondents may experience a time delay like the one usually needed for order fulfillment in real-world procurement situations. We examine exchange features in a context in which users need to fulfill important orders. This adds to the situational importance of this study’s context, which is needed in order to produce a more meaningful cognitive perception [23].

We chose to examine exchanges at T1 and T2 (the first two transactions) for two reasons. First, the initial time frame is influential because it often sets a pattern for beliefs between parties [6]. Second, the first two periods represent a time frame in which beliefs are relatively unstable and subject to change as new information is obtained. Therefore, T1 and T2 should provide a better contrast in beliefs than would two later time periods.
We study exchange system design features because prior research suggests they provide cues that will be important in determining exchange outcomes [37]. We utilize concepts developed in past research to study “control transparency” and “outcome feedback” [64]. Control transparency is defined as providing adequate information to verify that a data exchange is operating properly, whereas outcome feedback is defined as providing interim result data about the transaction.

The PIQ construct is defined as beliefs about the favorability of the characteristics of the exchange information [10, 18, 62, 64]. High PIQ gives the system user confidence in the vendor because having quality information suggests that exchange information is reliable, correct, responsive, and timely [33]. Within an expectation-disconfirmation framework, McKinney et al. [55] use PIQ to predict Internet consumer satisfaction, and DeLone and McLean [18] use PIQ to predict user satisfaction and system use. Our research model also controls for the effects of structural assurance on intent to use the exchange. Structural assurance is defined as “one’s sense of security from guarantees, safety nets, or other impersonal structures inherent in a specific context” [32, p. 64]. In a business-to-consumer (B2C) context, some level of structural assurance encourages the kind of cooperation and trust that produce Web site use, as Gefen et al. [32] found. B2B players also have a need for assurances that the transactional environment is safe and secure, so structural assurance applies here also.

Social Cognition Theory and Data Exchange Relationships

Social cognition means cognition within a social context [25, 49]. Many of the topics it addresses are treated in other domains without either the social or the cognitive component (e.g., motivation, per [25]). Social cognition focuses on specific social topics such as interaction, group memory, collaboration, social comparison, communication, and interpersonal conflict [49]. Several types of cognition are addressed by social cognition, including attribution, consciousness, automaticity, memory, and social categorization [25, 26, 49]. Social cognition assumes people perceive things “well enough” to address the events and decisions they encounter [24]. They are cognitive misers who analyze their relationships just enough to guide their interactions. The situation (e.g., their goal) governs how much attention they pay to relational events.

Social cognition principles include the idea that people make judgments at first based on whatever they know, but later they update their judgments as new information becomes available. This is especially applicable to the ongoing exchange relationship, as discussed later. Social cognition research finds that people make attributions in ways that are sometimes surprising. People treat negative information differently than positive information. This is also key to an exchange in which the user may receive either positive or negative information from the provider. People often change how they view negative information over different time periods of a relationship. They interpret events as if looking through the lens of organizational or personal objectives. Given these assumptions, social cognition provides an appropriate theoretical context for our two-period relational exchange study. In the following, we explain how social cognition complements SET.
Social Exchange Theory and Data Exchange Relationships

SET was developed to understand human social behavior in economic undertakings [40, 79]. Exchange relationships between actors involve actions contingent on rewarding reactions from others [7]. Social exchanges differ from economic exchanges in that obligations are not defined with contractual precision. Rather, two actors each expect a reciprocal but unspecified benefit that reflects a fair share or good efforts from the other [30]. The interaction may involve exchanging intangible resources, such as favors or information about a product or the status of an order. The quality and value of the information exchanged cannot be objectively measured, and neither can the reciprocal benefits. Thus, a dyadic social exchange involves both benefits and costs, both measured intangibly.

Each party is assumed to weigh the costs and benefits of the exchange in a rational manner. SET posits that people try to maximize their benefits and minimize their costs or seek the greatest net benefit possible [59]. SET implies that reciprocity is present and will be beneficial. One party would expect positive reciprocal actions, as confirmatory evidence that one can expect future benefits from the other. While SET entails an expectation of future return, such benefits are primarily valued as symbols of the supportiveness they express, rather than as tangible rewards [7]. SET was first developed by George C. Homans, a sociologist who tried to merge or combine principles from economics, sociology, and psychology to understand exchange relationships. As the theory examines human exchanges, we also employ its theoretical tenets to help us develop theoretical relationships in the context of our study.

SET has good explanatory power, but displays several weaknesses. Miller [57] critiques SET as being too atomistic, that is, reducing human behavior to a simplistic, two-person game. The same criticism has been levied at economic game theory for similar reasons. SET assumes that some kind of rational, calculative process underlies human behavior. As mentioned above, SET also displays the weakness of not always being able to explain the mental mechanisms that take place during a particular exchange.

Thus, social cognition and social exchange theories complement each other. SET addresses a phenomenon mainly at the dyadic interaction level. By contrast, social cognition emphasizes dyadic analysis on what the mind is perceiving during the interaction. Hence, social cognition helps us study data exchange relationships at a more detailed level of analysis. Based on this theoretical background, we now argue for hypotheses about how exchange relationships proceed over the two time periods.

Hypotheses Development

Hypothesized Effects of Control Transparency and Outcome Feedback on Perceived Information Quality

In line with the contingent nature of economic benefits due to system design features, Kayande et al. [43] find that the design of different types of feedback in a decision model affects user evaluations of the model. Outcome feedback is defined as the
availability of *specific* information about exchange outcomes, which in our case relates to shipment status, an interim (i.e., not a final) outcome. Obtaining specific positive feedback, for example, suggests that the exchange is working fine, and knowing this implies that the information the exchange provides is probably also of high quality. A more general form of outcome feedback that provides only general confirmatory information about exchange outcomes should elicit similar but perhaps not as strong beliefs about the vendor or the system. Receiving specific negative feedback, on the other hand, casts doubts on the exchange, including concerns about whether the information provided to the user is transmitted in a complete and accurate manner, thus questioning the quality of the information provided by the exchange. Outcome feedback should affect PIQ because it provides information that leads one to form opinions about the vendor or its system. A similar process takes place in game theory experiments. Participants decide their level of cooperation and then receive feedback in terms of the outcomes of that decision; then the cycle repeats. Game theory researchers have found that people adjust their behavior depending on the feedback they receive from prior rounds (e.g., [2]).

Outcome feedback will probably not be an effective predictor of PIQ at T1. People tend to give the other party in the exchange the benefit of the doubt when they begin to interact [52, 58, 71], and this is beneficial to the early relationship [48]. Since both exchange parties are ready to transact for mutual benefit, it is natural to assume that the other party is reliable and that the relationship can be improved over time; otherwise, relational conflict and distrust will escalate [74]. SET would suggest that the benefits of moving forward in such a reciprocal relationship would offset the small risk that a party would both begin poorly and continue poorly. Likewise, most people would initially assume that the exchange system will provide high-quality information, unless proven otherwise. This attitude is reflected in what is sometimes called the “trusting stance” people take [56], temporarily suspending judgment to assume that the other is either benevolent or at least benign [54]. Because of this stance, social cognition suggests that people often overlook initial bad feedback about the other party, creating positive illusions about them [24] or choosing to give them another chance, in the hope that the original negative feedback was the exception rather than the rule. This is especially true if the other party is able to help one meet one’s objectives, such as obtaining needed products or services. Because general confirmatory or specific positive feedback types are anticipated and negative feedback is overlooked at T1, outcome feedback is not expected to affect PIQ at this point. Even negative feedback will usually be overlooked at first. Social cognition supports this. Social cognition researchers find that “people make judgments when they believe the information they have is of a socially acceptable quality and quantity” [24, p. 161]. The exchange member will not feel that the information from a single exchange experience is enough to conclude that the other’s PIQ is good or bad. In part, this is because they tend to socially categorize a new partner as one who will behave like regular business partners. Thus, specific positive or general types of feedback will not likely influence PIQ just after T1.

As the parties interact over time, however, they refine and solidify their judgments of each other. SET suggests that relationships become stronger based on feedback [7].
Jarvenpaa et al. [41] found that if online course team members did not respond positively to each other at first, their opinions of each other decreased rapidly. In our setting, each interaction provides more evidence that the exchange partner either is, or is not, a good partner. Feedback at T2 provides the needed information to confirm one’s initial opinion. Therefore, experiential outcome feedback is likely to replace initial assumptions about the other party, which are not based on solid evidence [22]. Similarly, social cognition research shows that people make judgments over time based on what they consider reliable information [24]. Repeated information would seem more reliable than one data point, which is easy to explain away. For this reason, outcome feedback is likely to affect PIQ at T2, even though it does not at T1:

_Hypothesis 1a: While PIQ will not be significantly affected by general or specific positive outcome feedback at T1, PIQ will be significantly higher when outcome feedback is not negative at T2._

Control transparency means having adequate information to verify that a data exchange is operating properly. For example, when an order system provides order input validation (i.e., “this order is correctly entered”), it makes the order process transparent to the user and helps the user feel that the process is properly controlled. Control transparency is a key factor influencing PIQ because it provides positive cues about the vendor. It is also an important dimension of the IT artifact in a data exchange relationship [65], one that helps shape PIQ [62]. Exchange providers who offer control transparency enhance the availability of information about how well transactions are proceeding. Thus, the availability of control transparency should enable a user to more readily evaluate PIQ in the initial exchange relationship. Social cognition suggests that people make quick judgments to categorize the other party as good or bad [25]. In the absence of solid facts about the partner, control transparency provides a solid cue that would be readily transformed into PIQ beliefs.

Providing control transparency makes information available to the buyer, which signals that the data exchange provider wants to cooperate and help the buyer. This is a positive cue that will then be reciprocated by the buyer. To the extent that increased transparency shows that controls are effective, then under this context, SET would suggest that the norms of reciprocity would encourage the buyer to have positive thoughts toward the exchange [7], which will induce favorable PIQ.

We argue that this effect will continue over time. SET, with its emphasis on iterative cooperation [7], supports the idea that one’s opinions about the other are enhanced over time as beliefs are reinforced through interactive experiences. Mutual reciprocation would take place [7]. Each time customers use an exchange with control transparency, they will see the system validate their order inputs, building their confidence in the system’s information quality. The transparency of the information thus provides information that allows one to verify that things are going right. Each time a transaction takes place, this information should confirm or reinforce exchange partner beliefs that the vendor system provides adequate information quality.

Social cognition theory also supports this effect. People feel a need to have more information about their partner, especially at first, and try to structure things to gain
that information [24]. People are interested in interactions that allow them to meet their goals [23]. Control transparency provides information relevant to goals. Each event provides information that allows users to update their beliefs about the other party. In our case, control transparency continues to give cues and hints about the quality of the information received. Hence, control transparency should continue to influence PIQ at T2 as well as T1:

Hypothesis 1b: Just as PIQ will be higher at T1 under conditions of high (rather than low) control transparency, this effect will continue at T2.

Feedback about interim outcomes is likely to be an important predictor. If one finds out through feedback that the goods one ordered have been shipped and are arriving on time, this should have a positive effect on intent to use because it appears that the vendor has fulfilled its obligations well. Social cognition theory would suggest that feedback about the partner’s actions allow one to achieve one’s goals, which are monitored over time (e.g., [24]). While specific positive or general feedback encourages one to continue to use the exchange, specific negative outcome feedback discourages one from continuing to use the exchange. As presented in H1a, PIQ is expected to be affected by outcome feedback at T2. However, because of the potential effect of outcome feedback on intent to use, PIQ might not mediate the relationship between outcome feedback and intent to use. Social cognition theory suggests that failure to meet goals in an exchange relationship (which is equivalent to providing negative feedback) is more discernible and more readily recalled in memory than the act of confirming expected behavior (which is more similar to specific positive or general outcome feedback). Because of this, we do not advance a theoretical expectation as to whether PIQ will mediate the effects of specific positive or general outcome feedback on intention to use the exchange.

Hypothesized Effect of Negative Outcome Feedback on Intent to Use

We do expect, however, that negative outcome feedback will have a specifically identifiable effect. This effect emphasizes the predictive power of negative feedback. To our knowledge, SET does not distinguish in any explanatory way between positive and negative feedback. However, social cognition theory does. Social cognition suggests that negative feedback regarding the other party “is perceived to be highly diagnostic” [24, p. 165]—that is, more weight is put on negative information, perhaps because it presents a threat that one will not be able to achieve one’s objectives. Negative feedback is remembered better than positive feedback about the other unless positive expectancies about the other are strongly ingrained [24]. In our study, we examine the first two transactions between exchange partners, so the expectancies are probably not ingrained. This suggests that negative feedback will tend to be a strong predictor, perhaps strong enough to overpower the effect of control transparency.

Social cognition suggests that this is because perception is goal oriented [23]—that is, “interpersonal thinking is embedded in a practical context” [23, p. 882]. People analyze the other party within the context of their own goals. For example, if the ex-
change user has a goal to procure 1,000 pounds of sheet aluminum by a certain date, he or she will evaluate the exchange partner based on how well the exchange partner helps the user achieve that goal. Positive feedback on this is simply confirmatory. But negative feedback will likely cause serious concern about one’s ability to achieve a goal. Therefore, negative feedback will affect perceptions in a powerful way.

Similarly, cognitive research on trust supports the strength of negative feedback. Hart and Saunders suggest “trust may be challenged at any given time by any number of IOR events” [38, p. 24]. Lewicki and Bunker [50] theorize, for example, that building trust takes place gradually, one step at a time. However, as in the game “Chutes and Ladders,” distrust can be created both easily and quickly. Scholars studying the rebuilding of trust note that it is harder to restore trust than to build initial trust [45]. Negative events are better remembered than are positive events [76], indicating that negative feedback from events will often have a profound effect.

Applied to our context, we argue that customers will pay increasing attention to negative outcome feedback over time. When negative feedback is repeated, it becomes a clear, experiential factor predictive of one’s beliefs in the other party. For example, if someone loses his or her identity online once, he or she may think of it as a chance occurrence. But if it happens again, that person will likely seriously consider never again providing personal information online. Similarly, negative outcome feedback will exert a very strong influence on such exchange outcomes as intention to use the exchange. We predict that negative outcome feedback at T2 will be salient enough to outweigh or negate the effects of control transparency on intention to use:

Hypothesis 2: By T2, in the presence of negative outcome feedback, a change from low to high control transparency will no longer be associated with a significantly positive increase in intention to use the exchange. The same will not be true in the presence of specific positive or general outcome feedback.

Hypothesized Mediation Effects of Perceived Information Quality on Intent to Use

PIQ should positively affect system outcomes, as proposed by DeLone and McLean [19]. A new exchange customer who believes the vendor provides quality information is also likely to form an intent to use the system in the future. This is because a high level of PIQ sends a strong signal to the user that the transaction will be performed properly, and this encourages future use. A similar effect could be expected at the second time period of use. As a result, PIQ is likely to have a strong effect on intention to use at both T1 and T2. Control transparency will also be positively related to intention to use the exchange. If control transparency is high, it indicates that the vendor is providing enough information about how the transaction is progressing, which should positively influence a customer’s intent to continue using the exchange.

However, PIQ should fully mediate the effects of control transparency on intention to use. Control transparency plays a key role in the development of PIQ because it is the transparency of the system information that allows positive PIQ to be formed initially.
Thus, the specific communication built into control transparency forms, and relates to, the general belief that the vendor’s information has high quality. Because they are strongly related, control transparency will not add much to the predictive effects of PIQ. Further, PIQ is likely to be a strong predictor of intention to use, and its effects should dominate those of control transparency, rendering it a nonsignificant predictor. This is because people are more concerned about the quality of the information given (as in PIQ) than about the amount of information given (as in control transparency). Thus, PIQ should fully mediate the effects of control transparency at T1. At T2, PIQ will continue to be an influential factor and will thus continue to mediate control transparency. SET would suggest that each interaction of the user with the exchange system provides a more solid factual basis for PIQ, and therefore it should become an even more powerful predictor of intention to use the exchange. Social cognition would suggest that people seek more information to back up their judgments. Thus, they will increasingly rely on the belief (e.g., on PIQ) as more information is made available that underlies the formation of such a belief:

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\text{Hypothesis 3: In both T1 and T2, PIQ will fully mediate the relationship between control transparency and intention to use the exchange.}
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Research Method

Research Approach

This study employs a web-based exchange that simulates a real-world exchange environment. Because the simulated exchange was designed to manipulate the factors of interest in this study, it provides an appropriate context for experimental control. Like prior studies, our research approach relies on experimental manipulation of certain variables and questionnaire-based measures of other variables [44, 80, 88]. Our research approach is also similar to the one in Webster and Trevino [87], in that we provide subjects an experimental experience meant to simulate a real-world exchange and then elicit their reactions via a questionnaire. As described in the Experimental Design section below, we manipulate control transparency and outcome feedback. Because real-world exchanges employ different levels of such design features, we experimentally examine the effects of such system design interventions. Use of a two-phase simulated exchange increases the study’s relevance, in that we introduce conditions similar to those found in real-world exchanges.

While attaining relevance in our setting is important, our use of experimental controls in a repetitive-use environment also increases the study’s rigor, as follows. First, we administered the experiment at two time periods (T1 and T2) with an intervening two-week time lag, which reinforces expectations of future exchange performance. Second, we more reliably capture the formation of perceptions in a dual-period setting than in a single-period experiment. Thus, it is appropriate to manipulate control transparency and outcome feedback both to improve study rigor and also to reflect exchange design differences seen in practice. We researched a number of actual exchange sites as input to our exchange design.
Participants

We employed subjects enrolled in an executive/evening MBA program at a large U.S. university as well as professionals who were co-workers of those subjects. The timing of distribution of the experimental packages was thus controlled and monitored electronically.

Data were collected from 158 subjects in T1 (57 students and 101 professional colleagues), and from 145 of the same individuals in T2 (55 students and 90 professionals). As part of subject attrition, four observations were dropped from further analysis because of their use of the extreme point on all of the response scales. In T1, the 101 professional participants were employed full-time as procurement managers (20 percent procurement/purchasing/supply chain managers), business experts (19 percent general managers, 17 percent accountants/auditors/consultants, and 14 percent marketing/sales associates), and technical experts (15 percent design engineers/production managers, and 15 percent systems administrators/programmers). T1 participants also included 57 full-time graduate students (36 percent of the total), 81 percent of whom also reported having some real-world experience. Because real-world experience helped respondents relate to the exchange buyer role, this sample was appropriate for this study. We gave the participants detailed instructions and practice so they felt comfortable with the task (described below). Further, of the 158 T1 subjects, 65 reported having purchasing management responsibility at some time in their professional careers (for an average of 6.93 years). Sometimes studies are questioned because they ask subjects to play a role to which they cannot relate [35]. We address this concern by using subjects with business experience.

The mean participant age was 30 years, with a standard deviation of 9.5 years. On average, full-time professionals had worked 11 years, and 53 percent were male, while students had worked 1.74 years and 52 percent were male. t-tests revealed no significant mean differences on any measured construct when classifying sample groups according to professional expertise (purchasing managers, technical experts, business experts), student versus nonstudent, or past purchasing management responsibility versus none.²

Experimental Design

The experimental design varied control transparency (high/low) and outcome feedback (specific positive feedback, specific negative feedback, and general feedback). Thus, the design is a 2 × 3 fully-crossed between-subjects arrangement (Table 1). We randomly assigned treatments by varying the Web-based data exchange model that the subjects used (see Figure 2 for a pictorial description of the workflows of simulated data exchange designed for this study). Exchanges A and B varied control transparency. Exchange A applied input format and data content validation controls, in that it included programmed edit checks on input data and also evaluated validity of input values through real-time verification against values stored in a Web accessible database. Exchange B applied none of these controls. Users of Exchange A were shown
Table 1. Experimental Design

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<tr>
<th>Control transparency</th>
<th>General feedback</th>
<th>Specific positive</th>
<th>Specific negative</th>
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<tr>
<td>High</td>
<td>Exchanges A and C</td>
<td>Exchanges A and D</td>
<td>Exchanges A and E</td>
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<tr>
<td>Low</td>
<td>Exchanges B and C</td>
<td>Exchanges B and D</td>
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</tbody>
</table>

Notes: Letters indicate the types of data exchanges used in each experimental cell. The first letter indicates the exchange used to vary control transparency (A or B; high/low transparency, respectively) and the second letter indicates the exchange used to vary outcome feedback (C, D, or E; general, specific positive, specific negative feedback, respectively).

Figure 2. Workflow of Simulated Data Exchange System

an additional screen notifying them about the successful or unsuccessful outcome of controls applied while no control validation screen was shown to users of Exchange B (see Figure 3 for an example of one screen display viewed). Exchanges C, D, and E varied outcome feedback. Once a transaction was accepted, the user received one of three messages. In the general feedback condition (Exchange C), the user was notified that his or her order was received and would be shipped the next business day. In the specific positive feedback condition (Exchange D), the user received a shipping notification report stating that all items ordered were shipped with an expected delivery date that matched exactly the user specifications. In the negative feedback condition (Exchange E), the shipping notification report said that only half of the quantity ordered was shipped, and that it was expected to arrive at the customer’s location five business days later than required (see Figure 4 for an example of one screen display viewed). Subjects were assigned to the same experimental condition across T1 and T2.
Figure 5 presents in diagrammatic form the steps followed in the experiment. In T1, participants typed into a browser a Web address that corresponded to their treatment. The online page welcomed subjects to the “PanAmerican Industries, Inc.” Web site, a fictitious supplier of industrial raw materials. It then provided an additional page of information about the role of Web-based data exchanges in today’s business environment. This provided the subjects a common knowledge base. Next, three pages of step-by-step directions taught participants how to use their assigned data exchange. Specific directions ensured that subjects assigned to the high control transparency
condition (Exchange A) entered invalid data that should result in an error message, thus experiencing the real-time controls applied by the programs (see Figure 3 for an example screen display after controls were validated). All of the subjects worked with two practice transactions and interacted with the programs through the whole cycle of registering a new customer, logging in the customer, completing a raw materials order form, viewing transaction data validation information (if in Exchange A), and receiving notification about the disposition of their processed purchase order (according to their feedback condition). Each subject’s practice session had the identical exchange features as their treatment did, thus familiarizing subjects with their assigned exchange.

After the practice session, the instructions asked all the subjects to portray the role of a plant purchasing manager ordering raw materials (aluminum sheets) required for their plant’s production process. The subjects were told they needed to have the materials in stock within five business days because their plant produces expensive products for large industrial customers, and they operate on a just-in-time format with very short lead times. Next, we told the subjects their plant’s supplier had recently developed the Web-based ordering exchange on which they had just practiced. The subjects were then asked to enter an actual order transaction. All transaction data used, including product ordered, price, required quantity, and required delivery date, were identical across treatments. At T2, the same procedures were followed, both in the practice session and in the transaction session.

Construct Measurement

The experimental packages in both phases of the experiment then asked the subjects to answer questions measuring the endogenous model variables (see the description
below and the Appendix). The study used a reflective PIQ scale, with items selected from Bailey and Pearson [3], Bovee [9], Doll and Torkzadeh [20], and Goodhue [33, 34]. The items represent the currency, accuracy, relevance, completeness, and reliability aspects of the data exchange, all often-used PIQ dimensions. These sources provide a well-rounded sample of PIQ scale items.

The first four intention to use items were adapted from Davis [16] and Liu et al. [51]. To supplement these, intention to use items five and six were adapted from Pavlou [66]. The four items measuring structural assurance in the specific Web exchange were adapted from Gefen et al. [32]. Structural assurance was used as a control variable due to its significant effects in Gefen et al. [32].

Manipulation and Control Checks

The last section of the Appendix displays the manipulation checks for control transparency and outcome feedback. Manipulation check items were placed after all the model variable items in order to avoid inducing demand effects. We used data from both phases of the experiment in order to test for experimental manipulation effects and to carry out control checks. $F$-tests on the control transparency manipulation check item show that subjects in the high control transparency condition provided significantly higher ratings ($t_1 \mid t_2$ means: high = 4.08 | 4.59, low = 3.00 | 2.88, $F = 16.83 | 47.92$).

The general feedback manipulation check item differed across the three feedback conditions ($t_1 \mid t_2$ means: general = 5.29 | 5.39, specific positive = 3.73 | 4.32, specific negative = 3.00 | 2.38, $F = 18.20 | 46.75$), as did the manipulation item for positive feedback ($t_1 \mid t_2$ means: general = 3.45 | 3.17, specific positive = 4.85 | 5.04, specific negative = 2.37 | 1.85, $F = 15.61 | 49.58$), and the item for specific negative feedback ($t_1 \mid t_2$ means: general = 2.58 | 2.90, specific positive = 3.01 | 2.78, specific negative = 5.57 | 5.90, $F = 59.37 | 81.17$). These results show that each manipulation worked. Also in support, we found significant mean PIQ item differences ($p < 0.001$) between exchange pairs C, E (general and specific negative feedback), and D, E (specific positive and specific negative feedback). However, no significant differences in mean PIQ values were observed in exchange between pairs C, D (general and specific positive feedback). These results persisted in both T1 and T2. Hence, we combined the general and specific positive feedback conditions into a single positive feedback group for further analysis. Further, $F$-tests of demographics showed that gender ratio, age, and work experience did not differ across the six experimental conditions.

Questionnaire Item Quality Checks

We used the T1 data ($n = 158$) to initially establish the quality of items. In accordance with research guidance [8, 13], we took three steps to cull out measures that did not perform. First, we examined measurement invariance of each scale to see whether the measurement items varied/covaried in the same manner across treatments, using Box’s $M$ [11]. The test examines differences in the variance–covariance matrix of each set of scale items forming the same construct across the six treatment groups.
(when all items measuring a single construct are entered in the same model at the same
time). We first determined the $F$-value of the full model with all items included. If this
results in an nonsignificant $F$-value, the null hypothesis of measurement equivalence
is not rejected and the test is satisfied. If the null was rejected, we then examined indi-
vidual item invariance by following a variant of a nested models procedure (e.g., [1]).
Each item is sequentially dropped from the set (with replacement) and changes in
the Box’s $M$ and related $F$-statistic are recorded. An item is declared invariant if the
$F$-statistic changes from significant to nonsignificant when that item, by itself or with
a different item, is dropped from the set. As a result of this test, the following items
violated measurement invariance conditions and were eliminated: PIQ items 1, 2, 5,
7, and 10, intention to use items 4 and 5, and structural assurance item 4.

Second, we assessed individual item reliability by examining an item’s factor loading
on its own construct. As a rule of thumb, an item must load at least 0.5 on its own
construct (e.g., [88]). All items passed this test. Third, we examined item loadings
and cross-loadings derived from a partial least squares (PLS) measurement model,
with no problems. Before eliminating any of the items in each of the above three
steps, we made sure that their removal did not affect the theoretical significance of
their respective constructs [32]. For example, the remaining PIQ items still cover all
the dimensions mentioned above.

Data Analysis and Results

to ensure the comparability of our results across the two time periods, we used
observations that survived both rounds ($n = 145$) to examine the measurement model
and to test our hypotheses. We used analysis of variance (ANOVA) methods to test
the experimental effects and PLS to test the measured part of the research model.
The PLS method applies best to such nascent theories and complex models as this
study embodies [12, 27]. PLS simultaneously assesses the structural (theoretical)
and measurement model and produces $R^2$ estimates used to examine model fit, as in
traditional regression analysis. We used bootstrapping with 200 resamples to assess
path estimate significance.

Measurement Model and Validity Tests

We used the 145 observations to test the measurement model for convergent and dis-
criminant validity [8, 78]. Convergent validity means how well each latent construct
captures the variance in its measures. Convergent validity is tested via individual
item reliability (standard: 0.5 or above), composite construct reliability (similar to
Cronbach’s alpha—standard: 0.7 or above), and average variance extracted (AVE),
which measures whether the variance the construct captures exceeds the variance
due to measurement error (standard: 0.5 or above) [28]. We used PLS-generated
data to estimate item-latent construct loadings and cross-loadings by correlating the
standardized rescaled indicators of items on constructs with the construct scores (see
also Gefen et al. [31]). In both phases, each item loaded on its own construct at 0.5 or
Discriminant validity means the extent to which measures of constructs are empirically distinct [16]. First, we assessed discriminant validity by examining the extent to which each measured construct has higher loadings on the indicators in its own block than indicators in other blocks [12]. All the items passed this test. Second, we compared interconstruct correlation coefficients to the square root of the AVE of each construct (shown on the diagonals of the Table 2 correlation matrix for each phase). This test was also met. We also performed an exploratory factor analysis, which supported these convergent and discriminant validity results.

Experimental Treatment Effects

We further examined the efficacy of experimental manipulations using multivariate analysis of variance (MANOVA) with PIQ and INTENT as dependent variables and control transparency and outcome feedback as factors. The model estimated values of PIQ and INTENT at both T1 and T2, while the two conditions of general and positive feedback were combined for analysis (similar results were obtained using all three feedback levels). Table 3 presents the results.

Table 3 shows the main effect of control transparency was significant in both phases on PIQ and INTENT. A comparison of the levels of significance across the two phases (Panels A and B of Table 3) indicates that control transparency consistently affects model constructs in both experimental phases. The effects on both constructs increase in strength across time. The consistent effect of control transparency on PIQ across T1 and T2 supports H1b.

The effect of outcome feedback, by contrast, varied across time periods. Supporting H1a, outcome feedback had nonsignificant effects on PIQ at T1, but significant effects at T2 ($p < 0.01$). Feedback significantly affected intention to use the exchange in both periods (Table 3). At T2, outcome feedback gained in importance in its effects on both constructs (Table 3). Interaction effects between outcome feedback and control transparency were not significant at T1 or T2. The mean scores of the endogenous constructs across conditions were as expected (Table 3).

Testing of Research Hypotheses 1a, 1b, and 2

To further examine research H1a, H1b, and H2, we used the orthogonal planned contrasts reported in Table 4. To test H1a (outcome feedback yields higher PIQ only in T2), the planned contrasts compare the effect of outcome feedback on the endogenous constructs under high and low control transparency conditions (planned contrasts “c” and “d” to test H1a). Table 4 shows that the contrast between positive and negative outcome feedback (contrasts “c” and “d”) did not result in any significant differences for PIQ at T1 (Panel B, contrast “c”: $p = 0.12$; contrast “d”: $p = 0.57$). However, at T2, feedback resulted in significant differences in PIQ when high control transpar-
Table 2. Measurement Model Results ($n = 145$)

<table>
<thead>
<tr>
<th>Items</th>
<th>T1 model</th>
<th>T2 model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PIQ</td>
<td>INTENT</td>
</tr>
<tr>
<td>PIQ3</td>
<td>0.74</td>
<td>0.48</td>
</tr>
<tr>
<td>PIQ4</td>
<td>0.73</td>
<td>0.45</td>
</tr>
<tr>
<td>PIQ6</td>
<td>0.8</td>
<td>0.54</td>
</tr>
<tr>
<td>PIQ8</td>
<td>0.75</td>
<td>0.53</td>
</tr>
<tr>
<td>PIQ9</td>
<td>0.84</td>
<td>0.62</td>
</tr>
<tr>
<td>PIQ11</td>
<td>0.88</td>
<td>0.61</td>
</tr>
<tr>
<td>PIQ12</td>
<td>0.84</td>
<td>0.51</td>
</tr>
<tr>
<td>INT1</td>
<td>0.66</td>
<td>0.97</td>
</tr>
<tr>
<td>INT2</td>
<td>0.63</td>
<td>0.98</td>
</tr>
<tr>
<td>INT3</td>
<td>0.66</td>
<td>0.96</td>
</tr>
<tr>
<td>RINT6</td>
<td>0.6</td>
<td>0.87</td>
</tr>
<tr>
<td>STR1</td>
<td>0.66</td>
<td>0.63</td>
</tr>
<tr>
<td>STR2</td>
<td>0.58</td>
<td>0.62</td>
</tr>
<tr>
<td>STR3</td>
<td>0.52</td>
<td>0.52</td>
</tr>
</tbody>
</table>

**T1: Descriptives and correlations**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard deviation</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PIQ</td>
<td>3.92</td>
<td>1.42</td>
<td>0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. INTENT</td>
<td>4.26</td>
<td>1.70</td>
<td>0.67</td>
<td>0.94</td>
<td></td>
</tr>
<tr>
<td>3. STRasr</td>
<td>3.41</td>
<td>1.53</td>
<td>0.62</td>
<td>0.62</td>
<td>0.94</td>
</tr>
<tr>
<td>ICR</td>
<td>0.93</td>
<td>0.97</td>
<td>0.96</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AVE</td>
<td>0.64</td>
<td>0.89</td>
<td>0.89</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**T2: Descriptives and correlations**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard deviation</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PIQt2</td>
<td>3.85</td>
<td>1.49</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. INTENTt2</td>
<td>3.84</td>
<td>1.72</td>
<td>0.76</td>
<td>0.93</td>
<td></td>
</tr>
<tr>
<td>3. STRasrt2</td>
<td>3.45</td>
<td>1.51</td>
<td>0.65</td>
<td>0.65</td>
<td>0.95</td>
</tr>
<tr>
<td>ICR</td>
<td>0.95</td>
<td>0.97</td>
<td>0.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AVE</td>
<td>0.74</td>
<td>0.87</td>
<td>0.91</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Notes:* Correlations greater than |0.22| are significant at $p < 0.01$. ICR = internal consistency coefficient; AVE = average variance extracted estimate. Entries on the diagonal (shown in boldface) represent the square root of the AVE.

*Item notation:* Item shorthand names are used in this and the following tables; full names and descriptions of items and variables are shown in the Appendix.
ency was present (Panel C, contrast “c”: $p < 0.01$), but given low control transparency, the feedback treatment only weakly affected PIQ (Panel C, contrast “d”: $p = 0.09$). The latter result is much closer to significance, however, than the T1 $p$-value. These contrasts generally support H1a.

To test H1b (higher control transparency yields higher PIQ in T1 and T2), the planned contrasts compare the effect of control transparency on PIQ under both positive and negative feedback conditions (planned contrasts “a” and “b”). The contrast between high and low control transparency at T1 resulted in significant differences in PIQ. At T2, in support of H1b, control transparency increased its significant effect on PIQ under either positive (contrast “a”: Panel B (T1): $t = 5.28$; Panel C (T2): $t = 6.31$) or negative (contrast “b”: Panel B (T1): $t = 2.90$; Panel C (T2): $t = 3.50$) outcome feed-

Table 3. Multivariate ANOVA of Experimental Manipulations on Endogenous Constructs

Panel A: Effects of experimental manipulations at T1

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>PIQ</th>
<th>INTENT</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CTRL</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control transparency (CTRL)*</td>
<td>28.97; $p &lt; 0.0001$</td>
<td>14.74; $p &lt; 0.001$</td>
<td></td>
</tr>
<tr>
<td>Outcome feedback (FB)*</td>
<td>2.02; $p &lt; 0.158$</td>
<td>14.40; $p &lt; 0.001$</td>
<td></td>
</tr>
<tr>
<td>CTRL $\times$ FB*</td>
<td>0.40; $p &lt; 0.529$</td>
<td>0.02; $p &lt; 0.900$</td>
<td></td>
</tr>
<tr>
<td>$F_{3,141}$; $R^2$</td>
<td>12.79; 21.40%</td>
<td>10.43; 18.16%</td>
<td></td>
</tr>
</tbody>
</table>

Means (standard deviation)

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>PIQ (std dev)</th>
<th>INTENT (std dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High CTRL</td>
<td>69</td>
<td>4.59 (1.15)*</td>
<td>4.82 (1.43)</td>
</tr>
<tr>
<td>Low CTRL</td>
<td>76</td>
<td>3.32 (1.37)</td>
<td>3.76 (1.77)</td>
</tr>
<tr>
<td>Positive FB</td>
<td>98</td>
<td>4.03 (1.42)</td>
<td>4.60 (1.65)</td>
</tr>
<tr>
<td>Negative FB</td>
<td>47</td>
<td>3.70 (1.41)</td>
<td>3.54 (1.60)</td>
</tr>
</tbody>
</table>

Panel B: Effects of experimental manipulations at T2

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>PIQ</th>
<th>INTENTt2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CTRL</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control transparency (CTRL)*</td>
<td>41.92; $p &lt; 0.001$</td>
<td>20.25; $p &lt; 0.001$</td>
<td></td>
</tr>
<tr>
<td>Outcome feedback (FB)*</td>
<td>9.15; $p &lt; 0.003$</td>
<td>37.61; $p &lt; 0.001$</td>
<td></td>
</tr>
<tr>
<td>CTRL $\times$ FB*</td>
<td>0.52; $p &lt; 0.474$</td>
<td>1.55; $p &lt; 0.216$</td>
<td></td>
</tr>
<tr>
<td>$F_{3,141}$; $R^2$</td>
<td>20.54; 30.41%</td>
<td>22.32; 32.20%</td>
<td></td>
</tr>
</tbody>
</table>

Means (standard deviation)

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>PIQ (std dev)</th>
<th>INTENTt2 (std dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High CTRL</td>
<td>69</td>
<td>4.64 (1.92)</td>
<td>4.50 (1.48)</td>
</tr>
<tr>
<td>Low CTRL</td>
<td>76</td>
<td>3.13 (1.37)</td>
<td>3.23 (1.70)</td>
</tr>
<tr>
<td>Positive FB</td>
<td>98</td>
<td>4.07 (1.48)</td>
<td>4.34 (1.61)</td>
</tr>
<tr>
<td>Negative FB</td>
<td>47</td>
<td>3.39 (1.40)</td>
<td>2.78 (1.44)</td>
</tr>
</tbody>
</table>

* $F$-value reported in cells with 1 degree of freedom. All model $F$-values ($F_{2,142}$) are significant at $p < 0.001$. 

---
Table 4. Planned Contrasts to Test Research Hypotheses 1, 2a, and 3

Panel A: Experimental design (letters correspond to different exchange types used)

<table>
<thead>
<tr>
<th>Control transparency</th>
<th>C, D (general and positive combined)</th>
<th>E (negative)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (high CTRL)</td>
<td>AC, AD—Group 1</td>
<td>AE—Group 3</td>
</tr>
<tr>
<td>B (low CTRL)</td>
<td>BC, BD—Group 2</td>
<td>BE—Group 4</td>
</tr>
</tbody>
</table>

The following define planned contrast groups in Panels B and C:

a. Group 1 versus group 2 (1,–1,0,0): Control transparency effect under positive feedback.

b. Group 3 versus group 4 (0,0,1,–1): Control transparency effect under negative feedback.

c. Group 1 versus group 3 (1,0,–1,0): Feedback effect under high control transparency.

d. Group 2 versus group 4 (0,1,0,–1): Feedback effect under low control transparency.

Panel B: Planned contrasts—T1

<table>
<thead>
<tr>
<th>Contrast</th>
<th>PIQ difference</th>
<th>INTENT difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>“a”</td>
<td>1.357</td>
<td>1.026</td>
</tr>
<tr>
<td>“b”</td>
<td>1.073</td>
<td>1.095</td>
</tr>
<tr>
<td>“c”</td>
<td>0.463</td>
<td>1.013</td>
</tr>
<tr>
<td>“d”</td>
<td>0.178</td>
<td>1.083</td>
</tr>
</tbody>
</table>

Panel C: Planned contrasts—T2

<table>
<thead>
<tr>
<th>Contrast</th>
<th>PIQt2 difference</th>
<th>INTENTt2 difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>“a”</td>
<td>1.603</td>
<td>1.459</td>
</tr>
<tr>
<td>“b”</td>
<td>1.283</td>
<td>0.827</td>
</tr>
<tr>
<td>“c”</td>
<td>0.834</td>
<td>1.874</td>
</tr>
<tr>
<td>“d”</td>
<td>0.514</td>
<td>1.242</td>
</tr>
</tbody>
</table>

Note: The first row in each cell represents result of contrast differences; the second row shows the t-statistic of difference and probability value.
back (Table 4). Hence, per H1b, control transparency consistently influences PIQ in both T1 and T2 under either outcome feedback condition.

To test H2 (at T2, under the presence of negative outcome feedback, an increase in control transparency will not yield higher intention to use), the effect of contrast “b” was further analyzed. Table 4 reveals that under the presence of negative outcome feedback, the effect of control transparency on intent to use decreased in significance across time (contrast “b”: Panel B (T1): $t = 2.41$, $p < 0.02$; Panel C (T2): $t = 1.98$, $p < 0.05$). By contrast, in the presence of positive feedback, control transparency became a more significant predictor (contrast “a”: Panel B (T1): $t = 3.27$, $p < 0.01$; Panel C (T2): $t = 5.05$, $p < 0.01$).

In general, these results support H1a, H1b, and H2. The reaffirmation of positive feedback enhances the significance of the effects of outcome feedback on PIQ across time (H1a). As H1b predicted, the continued communication of information cues about exchange processing helps reinforce the strong effects of high control transparency on PIQ across time. Interestingly, the continued communication of negative feedback significantly decreases the T2 effects of control transparency on the outcome constructs, as H2 predicted.

Structural Tests of Effects Across Time

To provide a comprehensive test of the research hypotheses, the structural model in Figure 1 was evaluated using PLS. We followed past research practice for testing two-period effects [31, 67, 68, 83]. We estimated the identical PLS structural model at each phase of data collection and used bootstrapping with 200 resamples to test path coefficient significance (Table 5).

At both time periods, the main model explained a significant part of the variance in PIQ (T1: 21.4 percent; T2: 30.0 percent) and intention to use (T1: 58.4 percent; T2: 70.7 percent). To simplify the comparative analysis across time, we compare the corresponding path coefficients across time and test the significance of differences in the coefficients. For this purpose, we estimate a test statistic that uses the estimator of the pooled sample variance [29]. Table 6 presents the differences in the path coefficients estimated at T1 and T2.

The values shown in Table 6 represent $t$-values estimated using Equation (1a) (see note 3). These are estimated based on differences between T1 and T2 path coefficients, as shown in the two panels of Table 5. As all path coefficients in Table 5 had positive signs, a negative sign in a $t$-value of the difference in Table 6 denotes an increase in the magnitude of the path coefficients from T1 to T2, while a positive sign represents a relative path coefficient decrease from T1 to T2.

Some ANOVA results earlier reported are corroborated by the Table 6 findings. The effects of control transparency on PIQ significantly increase from T1 to T2 ($t = -7.20$; $p < 0.01$), thus corroborating the ANOVA results on H1b. The effect of outcome feedback on PIQ is not significant at T1 ($t = 1.43$; Table 5, Panel A); nonsignificant [ns]), while at T2 it is significant ($t = 2.97$; $p < 0.01$; Table 5, Panel B), and the effect difference is significantly higher across time (difference $t = -12.48$; $p < 0.01$). While
### Table 5. Measured Model Results

#### Panel A: T1 measured model results

<table>
<thead>
<tr>
<th></th>
<th>Including PIQ effects on intent</th>
<th>Excluding PIQ effects on intent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PIQ</td>
<td>INTENT</td>
</tr>
<tr>
<td>Control transparency</td>
<td>0.45; 7.16**</td>
<td>0.04; 0.66ns</td>
</tr>
<tr>
<td>Outcome feedback</td>
<td>0.11; 1.43ns</td>
<td>0.25; 4.47**</td>
</tr>
<tr>
<td>Perceived information quality</td>
<td>0.40; 4.89**</td>
<td></td>
</tr>
<tr>
<td>Structural assurance</td>
<td>0.37; 4.34**</td>
<td></td>
</tr>
<tr>
<td>$R^2$ (percent)</td>
<td>21.4</td>
<td>58.4</td>
</tr>
</tbody>
</table>

#### Panel B: T2 measured model results

<table>
<thead>
<tr>
<th></th>
<th>Including PIQ effects on intent</th>
<th>Excluding PIQ effects on intent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PIQt2</td>
<td>INTENTt2</td>
</tr>
<tr>
<td>Control transparency</td>
<td>0.50; 8.02**</td>
<td>0.04; 0.74ns</td>
</tr>
<tr>
<td>Outcome feedback</td>
<td>0.21; 2.97**</td>
<td>0.30; 4.99**</td>
</tr>
<tr>
<td>Perceived information quality</td>
<td>0.48; 6.46**</td>
<td></td>
</tr>
<tr>
<td>Structural assurance</td>
<td>0.31; 5.12**</td>
<td></td>
</tr>
<tr>
<td>$R^2$ (percent)</td>
<td>30.0</td>
<td>70.7</td>
</tr>
</tbody>
</table>

**Notes:** Numbers represent path coefficients and corresponding $t$-values after the semicolon. One-tailed significance levels: * $p < 0.05$ ($2.326 > t > 1.645$); ** $p < 0.01$ ($t \geq 2.326$); ns = nonsignificant.

### Table 6. Differences in Path Coefficients Between T1 and T2 Measured Model Results

<table>
<thead>
<tr>
<th></th>
<th>Perceived information quality</th>
<th>Intent to use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control transparency</td>
<td>−7.20**</td>
<td>−0.31ns</td>
</tr>
<tr>
<td>Outcome feedback</td>
<td>−12.48**</td>
<td>−7.78**</td>
</tr>
<tr>
<td>PIQ</td>
<td>−8.78**</td>
<td></td>
</tr>
<tr>
<td>Structural assurance</td>
<td>7.03**</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Numbers represent $t$-values on differences of respective path coefficients as measured in the T1 and T2 research models (as shown on left half of Table 5). Negative $t$-values denote increases from T1 to T2, positive $t$-values denote decreases. One-tailed significance levels: * $p < 0.05$ ($2.326 > t > 1.645$); ** $p < 0.01$ ($t \geq 2.326$); ns = nonsignificant.
we have not proposed a formal hypothesis for the effect of outcome feedback, this finding evidences the stronger effects of outcome feedback at T2.

H3 predicts that the effects of control transparency on intent to use will be mediated by PIQ across time. Using Baron and Kenny’s [4] causal steps strategy, we reason: first, as shown in the right side of Table 5, control transparency has significant direct effects on intention to use in the absence of a direct link from PIQ to those constructs (Intent at T1: $t = 2.68$ and Intent at T2: $t = 3.77$). Second, as shown in the left side of Table 5, PIQ does have a strong direct effect on intent to use at both T1 and T2. Finally, in the presence of the PIQ direct effect, the impact of control transparency on intent to use is no longer significant (see the left-side panels of Table 5). This satisfies the Baron and Kenny [4] criteria. Hence, we conclude (1) that the effects of control transparency on intent are fully mediated by PIQ and (2) that PIQ is a dominant mediator in that process.

While we did not propose a formal hypothesis, we also examined whether PIQ will mediate the effects of outcome feedback on the two dependent variables. As shown in Table 5, at T1, whereas outcome feedback has no direct effect on PIQ, it does have a significant effect on intent to use, irrespective of whether PIQ is modeled to affect the same constructs or not. These results fail to satisfy the Baron and Kenny [4] criteria for testing mediation. At T2, the direct effect of outcome feedback on PIQ is significant (Panel B of Table 5). When PIQ is excluded from the model, the direct effects of feedback on intent are significant; when PIQ is added to the model, those direct effects decrease but do not lose significance (Intent: $t = 7.10 \rightarrow t = 4.99$). These exploratory results show that at T2, PIQ partially mediates the effects of feedback on intent, and that the mediation effect does not dominate the direct effect of outcome feedback on intent.

We also applied the Sobel test, which calculates a critical ratio to test whether the indirect effects of control transparency and outcome feedback on intent to use via PIQ are significantly different from zero [4, 53, 77]. The test statistic for the indirect effect of control transparency on use intent is significant at both time periods, thus confirming the previous mediation analysis (at T1: intent $z = 4.03$, $p < 0.001$; at T2: intent $z = 5.03$, $p < 0.001$). The test statistic for the indirect effects of outcome feedback at T1 is not significant (intent: $z = 1.37$, $p < 0.09$). At T2, the indirect effects of outcome feedback on intent are significantly mediated via PIQ ($z = 2.67$, $p < 0.01$). Combined with the causal steps analysis, this shows the significance of a dominant mediation effect of PIQ on control transparency effects, while PIQ is a significant, but not dominant, mediator of outcome feedback’s effects at the second time period only.

Our research question was: How will exchange outcome feedback and control transparency features affect PIQ and user intent to use the exchange system over the first two transactions? We answer that (1) outcome feedback did not affect PIQ in T1, but affected it in T2; (2) control transparency affected PIQ in both T1 and T2; (3) in T2, control transparency affected intent to use less than it did in T1 under negative feedback conditions; and (4) PIQ fully mediated control transparency’s effects on intent to use in both T1 and T2, but PIQ only partially (or even marginally) mediated the T1/T2 effects of outcome feedback.
Results Robustness Test

To secure against the possibility that our H2 and H3 results are just a function of our dependent variable, we also tested the model on a second dependent variable, perceived supplier performance. We define supplier performance as the extent to which the supplier has fulfilled the buyer’s requirements in terms of price, timeliness of delivery, input quality, and supplier flexibility [89]. Supplier performance captures the customer’s perception that the vendor is doing an acceptable job as an exchange partner. Because the buyer organization is the final arbiter of the extent to which exchange goals have been satisfactorily met [39, 85], supplier performance is a key IOR outcome [16, 17]. The supplier performance scale (see the Appendix) is based on a Zaheer et al. [89] measure. Item 2 was adapted from Zaheer et al. [89], while other items were developed in this study. After conducting Box’s $M$ test, we eliminated items 3 and 4. We found convergent and discriminant validity for supplier performance using the same methods described above.

At both time periods, the main model explained a significant part of the variance in supplier performance (T1: 55.6 percent; T2: 67.2 percent). We found that when negative feedback was present, in support of H2, the T2 effect of control transparency on supplier performance was not significant (T2: $t = 1.53, p < 0.13$), in direct contrast to the significant effect observed at T1 (T1: $t = 2.92, p < 0.01$). H3 predicts that the effects of control transparency on the dependent variable will be mediated by PIQ across time. We find control transparency has significant direct effects on supplier performance in the absence of a direct link from PIQ to those constructs (T1: $t = 3.38$; T2: $t = 3.39$). PIQ has a significant direct effect on supplier performance at both T1 and T2. But in the presence of the PIQ direct effect, the impact of control transparency on supplier performance was no longer significant, as was the case with the intention to use the dependent variable.

Discussion and Implications

Study Contributions

First, this paper contributes to the literature by showing that control transparency and positive/negative outcome feedback work differently over two time periods. We find that positive/negative outcome feedback only affects PIQ in T2. Initial feedback is discounted as tentative, just as social cognition would predict. However, as negative feedback is repeated over two periods, strong doubts develop about PIQ. Hence, outcome feedback predicts PIQ in T2. On the other hand, we demonstrate that control transparency has a large effect on PIQ in T1 and an increased effect in T2. This supports the SET idea that beliefs are reinforced through interactive transparency over time.

Table 3 shows that control transparency consistently affects use intent at T1 and T2. In spite of control transparency’s consistent overall effects on use intent, we also show that this does not hold under all T2 conditions. Rather, we find that repeated negative outcome feedback attenuates the effects of high control transparency on the exchange user’s intent to continue using the exchange (Table 4). This supports social cognition
theory, suggesting that people give others the benefit of the doubt at first, even when feedback is negative. However, as SET suggests, people learn from their experience, and therefore repeated negative feedback decreases outcome perceptions.

Second, this study contributes by showing PIQ to be an important IS variable in an IOR setting. PIQ is important because it fully mediates the effects of control transparency on intention to use the exchange. We also find that PIQ has a strong effect on use intent (Table 5), and that this influence significantly increases from T1 to T2. The incremental effect of PIQ in each time period is also shown by the significant decrease in the explanatory power of our models when the effect of PIQ is restricted from consideration (from Panel A of Table 5 for T1: $\Delta R^2 = 7.9$ percent, $F = 6.69$, $p < 0.001$; from Panel B of Table 5 for T2: $\Delta R^2 = 9.9$ percent, $F = 11.91$, $p < 0.001$). This shows the significant effects that PIQ has on usage intention in both T1 and T2 as well as its increasing influence in T2. While IS effectiveness studies primarily examine initial PIQ effects (e.g., [19, 64]), we contribute by finding that PIQ both maintains as well as increases its significant effect in T2. PIQ is a perception based on user experience with the exchange. Hence, the increasing strength of PIQ in the model supports SET that concrete, experience-based cues are central to the exchange relationship.

Third, this study contributes by testing supplier performance in the model. This study places PIQ in an expanded nomological network that demonstrates the supplier performance aspect of the importance of PIQ to interorganizational exchanges. Supplier performance is a key user perception that indicates the health of the relationship. The supplier performance results reinforce the use intent results, emphasizing that T2 effects differ from T1 effects. Table 7 shows in summary form the findings on all research hypotheses proposed in this study.

Research Implications

These results show how important it is to study interorganizational phenomena over time. The study presents findings consistent with past research (e.g., [64]) in which initial (T1) outcome feedback did not have a significant effect on data exchange information quality beliefs. In T2 use of electronic data exchanges, however, outcome feedback was found to have a significant effect on PIQ. As a result, the measurement of constructs across time should enable the examination of a network of beliefs that relate to the success of data exchanges. Limiting the examination to initial use exchanges fails to capture this.

We used structural assurance [32] as a control variable, and found that it affected intention to use directly, although this effect decreased somewhat in T2. Table 5 shows that while much of structural assurance’s effect was suppressed by PIQ (as shown in the two halves of Table 5, where structural assurance had highly increased effects when PIQ was not present), it still had a significant effect. Structural assurance implies that institutional controls are in place to protect the exchange user from transactional problems, providing a safe and secure environment. This should be important to exchange customers. Future research should expand on this finding by modeling the effects of other variables (e.g., asset specificity, goal incongruence).
Table 7. Summary of Hypothesis Testing Results

<table>
<thead>
<tr>
<th>Research hypothesis</th>
<th>MANOVA (Table 3)</th>
<th>Planned contrasts (Table 4)</th>
<th>Structural model—PLS (Table 5)</th>
<th>Structural model—differences in PLS path coefficients (Table 6)</th>
<th>Sobel mediation tests (untabulated)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a</td>
<td>Supported</td>
<td>Supported</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>(PIQ will not be affected by positive outcome feedback at T1; but it will be affected at T2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H1b</td>
<td>Supported</td>
<td>Supported</td>
<td>n/a</td>
<td>Supported</td>
<td>n/a</td>
</tr>
<tr>
<td>(High PIQ at both time periods under high control transparency)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H2</td>
<td>n/a</td>
<td>Supported</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>(At T2, negative outcome feedback will eliminate effects of control transparency on Intent to Use)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H3</td>
<td>n/a</td>
<td>n/a</td>
<td>Supported</td>
<td>n/a</td>
<td>Supported</td>
</tr>
<tr>
<td>(Mediation hypothesis: PIQ will mediate effects of control transparency on Intent to Use at both T1 and T2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note: n/a = not applicable.*
The results show PIQ becoming a more powerful predictor of intent to use over two time periods, which expands on the findings of Nicolaou and McKnight [64]. Future research should examine whether this trend continues indefinitely or slows/stops over time. We speculate that it continues for a while and then slows, as direct quality of the user’s exchange experience becomes more salient.

Table 8 shows several other ways to expand beyond this study. First, researchers should use other theoretical perspectives to examine the electronic data exchange across time. The table shows that exchanges could be researched by comparing our theory to other theories such as the elaboration likelihood model [69] or the vulnerability-stress-adaptation model of Karney and Bradbury [42]. Second, research studies could use the current research model to study people-to-people relationships in other IS domains. For example, the IS–vendor outsourcing relationship and the user–systems developer relationship could also be studied using similar relational constructs as this study used. Control transparency could be adapted to reflect a similar enhancer of communication between people. Quality of information exchanged between people would be the result. Third, this and similar models should be tested using other methods. Our two-period study should be retested with more time periods in order to examine longer-term effects. In conjunction with the elaboration likelihood model of cognitive processing and attitude change, for example, future models could examine repeated interactions and simulate the optimal number of repetitions needed to achieve enduring attitudes that are resistant to incremental cues and predictive of future behavior. We also recommend including measures that are not self-reported [42].

Study Limitations

This study is limited to one experimental context that may or may not generalize to other contexts. Future research in other contexts and with other experimental or field study methods can test how well these results generalize. The experimental setting used here does not represent the complexity one would find in real-world exchanges.
among competing and cooperating partners [61]. Our setting more closely resembles a “spot market” exchange than the complex, relational exchange one would find between a major manufacturer (e.g., Ford) and its suppliers. Future research should attempt to capture more of the richness of such real-world exchange settings. Another limitation is that several of the PIQ items did not work, so we had to eliminate them. This suggests that more measurement work is needed to further refine and validate the PIQ scale of measurement. The control transparency treatment is another limitation. While we tried to form the treatment to represent the transparency of the data coming back to the user about the order he or she placed, the treatment also may indicate to the user that proper controls exist. We caution that the results may be due to either the data transparency or the control transparency communicates or both.

Implications for Practice

Exchange providers should be careful to provide the right kind of information transparency and outcome feedback on their exchange. Our study finds that both design features influence PIQ, but at different points in time. We also find that PIQ affects exchange success; that is, favorable perceptions of information quality produce greater customer intent to continue to use the exchange. Hence, efforts to improve control transparency, outcome feedback, and PIQ will have a large impact on intent to use the exchange. But at T1, users provide the supplier some outcome feedback slack that is not continued long.

No matter how transparent the exchange communication is, the repeated reception of negative feedback about exchange fulfillment outcomes will harm customer PIQ perceptions. This research shows that while positive feedback becomes more valued with continued use, two rounds of negative shipment feedback will negate any positive initial impressions gained from a best-practice exchange design. Therefore, providers should make sure their fulfillment mechanisms work well, and they should provide this positive feedback to their customers on a timely basis. This study not only guides organizations to design online data exchanges properly but also demonstrates the consequences of repeated online transaction failure.

Conclusion

This study produced two key findings. First, it demonstrated clearly that outcome feedback affects PIQ and intent to use the exchange differently between the first and second transaction (T1 and T2), occurring within a two-week time period. Second, it showed that negative outcome feedback decreases the effects of control transparency on the intent to use the exchange from T1 to T2. In addition, this study shows that PIQ becomes even more predictive of a user’s intent to continue using the exchange by the second transaction. Overall, it shows that the two system design interventions of control transparency and outcome feedback can influence intent to use electronic data exchanges. However, a system designer should not rely solely on providing transparent
signals about the data exchanged. This is found to be important in both of the first two transactions of use, but the effects diminish due to outcome feedback change from the first to the second transaction. System designers who employ electronic data exchanges as well as researchers who examine their effective design must consider the effects of both control transparency and outcome feedback interventions across time.

Notes
1. Subject attrition was mainly due to work responsibilities of participants that caused their absence from their location of contact within the two-week interval in which our study was conducted.
2. We also tested our models by splitting the sample between students ($n = 55$) and nonstudents ($n = 90$) with no changes in our hypothesis test conclusions.
3. The test statistic is estimated as

$$T = (b_1 - b_2) [S_p \sqrt{1/(N1 + 1/N2)}]$$

where $T$ has the $t$-distribution with $(N1 + N2 - 2)$ degrees of freedom; $b_1$ and $b_2$ are the T1 (phase 1) and T2 (phase 2) path coefficients being compared; N1 and N2 are the sizes of the T1 and T2 samples; $S_p$ is the estimator of the pooled sample variance, which is constructed using the standard deviations of the T1 and T2 samples and equals the square root of

$$S_p^2 = [(N1 - 1)S_{T1}^2 + (N2 - 1)S_{T2}^2]/[N1 + N2 - 2]$$

References


Appendix

Measurement Items and Manipulation Checks

Perceived Information Quality (PIQ) (seven-point scale, “strongly agree” to “strongly disagree”)

PIQ1: The exchange provides data that are current enough to meet my business needs. (dropped)
PIQ2: The exchange data are up to date enough for my purposes. (dropped)
PIQ3: The exchange provides up-to-date information with regard to transactions.
PIQ4: The data this exchange provides are never outdated.
PIQ5: The exchange data that I use are accurate enough for my purposes. (dropped)
PIQ6: I feel satisfied with the data accuracy of the exchange system.
PIQ7: There are no accuracy problems in the data I use in this exchange. (dropped)
PIQ8: Data provided by this exchange are completely error-free.
PIQ9: The information content of the exchange meets my needs.
PIQ10: The data maintained by the data exchange are pretty much what I need to carry out my tasks. (dropped)
PIQ11: The exchange maintains the right data for my purposes.
PIQ12: Based on my needs, this exchange has no missing data items.

Intention to Use (INTENT) (seven-point scale, “extremely likely” to “extremely unlikely”)

INT1: What is the likelihood that you would continue using this exchange in the future to carry out transactions similar to the ones described in your case?
INT2: If I was faced with a similar purchasing decision in the future, I would use this data exchange again.
INT3: If a similar ordering need arises in the future, I would feel comfortable using this data exchange again to place my order.
INT4: I would recommend use of this data exchange to other colleagues who may be faced with similar ordering needs as the one described in my case. (dropped)
INT5: If I was continuing to do similar purchasing in the future, I would intend to transact for a long time with this data exchange. (dropped)
RINT6: If I continued to do such purchasing as this, I would not intend to continue transacting with this data exchange. (reverse-scored)
Structural Assurance (STRasr) (seven-point scale, “strongly agree” to “strongly disagree”)

STR1: The data exchange provided by PanAmerican Industries has enough safeguards to make me feel comfortable using it to transact business.
STR2: I feel assured that legal and technological structures adequately protect me from problems on this data exchange.
STR3: I feel confident that encryption and other technological advances on this data exchange make it safe for me to do business there.
STR4: In general, this data exchange is a robust and safe environment in which to transact business. (dropped)

Supplier Performance (SP) (seven-point scale, with “very poor” and “excellent” endpoints and “fair” midpoint)

Please rate the vendor’s performance on fulfilling each of the following goals:

SP1: Quality of service.
SP2: Timeliness of expected delivery.
SP3: Efficiency of the ordering process. (dropped)
SP4: Completeness of order fulfillment. (dropped)
SP5: Accuracy of order fulfillment.

Items for Manipulation Checks (seven-point scale, “strongly agree” to “strongly disagree”)

Control Transparency: The exchange provides adequate information for me to assess the reliability, validity, and accuracy of the data exchanged.
General Outcome Feedback: The exchange tells me that my order has been accepted and will be shipped on the next business day.
Specific Positive Outcome Feedback: The exchange informs me that the whole quantity of my order has been shipped and that it is expected to arrive by my required delivery date.
Specific Negative Outcome Feedback: The exchange informs me that a partial quantity of my order has been shipped and that it is expected to arrive after my required delivery date.