國立雲林科技大學
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科　目：資訊科技文獻

Migration from Relational Database into Object Oriented Database

1. The authors address migration from RDBMS into OODBMS in this paper, please discuss their research method and findings. 20%
2. As this paper indicates that some authorities believe that object oriented database systems will take over the world replacing relational system whereas others believe that they are suited only to certain very specific problems and will never capture more than a small fraction of the overall market. What's your opinion on this matter? 20%
3. In your experience, what are the criteria (pro and con) to use relational vs. OO database design? 10%

Powers of 10: Modeling Complex Information-Seeking Systems at Multiple Scales

請以中文回答下列問題：

4. 請說明本篇論文的主要論點。(15%)
5. 請說明論文中公式二所代表的意義及其應用。(15%)
6. 請說明社會搜尋(social search)模式之運作，並舉例說明與此相關之資訊應用系統。(20%)

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Migration from Relational Database into Object Oriented Database

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Abstract: Object – Oriented Technology is an important discipline in the field of software engineering in general and it is, therefore, natural to ask whether it is relevant to the field of database management in particular and what that relevance is. There is, however, no consensus on answer to these questions. Some authorities believe that object oriented database systems will take over the world replacing relational system whereas others believe that they are suited only to certain very specific problems and will never capture more than a small fraction of the overall market. Object-Oriented technology represents real world very well, focusing on data rather than procedure and gives more security to data. Also, it is safe from unauthorized use of data because it provides three access specifiers viz. private, public and protected and strictly provides security to data in database. This technology also provides function as well as data together so that the data can be manipulated by the given function. In this paper, we show that how the data is more secure in object-oriented database than in relational database and also why do we migrate from RDBMS into OODBMS

Key words: Versant ODBMS, object-oriented database

INTRODUCTION

Relational database: A relational database stores all its data inside tables and nothing more. All operations on data are done on the tables themselves or produce another tables as the result. You never see anything except that tables. A table is a set of rows and columns and a set does not have any predefined sort order for its elements. Each row is a set of columns with only one value for each. All rows from the same table have the same set of columns, although some columns may have NULL values, i.e. the value for that row is not initialized. It is to be noted that a NULL value for a string column is different from an empty string. As an example, the Relational model[1,2] supports relations, which are set of tuples with fixed number of primitive data elements. The rows from a relational table are analogous to a record and the columns to a field. Here's an example of a table and the SQL statement that creates the table:

```
CREATE TABLE ADDR_BOOK (
                NAME char(30),
                COMPANY char(20),
                E_MAIL char (25) )
```

NAME	COMPANY	E_MAIL
Israr Ahmad	Software System	israrl@centroin.com.
Abid	IBM	Abidl@ibm.com

There are two basic operations that we can perform on a relational table. Viz. Retrieving a subset of its columns and retrieving a subset of its rows. Here are samples of the two operations:

SELECT NAME, E_MAIL FROM ADDR_BOOK

NAME	E_MAIL
Israr Ahmad	israr@centroin.com.br
Abid	abidl@ibm.com

SELECT * FROM ADDR_BOOK WHERE COMPANY = 'Software System'

NAME	COMPANY	E_MAIL
Israr Ahmad	Software System	israr@centroin.com

We can also combine these two operations as follows:
SELECT NAME, E_MAIL FROM ADDR_BOOK WHERE COMPANY = 'Software system'

NAME	E_MAIL
Israr Ahmad	israr@centroin.com.br

We can also perform operations between two tables treating them as sets: we can make Cartesian product of the tables and can get the intersection between two tables, we can add one table to another and so on. Later we should be discussing these operations in OODBMS and show how they are more useful and better.

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Object oriented databases: In this paper, we examine object systems by introducing and explaining basic object oriented concepts and offer some opinion regarding the suitability of incorporating such concepts into the database systems of the future. The advent and commercial success of well-engineered ODBMS products, such as ObjectStore[3], indicate that the time is ripe to seriously investigate migration from RDBMS to ODBMS.

The classical SQL systems being inadequate in a variety of ways, we are led to study object systems.

The need for object-oriented databases: The increased emphasis on process integration is a driving force for the adoption of object-oriented database systems. For example, the Computer Integrated Manufacturing (CIM) area is focusing heavily on using object-oriented database technology as the process integration framework. Advanced office automation systems use object-oriented database systems to handle hypermedia data. Hospital patient care tracking systems use object-oriented database technologies for ease of use. All of these applications are characterized by having to manage complex, highly interrelated information, which is the strength of object-oriented database systems. Clearly, relational database technology has failed to handle the needs of complex information systems. The problem with relational database systems is that they require the application developer to force an information model into tables where relationships between entities are defined by values. Mary Loomis, the architect of the Versant OODBMS compares relational and object-oriented databases as follow[4]. Relational database design is really a process of trying to figure out how to represent real-world objects within the confines of tables in such a way that good performance results and preserving data integrity are possible. Object database design is quite different. For the most part, object database design is a fundamental part of the overall application design process. The object classes used by the programming language are the classes used by the ODBMS. Because their models are consistent, there is no need to transform the program's object model to something unique for the database manager[5]. An initial area of focus by several object-oriented database vendors has been the Computer Aided Design (CAD), Computer Aided Manufacturing (CAM) and Computer Aided Software Engineering (CASE) applications. A primary characteristic of these applications is the need to manage very complex information efficiently. Other areas where object-oriented database technology can be applied include factory and office automation. For example, the manufacture of an aircraft requires the tracking of millions of interdependent parts that may be assembled in different configurations. Object-oriented database systems hold the promise of putting solutions to these complex problems within reach of users.

Object-orientation is yet another step in the quest for expressing solutions to problems in a more natural, easier to understand way. Michael Brodie in his book On Conceptual Modeling[6] states, "The fundamental characteristic of the new level of system description is that it is closer to the human conceptualization of a problem domain". Descriptions at this level can enhance communication between system designers,

Object-oriented concept: The object-oriented paradigm is the latest in the software development and the most adopted one in the developing project of today. RDBMS extensions have been spurred by competition from object-oriented database management systems (ODBMSs), which combine comprehensive database management functionality and full-fledged OO data modeling[7].

Limitation of Procedural Programming: A Program in a procedural language is a list of instructions where each statement tells the computer to do something. The focus is on the processing, the algorithm needed to perform the desired computation.

* In procedural paradigm, the emphasis is on doing things. And not on the data. But Data is, after all, the reason for a program's existence. The important part of an inventory program isn't a function that display or check data; it is the inventory data itself. Yet data is given second – class status while programming.
* In procedural programming, data type are used and worked upon by many functions. If a function makes any change to a data type, then it must be reflected to all the locations, within the program that process this data type. This is very time consuming for large sized programs.
* Procedural programming does not model real world very well.

For instance, a vehicle is an object, which is capable of moving in real world. However, the procedural programming paradigm would just be concerned about the procedure i.e. the procedure programming paradigm would just think of moving the part and not the vehicle.

OO programming: Now, the object oriented approach views a problem in terms of objects involved rather than procedure for doing it.

Object: object is an identifiable entity with some characteristics and behavior. For instance, we can say 'Orange' is an object. Its characteristics are: It is spherical shaped, its color is Orange etc. Its behavior is: it is juicy and it tastes sweet sour.

While using OOP approach the characteristics of an object are represented by its associated functions. Therefore, in Object Oriented Programming object represents an entity that can store data and has its interface through function.

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How OOP overcomes procedural paradigm's problems: This RDB shortcoming is being addressed by extended relational systems[8] and middleware such as object oriented relational database gateways products Persistence[9] Now, let us see how the Shortcomings of procedural paradigm are overcome by OOP.

The object-oriented approach overcomes these shortcomings in the following manners.

* OOP approach gives data the prime consideration and by providing interface through the functions associated with it.
* An object is a complete entity i.e. it has all the data and associated functions within it. Whenever, something is to be changed for an object, only its class gets changed because it is complete in itself. All the functions that are working on this data or using it are defined within the class, they get to see the change immediately and nowhere else the change is required.

An overview of object technology: It is a basic tenet of the Object approach that "everything is an object". Some objects are immutable; examples might be integer (3,65) and character string ("Delhi", "Pune"). Other objects are mutable; examples might be the department and employee.

Objects are encapsulated, which means that the physical representation i.e. the internal structure of such an object, say a Dept ("department") , is not visible to users of that object; instead, user knows only that the object is capable of executing certain operations (Methods).

Creation of object oriented database: Suppose we wish to define two object classes namely DEPT (departments) and EMP (employees). Also suppose that the user-defines classes MONEY and JOB and the class CHAR is built-in. Then the necessary class definition for DEPT and EMP might look somewhat as follows:

```
CLASS DEPT
  PUBLIC (Dep#   Char,
        Dname   Char,
      Budget      Money,
        MGR     REF(EMP),
        EMPS    REF(SET(REF(REF(EMP))))---
  METHODS (HIR_EMP(REF(EMP))---code---,
        FIRST_EMP(REF(EMP))---code---,---'
CLASS EMP
   PUBLIC (EMP#            CHAR
              ENAME       CHAR
          SALARY      MONEY
            POSITION     REF (JOB))---
METHOD (---)---;
```

Transparent persistence: Transparent persistence in object database product refers to ability to directly manipulate data stored in a database using an object oriented programming language. This is in contrast to a database sub-language used by embedded SQL or a call interface used by ODBC or JDBC. Using an object oriented database product means that you have higher performance and less code to write.

With transparent persistence, the manipulation and traversal of persistence objects are performed directly by the object oriented programming language in the same manner as in-memory. This is achieved through the use of intelligent caching as in given Fig. 1.

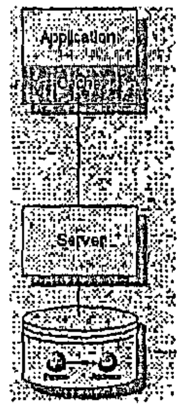

Fig. 1: Intelligent caching

Complex data: Complex data is often characterized by:

* A lack of unique, natural identification.
* A large number of many –to-many relation ships.
* Access using traversals.
* Frequently use of type codes such as those found in the relational schema

The discussion of complex data will use the following fragment of a clothing database that represents an XML data structure stored as objects.

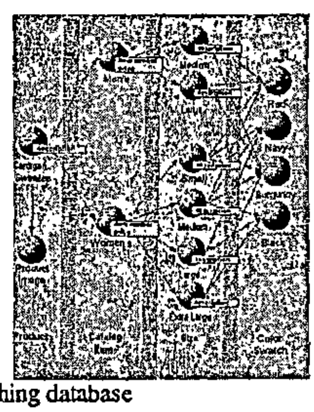

Fig. 2: Clothing database

High performance: With complex data, it is not unusual to find that an ODBMS will run anywhere from 10 to 1000 times faster than an RDBMS. The range of this performance advantage depends on the complexity of the data and the access patterns for the data.

Why are ODBMSs faster? ODBMSs are optimized for the traversals related to complex data. They also do not have any " impedance mismatch" when it comes to

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using object oriented programming languages such as Java and C++. High performance can impact business considerations in two ways:

We simply may need the best performance possible on complex data. We may take advantage of the high performance ODBMSs provide for complex data by purchasing cheaper hardware.

Lack of impedance mismatch: ODBMSs allow us to store objects directly without any mapping to different data structures. RDBMSs require mapping from object to tables. This mapping to different data structures is called " impedance mismatch". The Fig. 3 shows direct storage at the left and impedance mismatch at the right.

This lack of impedance mismatch in ODBMSs give them a performance advantage over RDBMSs, especially on complex data. Impedance mismatch slow down performance on complex data because of processing needed map from one data structure (tables) to another (object).

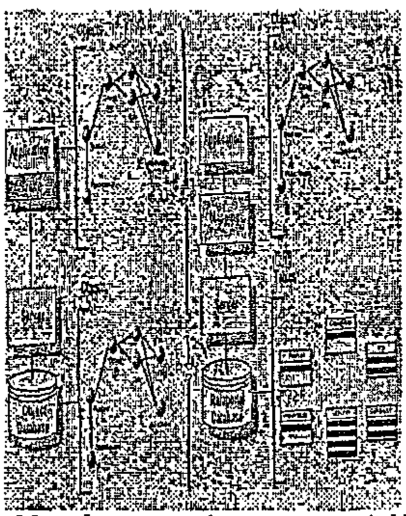

Fig. 3: Map from one data structure (tables) to another (object)

Everyday uses of object databases: We can use object database in the following:

* Pager
* Voicemail
* Flight booking
* PCs phone

Object databases are used more often than we might realize. Many times, using an object database is seen as competitive advantage and companies do not want to publicize this. As a result, object databases are invisible to users and not mentioned by companies and hence do not receive much media attention.

CONCLUSION AND FUTURE WORK

In this study we have focused on migration from RDBMS to ODBMS. We have also discussed that ODBMS is better and faster than RDBMS for complex Data. For ODBMSs, the virtue is direct manipulations of persistent objects by application software. The inseparable vices are the semantic and operational burdens attending such direct manipulation. Perhaps it is too much to ask for an application framework to support deft and natural manipulation of objects in both *off line* (RDB) and *on line* (ODBMS) forms. In any case, we offer the humble opinion that data representation issues — the subject of much research in the academic database community — are not the difficult problems. Instead, the core issues lie in areas long recognized to be among the most vexing of persistent data: object identity (copying vs. replication), transaction semantics (nature and lifetime of data ownership) and object naming (significance of OIDs and reference binding). Despite the cautionary tone of this paper, we are pleased with the relative success of this experiment and are encouraged to pursue several promising directions for future work. Consequently a full-fledged port and performance comparison is underway. The question thus arises: if the ODBMS port is a complete success and the RDB is retired, how will data volition be accommodated? We speculate that this dual database approach constitutes a "best of both worlds" solution. The ODBMS provides direct, fast, application-pertinent object access and the RDB provides a generalized evolution tolerant representation. The long-term solution thus may be a hybrid system, in which the ODBMS manages the live data, which is flushed to the RDB when data evolution is required.

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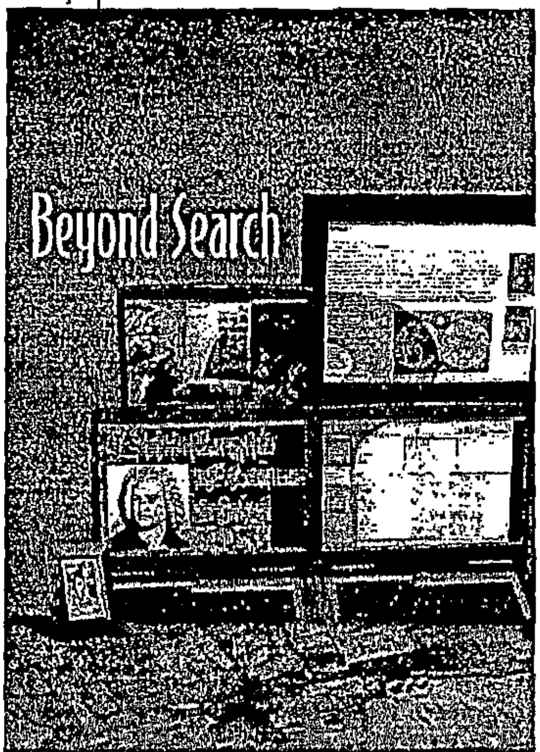

POWERS OF 10: MODELING COMPLEX INFORMATION-SEEKING SYSTEMS AT MULTIPLE SCALES

Peter Pirolli, *Palo Alto Research Center*

New models of information-seeking support systems offer two advantages: They move us from prescientific conceptual frameworks about information seeking to more rigorous scientific theories and predictive models while, at the same time, expanding the kinds of things we study and develop.

These are exciting times for scientists, designers, and engineers in the field of information-seeking support systems (ISSSs). New technology continues to fuel a staggering growth of available information, which in turn affects our lives by providing resources for adapting to an increasingly complex world, as well as new ways of being entertained.

We are witnessing an efflorescence of new ways to interact with—and produce—rich content. National efforts, such as the US Cyberinfrastucture initiative (www.nsf.gov/news/special_reports/cyber/index.jsp), aim to produce even more fertile platforms for information. This evolving domain offers science a great opportunity because there is so much new territory to explore and explain, so many new ideas about how to do so, and so much potential for having an impact on innovative engineering and imaginative design.

Two exciting opportunities await science and engineering in this field. The first moves us from prescientific conceptual frameworks about information seeking to more rigorous scientific theories and predictive models. Progress in cognitive science and human-computer interaction is moving toward a coherent set of theories and models to address the complexity of modern-day information seeking at a range of scales, from the long-term social to individual moment-by-moment interaction.

The second opportunity expands the kinds of things we study and develop. Information seeking in the current world involves much more than isolated solitary users working with a single tool to retrieve some document or fact. The information environment has become a place to explore and learn over longer periods. It has become much more social. People use many tools and systems fluidly for many purposes. Information is no longer just passive text, but includes rich media that often seek users as much as users seek media.

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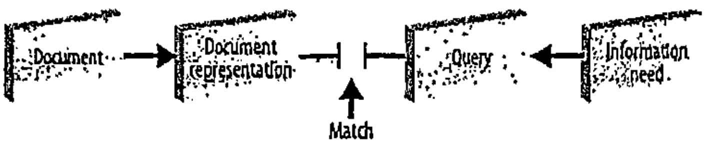

Figure 1. Classic information retrieval model. This conceptual framework for information retrieval prompts a user with an information need to reformulate it as a system query, which in turn retrieves a document whose system representation best matches the query.

CLASSIC CONCEPTUAL FRAMEWORKS

Researchers have a long tradition of developing ISSS conceptual frameworks (often called conceptual models) that provide a general pool of concepts, processes, assumptions, methods, and heuristics that orient researchers to a particular way of viewing and describing the world. For example, Figure 1 depicts a classic conceptual framework for information retrieval.[1] A user has an information need that must be reformulated as a query to a system, which in turn retrieves a document whose system representation best matches the query. This classic information-retrieval model motivated a wave of research that crested with the search engine technology now pervasive on the Web, which addresses a large class of everyday information needs for hundreds of millions of users.

However, it also became clear throughout the 1980s and 1990s that information-seeking systems and behavior must include more than just query-based search. For example, the model depicted in Figure 1 did not capture browsing in hypermedia systems, such as the Web. The classic model did not address more complex sense-making activities in which large amounts of information about a situation or topic are collected and deliberated on to form an understanding that becomes the basis for problem solving and action.

Researchers studying real user behavior and systems began to expand on the classic conceptual framework in Figure 1. For example, analysis of real-world information seeking[2] led to the identification of an expanded set of general processes and factors involved in information-seeking behavior. Conceptually, an information seeker is seen as situated in an environmental context with an embedding task or goal that triggers a need for more knowledge. Information systems provide interactive access to information (that must be shaped into knowledge) to meet those needs and achieve those tasks.

The system provides information that enhances the ability of searchers to find the right information for their purposes. This expanded conceptual framework leads to the identification of many factors that can shape information seeking, including those associated with the following:

- *information seekers*, including prior knowledge, skills, and other individual differences;
- *tasks*, which can vary greatly in terms of complexity, structure, and constraints; drive and shape information-seeking and problem-solving behaviors; and provide criteria by which information is evaluated;
- *domains*, which are the general bodies of knowledge that can vary in complexity, kinds of content, rate of growth, change, and organization, among other things;
- *contexts*, which can include physical, social, and temporal factors and constraints; and
- *search systems*, which can vary enormously in how domain information is represented and how they present and interact with users.

Information seeking as berrypicking[3] also became an influential metaphor and conceptual framework. Users often start with some vague information need and iteratively seek and select bits of information that cause the data needs and behavior to evolve over time; there is no straight line of behavior to a single best query and retrieval set.

In real libraries, users employ a variety of information navigation strategies, such as footnote chasing, citation chaining, reviewing a journal series, browsing entire areas at different generality levels, and browsing and summarizing an author's works. Today, all these techniques seem mundane, a testament to how specific system features and user interface designs provide better support for real-world information-seeking strategies.

THEORIES AND MODELS

Conceptual frameworks have proven useful for providing conceptual tools to analyze and describe observed behavior, which in turn can suggest new functions for information-seeking systems. They also provide a common ground for summarizing findings and accumulating results, formulating hypotheses and analyses, and contrasting and debating different ways of characterizing ISSS systems.

However, conceptual models are not scientific theories or models that provide a basis for making predictions about the design effects and engineering decisions for information-seeking support systems. Researchers construct scientific theories within frameworks by providing additional assumptions that let them make predictions they can test. Typically, researchers achieve this by specifying a model that makes precise predictions they can fit to observation and measurement for a specific situation or class of situations.

Two exciting challenges involve developing truly predictive and explanatory scientific theories and models, then applying them to address the full complexity of information-seeking behavior at multiple time scales. Among other applications, this permits the prediction of how minute changes at the microscale of individual-user interaction can percolate upward to emergent macroscale phenomena such as the evolution of wikis and tagging systems.

Predictive models can provide a basis for understanding and control over ISSSs and the behavior they support. In practical terms, it means that designers and engineers can explore and explain the effects of different ISSS design decisions before undertaking the heavy investment of resources for implementation and testing. With additional research, this design space exploration will become more efficient and innovative.

HUMAN-INFORMATION INTERACTION

To get a sense of what might be possible, we can consider the hierarchical organization of human behavior and the phenomena that emerge at different analysis time scales, as Table 1 shows.

Allen Newell and Stuart Card[4] argued that human behavior—including information seeking—can be viewed as the result of a hierarchically organized set of systems rooted in physics and biology at one end of the spectrum, and large-scale social and cultural phenomena at the other. Table 1 shows this framework, which has proven useful in cognitive science[5] and human-computer interaction research.

The basic time scale of operation for each system level in this hierarchy increases by a factor of approximately 10 when moving up the hierarchy in Table 1. Some behaviors, such as seeking information on the Web, can be modeled at multiple time scales. However, the most exciting work on developing models that map out this territory for different kinds of ISSSs and phenomena has yet to begin. Within the timeframes in Table 1, there are layered bands differentiated by the kinds of factors that shape behavior:

- *Biological band phenomena*—spanning approximately milliseconds to tens of milliseconds—are mainly determined by biochemical, biophysical, and especially neural processes, such as the time it takes for a neuron to fire.
- *Psychological band activity*—spanning approximately hundreds of milliseconds to tens of seconds—is where the elementary psychological machinery for perception, cognition, and action play a major part in shaping behavior. This has traditionally been the domain of cognitive psychology.
- *Rational band phenomena*—spanning approximately tens of seconds to minutes to days—are where the task structure and other environmental and contextual constraints come to dominate the linking of actions to goals. Longer-term goals are typically realized by task structures hierarchically composed of many shorter-term goals. Individuals tend to approximate a principle of rationality: Based on their perceptions of the ongoing situation and their current knowledge, they prefer actions that will move them toward their goals.
- *The social band*—spanning approximately days to weeks to months and beyond—addresses social systems that involve many individuals in communication and interaction. At this level, factors such as communication, coordination, cooperation, trust, reputation, and others play a role, as do the structure and dynamics of social networks.

Table 1. Human behavioral time scales: Different bands show different phenomenological worlds.

Scale (seconds)	Time Unit	Band
10^7	Months	Social
10^6	Weeks	
10^5	Days	
10^4	Hours	Rational
10^3	10 minutes	
10^2	Minutes	
10^1	10 seconds	Psychological
10^0	1 second	
10^{-1}	100 ms	
10^{-2}	1 ms	Biological

WEB NAVIGATION CHOICES

Consider this simple example of information-seeking on the Web, where accurate models[6] at the rational, psychological, and social bands have been developed for simple tasks such as finding products, event dates, and particular documents.

These have been incorporated into Bloodhound, an automated Web usability evaluator.[7] Analysis at the rational band of Web information seeking involves rational analysis,[8] which focuses on the task environment's performance, the information environment that structures access to valuable knowledge, and the adaptive fit of the human-information interaction system to these environments' demands. This method progresses through the following steps:

1. Specify the user's information-seeking goals.
2. Develop a formal model of the task and information environments—the Web's information architecture, for example.

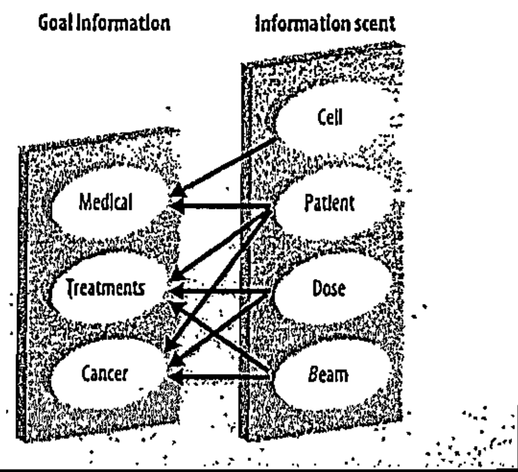

Figure 2. A cognitive structure in which cognitive chunks representing an information goal are associated with chunks representing information scent cues from a Web link.

3. Make minimal assumptions about cognitive costs.
4. Derive the user's rational behavior, considering steps 1 through 3.
5. Test the rational predictions against data.
6. Iterate.

In the case of the Web tasks, one focus of rational analysis concerns how users choose the most cost-effective and useful browsing actions to take, based on the relation of a user's information need to the perceived cues associated with Web links. Such user interface cues have been called information scent because users follow these cues on trails through an information architecture. A random utility model can predict link choices to an approximation.[9] This model asserts the probability that a user will choose a particular link L, having a perceived utility V_L, from a set of links C on a webpage, given a user information goal G:

$$Pr(L \mid G,C) = \frac{e^{\mu V_L}}{\sum_{k \in C} e^{\mu V_k}} \quad (1)$$

where μ is a scaling parameter.

A spreading activation model of information scent can model the details of how users judge the utility of Web links such as V_L at the finer-grained psychological band for text links. This model assumes that the user's cognitive system represents information scent cues and information goals in cognitive structures called *chunks*, as Figure 2 shows.

These chunks can be thought of as representing mental concepts in human memory. Figure 2 assumes that a user seeks information about "medical treatments for cancer" and encounters a Web link labeled with text that includes "cell," "patient," "dose," and "beam." We assume that when users focus on Web links, their attention to information scent cues activates corresponding cognitive chunks into conscious awareness. Activation spreads from those attended chunks along associations to related chunks. The amount of activation accumulating on the representation of a user's information goal provides an indicator of the utility—for example, V_L—of that link. When incorporated into a computational simulation of users, the rational and psychological band models can predict up to 90 percent of the variance in users' link choice behavior.[6]

These Web link choice models can be mapped to a social band model that simulates the flow of users through a website. This provides the core algorithm used by the Bloodhound Web usability systems.[7] A flow network can model the aggregate flow of users grouped for a particular task, where each node in the network represents a webpage, and each edge in the network represents the flow of users from one page to another. A simple version employs discrete steps corresponding to users clicking to move from one page to another. The number of users arriving at webpage node i at step $t+1$ from the k nodes that can reach it are modeled as follows:

$$N_{i,t+1} = f_t \sum_k S_{i,k} N_{k,t} \quad (2)$$

where f_t is the proportion of users who continue to surf after t time steps, and S_{ij} is the proportion of users who decide to move from page j to page i, which can be determined by Equation 1. Tests of this algorithm, when incorporated into the Bloodhound usability evaluator, showed that the predicted pattern of visits demonstrated moderate to strong correlations with observed patterns in 29 out of 32 tasks conducted across four different websites.

THREE THESES

This simple illustration about modeling the Web also demonstrates three theses[5] that promise a future science of ISSSs.

Decomposition

This thesis states that complex IS behavior occurring at large time scales—ranging from minutes through hours and days to months—can be decomposed into smaller elements and events. For example, the complex behavior of an individual interacting with a Web browser can be decomposed into individual elements of perception, judgment, decision, and action selection. Decomposition of the Web information-seeking task—of which link choice provides just one subtask—is required to develop rich user simulations. Specific features of ISSSs can improve or degrade those elements in a way that affects the full shape of IS behavior in complex situations.

Relevance

This thesis holds that the microstructure of behavior is relevant to macrostructure phenomena. For example, small perturbations in the quality of information scent can cause qualitative shifts in the search cost of Web navigation. There is also evidence[10] that changes in the time cost of fine-grained user interaction in information rating and social bookmarking systems have reliable effects at the social band on contribution rates in user populations. Tweaking a user interface's fine-grained structure can have effects on the phenomena that emerge at the level of large social groups.

Modeling

This thesis claims that predictive models can be developed to specify precisely how changes at the microstructure of individuals interacting with and through ISSSs can percolate upward to affect longer-term complex information seeking. In some cases, a single unified model can go from the lower bands to higher, as in the SNIF-ACT model.[6] More likely, however, there will be layers of models at different bands that capture essential features of models at the lower bands, just as statistical mechanics models particles at a level that only captures crucial features of individual particles' behavior. The graph flow models in Bloodhound, for example, only capture the average or asymptotic behavior of many individual users interacting with the Web.

ENRICHING THE IS TASKS CLASS

As the Internet and communication technologies become ever more pervasive, we see an astounding number of new ISSSs and behaviors. As a result, we must continually expand the kinds of phenomena that conceptual frameworks, theories, and models must address. A few interrelated conceptual frameworks can illustrate this expanding territory.

Sensemaking

Many information search tasks form part of a broader class of tasks called *sensemaking*. Such tasks involve finding and collecting information from large information collections, organizing and understanding that information, and producing some product, such as a briefing or actionable decision. Examples of such tasks include understanding a health problem to make a medical decision, forecasting the weather, or deciding which laptop to buy. In general, these tasks include subtasks that involve information search, but they also involve structuring content into a form that can be used effectively and efficiently in some task.

As an extreme example, intelligence analysts perform this sort of sensemaking as a profession, working to gather and sift through vast amounts of incoming information to write briefings that shape decisions affecting national security. Cognitive task analyses of intelligence analysis[9] suggest that the overall process can be organized into two major activity loops: an information foraging loop that involves processes aimed at seeking information, searching and filtering it, and reading and extracting information, and a sensemaking loop that involves iterative development of a mental model—a conceptualization—that best fits the evidence.

Information processing is both driven by bottom-up (from data to theory) and top-down (from theory to data) processes. The foraging loop essentially trades off among three process types: information exploration, enrichment, and exploitation. Typically, analysts cannot explore this entire space and must forego coverage to actually enrich and exploit the information.

> **Exploratory search involves three major kinds of activities: lookup, learn, and investigate.**

The sensemaking loop involves substantial problem structuring (the generation, exploration, and management of hypotheses), evidentiary reasoning (marshaling evidence to support or disconfirm hypotheses), and decision making (choosing a prediction or course of action from the set of alternatives). Many well-known cognitive limitations and biases affect these processes.

Exploratory search

This undertaking provides another rich domain,[11] one that includes activities involving information lookup, learning, and investigation, which can overlap in time. For example, looking for health-related information is one of the Web's most prevalent information-seeking activities. Typically, this involves a prolonged engagement in which individuals iteratively look up and learn new concepts and facts. These activities in turn dynamically change as searchers refine their information-seeking goals and ask better questions. The process can be viewed as a subcomponent of sensemaking.

Exploratory search involves three major kinds of activities: lookup, learn, and investigate. Whereas lookup activities have been the traditional focus of ISSSs, as Figure 1 shows, exploratory search emphasizes learning and investigation activities.

Searching to learn includes activities involved in making decisions, such as purchases, up through professional and lifelong learning. It also includes social searches to find communities of interest—via social network systems, for example. Investigative activities include analysis, synthesis, and evaluation.

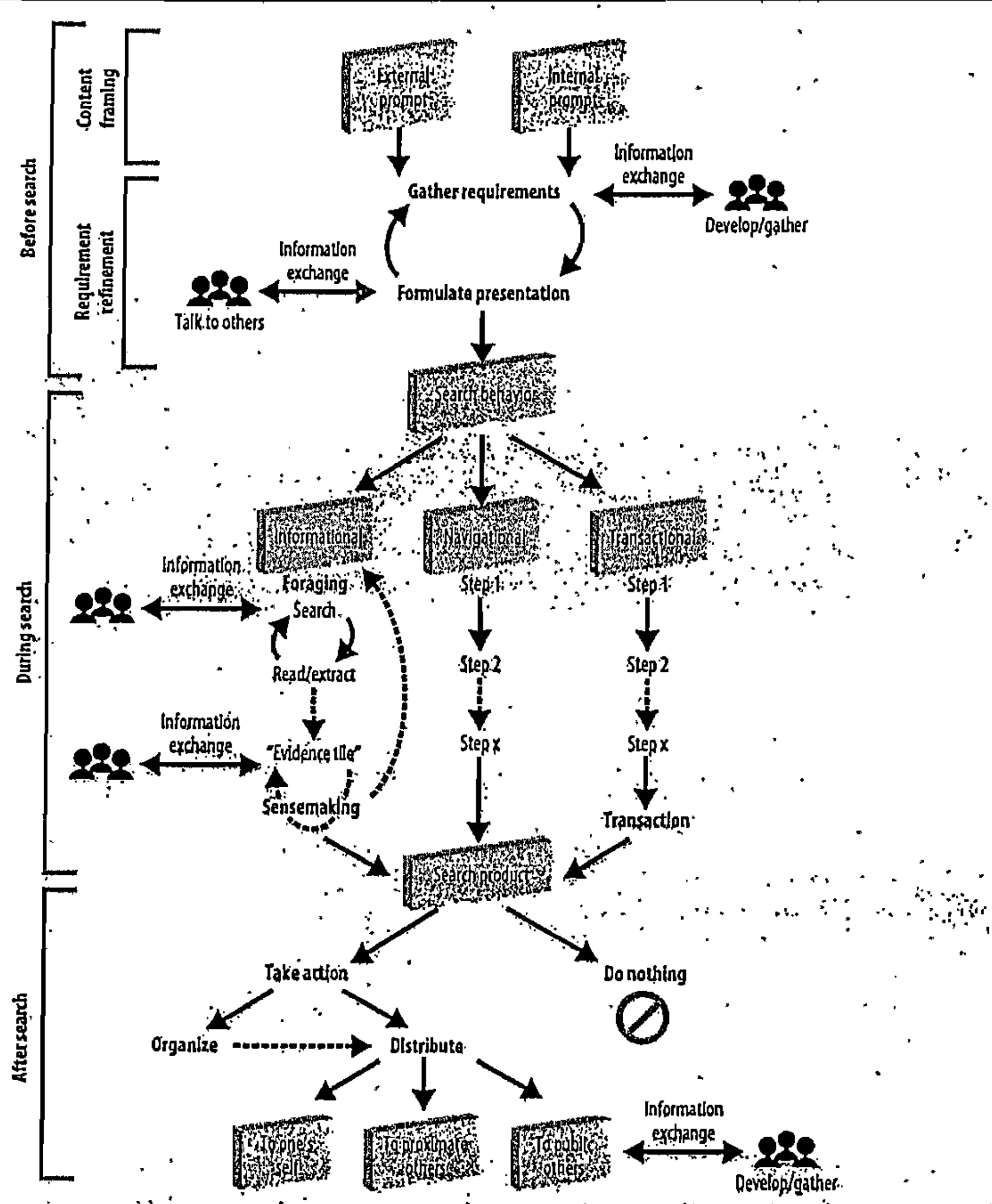

Figure 3. Conceptual model of social search. Social exchanges of information can occur before, during, and after an actual information search.

Social search

People frequently turn to their social networks to find information, thus social search has become a recent focus of study.[12] Figure 3 shows some of the complexity that arises in social search analysis. Social information exchanges can occur before, during, and after an actual search for information. Social transactions can influence the gathering of requirements and formulation of a problem representation before a search, the gathering and extraction of information during search, and the distribution of results after search.

Even more generally, new forms of sociotechnical information systems—such as social bookmarking or rating sites—let users participate with low effort and contribute their unique nuggets of knowledge—such as data about navigation, organization, and recommendations—in a

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PRECISION AND RECALL

Daniel Tunkelang, *Endeca*

Information retrieval (IR) research today emphasizes precision at the expense of recall. Precision is the number of relevant documents a search retrieves divided by the total number of documents retrieved, while recall is the number of relevant documents retrieved divided by the total number of existing relevant documents that should have been retrieved.

These measures were originally intended for set retrieval, but most current research assumes a ranked retrieval model, in which the search returns results in order of their estimated likelihood of relevance to a search query. Popular measures like mean average precision (MAP) and normalized discounted cumulative gain (NDCG)[1] mostly reflect precision for the highest-ranked results.

For the most difficult and valuable information-seeking problems, however, recall is at least as important as precision. In particular, for tasks that involve exploration or progressive elaboration of the user's needs, a user's progress depends on understanding the breadth and organization of available content related to those needs. Techniques designed for interactive retrieval, particularly those that support iterative query refinement, rely on communicating to the user the properties of large sets of documents and thus benefit from a retrieval approach with a high degree of recall.[2]

The extreme case for the importance of recall is the problem of information availability, where the seeker faces uncertainty as to whether the information of interest is available at all. Instances of this problem include some of the highest-value information tasks, such as those facing national security and legal/patent professionals, who might spend hours or days searching to determine whether the desired information exists.

The IR community would do well to develop benchmarks for systems that consider recall at least as important as precision. Perhaps researchers should revive the set retrieval models and measures such as the F1 score, which is the harmonic mean of precision and recall.

Meanwhile, information scientists could use information availability problems as realistic tests for user studies of exploratory search systems, or interactive retrieval approaches. In general, the effectiveness of such systems would be measured in terms of the correctness of the outcome (does the user correctly conclude whether the information of interest is available?), user confidence in the outcome, which admittedly may be hard to quantify, and efficiency—the user's time or labor expenditure.

Precision will always be an important performance measure, particularly for tasks like known-item search and navigational search. For more challenging information-seeking tasks, however, recall is as or more important, and it is critical that the evaluation of information-seeking support systems take recall into account.

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highly independent and modular way. These contributions in turn improve the system's performance as a whole. The emergence of such Web 2.0 technologies shows how systems that can efficiently let users make contributions, and that have architectures that harness those contributions in a highly efficient way, can win big in the public and commercial world.

Our conception of ISSSs has expanded from simple information search engines. Similarly, the field is moving from conceptual frameworks to scientific models, expanding the range of systems and phenomena studied. As the "Precision and Recall" sidebar explains, as the field moves away from a focus on simple precision and recall metrics to a more comprehensive understanding of information's utility to the range of human goals in modern-day society, the need arises to better understand user experience and evaluations of credibility, trust, and reputation.

The field is realizing that we need to understand why people search, explore, annotate, and decide to participate and share the efforts of their knowledge work. People no longer work with a single ISSS, but even for simple tasks will effortlessly move among an array of tools. This is a complex territory to map with scientific models. It spans 10 powers of 10 of time scale, from tens of milliseconds to years, with enormous complexity at multiple bands of phenomena, from the psychological to the social.

A great opportunity beckons as these phenomena increasingly happen online in large living laboratories. This great attractor for scientific minds in diverse areas will range across fields as varied as behavioral economics, incentive mechanisms, network theory, cognitive science, and human-computer interaction. ■

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◎ 本試題共分 A、B 兩個部份，各包括一篇論文(或論文摘錄)與相關的問答題，作答時，請注意各題之比例配分並清楚標示題號

Part A：(50%)
【論文】："A coordination-theoretic investigation of the impact of electronic integration on logistics performance" (第 2 頁~第 11 頁)
【問題】：

A-1. Write down this paper's abstract. (5%)

A-2. Discuss theoretical and managerial implications of this paper. (10%)

A-3. Why authors apply coordination theory for a post-e-integration issue. (10%)

A-4. Do their hypotheses completely illustrate this issue or not? What are your suggestions? (10%)

A-5. Suggest three theoretical or practical future studies and describe the main reasons. (15%)

Part B：(50%)
【論文】："Explaining information technology usage: A test of competing models" (第 12 頁~第 15 頁)
【問題】：

B-1. Describe and compare TAM and EDT, then comment on the roles they play regarding IT usage. (15%)

B-2. Give rationale for the integration of perspectives from TAM and EDT, then design and draw a research framework to implement this idea effectively. (15%)

B-3. Itemize major research processes in validating the research framework you proposed. (10%)

B-4. Discuss possible findings and their implications for research and practice. (10%)

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A coordination-theoretic investigation of the impact of electronic integration on logistics performance

1. Introduction

What can be done to improve the logistics performance of firms? This is a question facing managers in business and industry. Logistics has become an integral part of corporate strategy; it contributes to the primary activities of the value chain of firms. The logistics activities are inter-dependent, requiring careful allocation of resources to achieve service goals and to reduce wastes in the supply chain such as idle time, and duplication of efforts. Logistics deals with the processes of planning, implementing, and controlling the efficient flow and storage of raw materials, in-process inventory, finished goods, services, and related information from points of origin to consumption while conforming to customer requirements. These processes require the use of information technology (IT) for effective coordination. However, the logistics business processes of many firms are still confined to manual processes and to isolated functional automation [19], which lack coordination to manage the tasks effectively.

Electronic integration (e-integration) can be traced to Porter's Value Chain Model [33]. Electronic linkage is the enabling mechanism to coordinate logistics activities and integrate the business processes [20]. According to Stevens [38], there are different types of integration, ranging from functional to internal and external integration. Romano [36] suggested that there are two levels of e-integration in support of the coordination of business processes in a supply chain, (i) intra-company, spanning internal functional boundaries, and (ii) inter-company, improving communication between companies. A systematic investigation of the performance implications of e-integration is highly desirable as many reputable companies such as Dell Computer, Seven-Eleven Japan, Lucent Technologies, Wal-Mart, and Procter & Gamble have reported their benefits from integrating activities with their supply chain partners. To provide empirical evidence of the contribution of e-integration, we therefore examined through the use of empirical data, the extent of e-integration and its logistics performance implications.

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Although some case studies have documented intra- and inter-organizational e-integration for logistics operations, they only investigated the use of IT in logistics processes for better performance [37]; they provided limited understanding of the link between e-integration and logistics performance. But as Rogers' Innovation Diffusion Theory [35] says, there are multiple stages in the diffusion of IT from being exposed to an innovation to making a decision to adopt or reject it.

However, several research gaps still exist. First, past studies were limited to examining the prerequisite of e-integration and its related measures in the decision stage, focusing on analysis of the supplier selection process for logistics process integration, raising awareness of e-integration benefits, designing business networks for logistics management, etc. Second, work has tended to focus on the effects of antecedents, such as organizational characteristics, organizational support, organizational readiness, institutional pressures, and inter-organizational relationships, on the performance of e-integration. Such studies have only provided limited insights into the business value of e-integration. Third, there have been few empirical investigations into the performance implications, due mainly to a lack of appropriate measurements to cope with the complexity of electronic linkages between business processes.

There is a need for theoretical explanations for the observation that some firms perform better than others when using e-integration. In Fig. 1, we have summarized the research issues in the different stages of e-integration (decision, adoption, and implementation), and identified the position of this study in the literature.

The objective of our study was to examine the link between e-integration and logistics performance, providing reasons why such a link may exist from the Coordination Theory perspective. The questions were:

(1) Is the implementation of intra- and inter-organizational e-integration associated with cost- and service-related logistics performance?
(2) What are the different aspects (dimensions) of e-integration? and
(3) Why some firms perform better than others despite though they all have implemented e-integration?

2. Theoretical background

2.1. The Coordination Theory and logistics performance

The Coordination Theory investigates how activities can be integrated amongst multiple organizations working together towards common goals [26,27]. Four major components are considered in the coordination of activities: a set (i.e., at least two) of *actors*, who create or use *resources* to perform *tasks*, to achieve *goals* [8,28]..

Communication and information sharing between partners is essential for coordination of business activities. Establishing communication standards and electronic linkages is necessary to ease information flows. The coordination mechanism contributes to (1) a reduction in coordination costs, (2) allocation of organizational resources to handle complex tasks, and (3) an efficient coordination structure.

The Coordination Theory provides an appropriate theoretical way to examine if and how e-integration contributes to logistics performance. With it, parties (the actors) perform the tasks that require information sharing (resources) to achieve a set of goals. The implementation of e-integration requires reengineering of the logistics processes. e-Integration serves as the coordination mechanism to manage the task dependency between the logistics processes, extend their activities across intra- and inter-

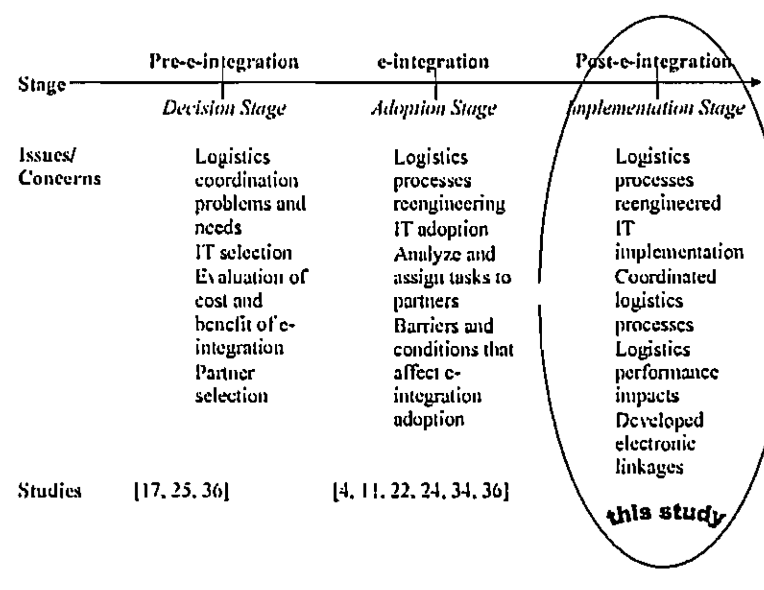

Fig. 1. Stages of e-integration [4,11,17,22,24,25,34].

organizational boundaries. Thus, the logistics processes shift from being locally optimized; e-integration is useful for managing the logistics processes.

3. Research model and hypotheses

3.1. Inter-organizational e-integration

Without e-integration of inter-organizational processes, a piece of data, e.g., a trade document, must be entered manually into different systems. In doing this, errors, inconsistencies, information loss, and costs may result. Hart and Saunders [14] observed that inter-organizational e-integration can speed up data interchange. In their investigation of the effects of various supplier and customer integration strategies on performance, Frohlich and Westbrook [10] found that firms attaining a high level of e-integration with suppliers and customers tend to perform better.

e-Integration enables the suppliers to replenish stocks to an agreed level of inventory, which allows fast replenishment for firms and improves the accuracy of the production forecasts for the suppliers. The inter-organizational e-integration of a firm is useful to reduce inventory and order processing costs for its supply chain. We therefore posit that

Hypothesis 1. The inter-organizational e-integration of a firm is positively associated with its logistics cost performance.

As e-integration provides an information processing mechanism to coordinate logistics activities, it enables a firm to improve the flows of goods along its supply chain, achieving without manual intervention in inter-organizational information interchange, errors in coordinating logistics processes can be reduced and reliability of the services provided can be improved. Therefore, we conjecture that

Hypothesis 2. The inter-organizational e-integration of a firm is positively associated with its logistics service performance.

3.2. Intra-organizational e-integration

Intra-organizational e-integration enables flows of information between internal business processes with electronic linkages. It allows firms to eliminate paperwork and to increase the timeliness, accuracy, and accessibility of the information in their internal business processes [16]. Thus, we posit that

Hypothesis 3. The intra-organizational e-integration of a firm is positively associated with its logistics cost performance.

Intra-organizational e-integration enhances the ability of firms to fulfill customer requirements and to cope with unpredicted events in their supply chains by increasing the effectiveness of information processing of the firms [6]. It also allows sharing of accurate market information, which enables firms to make timely changes to their internal operations, such as changing production and shipping schedules, and even product features. Thus, it is useful for firms to create customer value and excel in service performance through effective coordination of activities. We therefore hypothesize that

Hypothesis 4. The intra-organizational e-integration of a firm is positively associated with its logistics service performance.

4. Methodology

4.1. Sample characteristics

We tested the hypotheses with survey data collected from trading companies in Hong Kong. We chose trading companies because they are heavily involved with logistics activities because of their business nature. Our focus on a single industry allows us to customize items in our survey questionnaire to cater for the characteristics of the firms and obtain more accurate responses. Using the *Hong Kong Business Directory – Trading and Transportation*, we drew a sample of 1000 firms from the 3445 trading firms in the directory, using a random sampling procedure comparable to studies conducted in similar contexts. Top executives, i.e., Chairman, CEO, and Managing Director, of these trading firms were our target respondents. As the majority of our sample firms were small in size, i.e., with fewer than 100 employees, it was reasonable to assume that such high-level executives would have comprehensive and adequate knowledge of e-integration and logistics activities with their partner firms in their organizations.

We first sent a survey questionnaire to each of the 1000 sampled firms, together with a cover letter that explained the purpose of our study and enclosing a self-addressed postage-paid response envelop. After 2 weeks, a follow-up letter and a second copy of the questionnaire were mailed to all non-respondents. We finally sent a reminder to the non-respondents 2 weeks after the second mailing.

We received a total of 257 responses after the two waves of mailings and the follow-up reminder. We removed 30 responses due to either incomplete information or late receipt. Thus, we had 227 usable responses (155 in the first mailing and 72 in the second mailing) resulting in a 22.7% response rate, which was comparable to other studies of a similar nature. Table 1 shows the characteristics of the respondent firms. Over half of the firms reported annual sales revenues of less than US$ 12.8 million and had fewer than 25 employees.

4.2. Non-response bias

We tested the likelihood of non-response bias by the extrapolation technique, whereby the responses from the

Table 1
Profile of the respondents ($N = 227$)

Company characteristics	Number of observations	Percentage
Number of employees		
1–4	14	6.2
5–9	58	25.6
10–19	39	17.2
20–49	57	25.1
50–99	7	3.1
100–199	11	4.8
200–499	10	4.4
>499	3	1.3
Unknown	28	12.3
Level of turnover (HK$)		
Below 100 million	116	51.1
100–199 million	13	5.7
200–299 million	8	3.5
300–399 million	9	4.0
400 million or above	28	12.3
Unknown	53	23.3

Note: US$ 1 is approximately equal to HK$ 7.8.

first mailing were compared to those from the second one [2]. We computed the differences in the mean values of a random selection of the measurement items in the survey questionnaire and found no significant differences between the early and late respondents. We also checked the non-response bias based on the information obtained from the responding firms and archival data obtained from the *Hong Kang Business Directory – Trading and Transportation*. From these sources, we were able to compare the firm size (i.e., number of employees) between the responding and the non-responding firms; these were known from the company identification code number we stamped on each questionnaire. The difference in the mean values of number of employees between the respondents and non-respondents was tested using an unpaired t-test. The resulting t statistic was insignificant, suggesting that non-response bias was not a problem.

4.3. Common method variance

Of course, the problems of perceptual measures may have led to common method bias. However, the response rate of our survey would have suffered if we had requested sensitive and objective data from our respondents. Also, the cost performance data could be biased by differences in the accounting practices of the firms. Moreover, prior studies have cautioned that business research should devote more attention to understanding the perceived value of the participants. We therefore employed self-reported perceptual measures in our study. To detect the threat of common method bias, we conducted the Harman's one-factor test suggested by Podsakoff and Organ [32]. Four factors with eigenvalues greater than one were extracted from all the measurement items for intra- and inter-organizational e-integration, and cost and service performance, as detailed below, and they explained 75.6% of the variance, with the first factor accounting for 26.6% of it. Since no single factor emerged that accounted for most of the variance, common method variance did not appear to be a problem in our study.

4.4. Measurement development

We operationalized e-integration as the degree of electronic linkages and data interchange between business processes by measuring the extent of electronic data interchange that had been developed for intra- and inter-organizational information interchange. Thus, e-integration was assessed using a multi-dimensional measurement, covering the different dimensions of the electronic connectivity in business processes and used the dimensions of electronic connections developed by Massetti and Zmud [30]. This comprised four dimensions: volume, diversity, breadth, and depth. These dimensions of electronic linkages serve different strategic and operational purposes. They are complementary and co-vary with one another—thereby helping firms to attain performance improvements. To measure intra- and inter-organizational e-integration, we modeled them as reflective second-order constructs, consisting of four first-order dimensions as depicted in Table 2. The two e-integration constructs were measured using 30 items on a five-point Likert scale, where our study targets were asked to indicate the level of electronic data interchange between business processes within and between their organizations on individual items (1: very low, 0–20%; 2: low, >20–40%; 3: neither low nor high, >40–60%; 4: high, >60–80%; 5: very high, <80–100%).

Table 2
Descriptions of intra- and inter-organizational e-integration

Dimensions of electronic linkages	Inter-organizational e-integration	Intra-organizational e-integration
Breadth	The number of electronic linkages with different supply chain partners	The number of electronic linkages between different internal processes
Diversity	The variety of electronic linkages for different types of data	The variety of electronic linkages for different types of data
Volume	The number of data being interchanged electronically	The number of data being interchanged amongst internal processes
Depth	The number of business processes within a firm that has been migrated to electronic integration to facilitate bidirectional flows of information with partner firms	The number of internal processes that are electronically integrated to facilitate bidirectional flows of information between one another

Logistics cost refers to the costs incurred in coordinating and managing logistics activities, such as transportation, warehousing, order processing, customer service, and inventory management [23]. It represents a large portion of the operating costs of firms. Cost-related performance has been a traditional criterion in measuring logistics performance. However, studies have criticized the limitation of cost-related performance and advocated broadening it to embrace the operational aspects of logistics activities [3,12], including such indicators as delivery reliability, customer responsiveness, and customer satisfaction, to measure logistics service performance [21]. Logistics service refers to the customer value created in the logistics processes in such areas as availability, timeliness, and order condition [31]. The supply chain operations reference model (SCOR) also embraces the cost and service aspects of logistics performance in terms of costs, assets, reliability, and responsiveness/flexibility [39]. Following SCOR and previous studies, e.g. [18], we measured logistics cost and service improvements using nine- and seven-item sets, respectively. Our survey targets were asked to assess their logistics cost and service performance relative to their major competitors on a five-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree).

4.5. Validity and reliability

To ensure content validity of the measurement items, we first developed a draft survey questionnaire (instrument) and circulated it to five academics in the fields of supply chain management, logistics management, operations management, and information management for content validation and instrument refinement. The instrument was refined based on the feedback. Subsequently, we conducted a test with a group of practitioners who were pursuing a part-time postgraduate degree in logistics management. The pre-test was conducted to ensure the clarity and appropriateness of the instrument. Based on the feedback, some items were rephrased to avoid confusion. Finally, we conducted a pilot test with a sample of 30 randomly selected trading firms in Hong Kong. This test provided sample data that allowed us to perform statistical tests to establish face validity of the constructs and further refine the questionnaire. Since no major problems were found during the pilot test, we mailed the survey questionnaire to the sample firms in our study.

Validity and reliability of the constructs were initially assessed using Cronbach's alpha and item-total correlation analysis. Confirmatory factor analysis (CFA) using maximum likelihood estimation was conducted to evaluate the constructs. The results showed that all the measurement items had high loadings on their respective latent factors, ranging from 0.65 to 0.95. The alpha values of all the first-order factors exceeded the 0.70 cutoff level, ranging from 0.89 to 0.97, thus indicating that the factors of e-integration were reliable.

Since the number of factors could be specified in advance, we applied CFA instead of exploratory factor analysis (EFA) to test the measurement model of e-integration in our study. The details of the measurement model validation are discussed in Appendix A.

5. Hypotheses testing

The hypotheses and the research models were tested with path analysis using structural equation modeling (SEM) with maximum likelihood estimation using Amos 5.0. Both intra- and inter-organizational e-integration were taken as exogenous constructs, while logistics service and cost performance were taken as endogenous constructs. The results offered support for some of the hypothesized relationships. The results indicated that the model provides a reasonable fit to the data. Table 3 shows the parameter estimates and model statistics for the structural model.

- For Hypothesis 1 [inter-organizational e-integration → logistics cost performance], the structural link is positive and significant (0.18, $p < 0.05$). This provided support for Hypothesis 1.

Table 3
Standardized parameter estimates and model statistics

Paths	Supply chain performance	
	Service	Cost
Structural model		
Hypothesized relationships		
Inter-organizational e-integration → logistics cost performance (Hypothesis 1)		0.18*
Inter-organizational e-integration → logistics service performance (Hypothesis 2)	0.17	
Intra-organizational e-integration → logistics cost performance (Hypothesis 3)		0.23*
Intra-organizational e-integration → logistics service performance (Hypothesis 4)	0.12	
Goodness of fit statistics		
d.f.	25	25
Comparative fit index (CFI)	0.94	0.94
Goodness-of-fit index (GFI)	0.83	0.83
Normed fit index (NFI)	0.93	0.93
Root mean squared residual (RMR)	0.04	0.04

*$p < .05$.

- For Hypothesis 2 [inter-organizational e-integration → logistics service performance], the structural link is insignificant (0.17, $p > 0.05$). Thus, Hypothesis 2 was not supported.
- For Hypothesis 3 [intra-organizational e-integration → logisties cost performance], the structural link is positive and significant (0.23, $p < 0.05$). This lent support to Hypothesis 3.
- For Hypothesis 4 [intra-organizational e-integration → logistics service performance], the structural link is insignificant (0.12, $p > 0.05$). Thus, Hypothesis 4 was not supported.

Thus, intra- and inter-organizational e-integration is positively associated with logistics cost performance, but not with logistics service performance.

Appendix A. Measurement model estimation

The Cronbach's alphas, composite reliabilities, and the values of average variance extracted of the constructs are summarized in the following table[1] [9,13].

In CFA, we allowed all the factors to correlate freely in their respective measurement models [15]. All the items loaded significantly (i.e., $p < 0.001$ and $t > 2.0$) onto their underlying factors with loadings ranging between 0.650 and 0.993. Also, the average variance extracted (AVE) estimates of the constructs were greater than 0.50. These results suggest that convergent validity of the measurement items for e-integration was supported [1]. We assessed discriminant validity by examining the AVE estimates. The AVE of

Measurement model: first-order constructs

Constructs	*Items*	*Standardized loadings*	*Cronbach's alpha*	*Composite reliability*	*AVE*
Intra-Vol	InVol1[a]	0.936***	0.889	0.901	0.756
	InVol2	0.973***			
	InVol3	0.668***			
Intra-Div	InDiv1[a]	0.946***	0.952	0.954	0.873
	InDiv2	0.993***			
	InDiv3	0.859***			
Intra-Bre	InBre1[a]	0.980***	0.953	0.951	0.747
	InBre2	0.985***			
	InBre3	0.733***			
	InBre4	0.913***			
	InBre5	0.903***			
	InBre6	0.698***			
Intra-Dep	InDep1[a]	0.961***	0.951	0.955	0.876
	InDep2	0.989***			
	InDep3	0.853***			
Inter-Vol	ExVol1[a]	0.842***	0.955	0.950	0.828
	ExVol2	0.846***			
	ExVol3	0.973***			
	ExVol4	0.969***			
Inter-Div	ExDiv1[a]	0.829***	0.947	0.941	0.801
	ExDiv2	0.808***			
	ExDiv3	0.976***			
	ExDiv4	0.955***			
Inter-Bre	ExBre1[a]	0.933***	0.958	0.958	0.885
	ExBre2	0.965***			
	ExBre3	0.923***			
Inter-Dep	ExDep1[a]	0.962***	0.972	0.971	0.894
	ExDep2	0.973***			
	ExDep3	0.922***			
	ExDep4	0.923***			
Logistics service performance	SQ1[a]	0.650***	0.901	0.905	0.555
	SQ2	0.873***			
	SQ3	0.857***			
	SQ4	0.817***			
	SQ5	0.609***			

[1] Following Fornell and Larcker [9], we calculated composite reliabilities and AVE values using the following formulae:

$$\text{composite reliability}(\rho_\eta) = \frac{\left(\sum_{i=1}^{n} \lambda_{y_i}\right)^2}{\left(\sum_{i=1}^{n} \lambda_{y_i}\right)^2 + \sum_{i=1}^{n} \varepsilon_i},$$

$$\text{average variance extracted}(\text{AVE}_\eta) = \frac{\sum_{i=1}^{n} (\lambda_{y_i}^2)}{\sum_{i=1}^{n} (\lambda_{y_i}^2) + \sum_{i=1}^{n} \varepsilon_i},$$

where η is the construct, λ_y is the standardized factor loading for measurement item y_i, and ε_i is the measurement error for scale item y_i. The measurement error is

Appendix A (*Continued*)

Constructs	Items	Standardized loadings	Cronbach's alpha	Composite reliability	AVE
	SQ6	0.722***			
	SQ7	0.768***			
Logistics cost performance	CR1[a]	0.747***	0.939	0.945	0.610
	CR2	0.862***			
	CR3	0.865***			
	CR4	0.810***			
	CR5	0.860***			
	CR6	0.737***			
	CR7	0.791***			
	CR8	0.711***			
	CR9	0.761***			

***$p < 0.001$.
[a] Item was fixed to 1 in the original solution.

each construct was greater than the squared correlation between constructs, which suggests that the items share common variance with their hypothesized constructs more than with other constructs [9]. We also tested discriminant validity with the phi estimate, i.e., inter-correlation amongst the factors in the two constructs. All the phi values shown in the following table were significant at $p < 0.01$ level. Furthermore, we conducted a series of pairwise chi-square tests of the difference between two models involving two constructs. The first model fixed the covariance between the two constructs (e.g., cost and service performance) to 1.0 (i.e., a constrained model) while the second model allowed the covariance to be freely computed (i.e., an unconstrained model). A statistical difference between the models indicates that the models are different. Thus, discriminant validity was established.

Descriptive statistics and inter-correlations of first-order factors

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Intra-organizational volume	2.40	1.29	1									
2. Intra-organizational diversity	2.34	1.28	0.920	1								
3. Intra-organizational breadth	2.30	1.27	0.837	0.896	1							
4. Intra-organizational depth	2.27	1.28	0.854	0.907	0.909	1						
5. Inter-organizational volume	2.12	1.09	0.656	0.578	0.536	0.561	1					
6. Inter-organizational diversity	2.03	1.07	0.685	0.668	0.602	0.620	0.873	1				
7. Inter-organizational breadth	1.98	1.06	0.575	0.565	0.557	0.590	0.810	0.798	1			
8. Inter-organizational depth	2.04	1.08	0.625	0.621	0.612	0.683	0.803	0.836	0.852	1		
9. Service performance	3.58	0.64	0.230	0.220	0.227	0.233	0.220	0.216	0.194	0.282	1	
10. Cost performance	3.18	0.69	0.357	0.341	0.331	0.347	0.320	0.348	0.283	0.336	0.672	1

All correlation coefficients are statistically significant at the 0.01 level.

Using the composite scores of the factors by taking the arithmetic mean of the items, we estimated the measurement models of intra- and inter-organizational e-integration, respectively. The CFA results with Cronbach's alpha coefficients, standardized loadings, t-values, composite reliabilities, and AVE values of intra- and inter-organizational e-integration at the second-order level, where each of the constructs is composed of four first-order factors, are summarized in the following table on the measurement model for e-integration. The descriptive statistics and correlations amongst the constructs under this study are presented in the following table on descriptive statistics and correlations. All the Cronbach's alpha values for the second-order factors exceeded the 0.70 cutoff level [7], yielding satisfactory evidence of internal consistency. We also estimated the second-order factors, i.e., intra- and inter-organizational integration, by examining the target coefficient $(T)^2$ [29]. The T indicates the extent to which the second-order factor accounts for the variance amongst the first-order factors, i.e., volume, diversity, breadth, and depth. Both the intra- and inter-organizational e-integration constructs had high T ratios of 0.93 and 0.92, respectively, implying that the relationships amongst the first-order factors are sufficiently captured by the second-order factor. Moreover, the paths from the second-order factors to the eight respective first-order factors were significant and of a high magnitude greater than 0.70 [5], ranging from the lowest of 0.892 to the highest of 0.973. Thus, on both theoretical and empirical grounds, the conceptualization of intra- and inter-organizational e-integration as higher-order, multi-dimensional constructs was tenable. Having deter-

[2] The T is computed using the following formula:

$$T = \frac{\chi^2 \text{ (first-order model)}}{\chi^2 \text{ (second-order model)}}$$

mined that the latent constructs and their observed indicators possess acceptable measurement properties, we proceeded to estimate the hypothesized .structural paths of the constructs.

... internal documents that are processed between the business processes via EDI is

... trade documents that are processed between the business processes via EDI is

Measurement model for e-integration

Constructs	Items	Standardized loadings	Cronbach's alpha	Composite reliability	AVE
Intra-Org	Intra-Vol[a]	0.928***	0.970	0.969	0.888
	Intra-Div	0.973***			
	Intra-Bre	0.928***			
	Intra-Dep	0.939***			
Inter-Org	Inter-Vol[a]	0.915***	0.953	0.951	0.828
	Inter-Div	0.925***			
	Inter-Bre	0.892***			
	Inter-Dep	0.908***			

***$p < 0.001$.

[a] Item was fixed to 1 to set the scale.

Descriptive statistics and inter-correlations

	Intra-organizational e-integration	Inter-organizational e-integration	Service performance	Cost performance
Intra-organizational e-integration	1	0.690**	0.236**	0.347**
Inter-organizational e-integration		1	0.244**	0.322**
Logistics service performance			1	0.659**
Logistics cost performance				1
N	227	227	227	227
Mean	2.32	2.05	3.58	3.15
Standard deviation	1.22	1.00	0.64	0.69

**$p < 0.01$.

Appendix B. Questionnaire items

General instructions to respondents:

Internal documents in this study are defined as electronic copy of internal documents, e.g. purchasing approval, memos, and sales records. *Trade documents* refer to electronic copy of trade related documents, e.g. invoices, purchase orders, quotations, shipping notice, packing list. *External parties* are defined as the entities that are trading with your company, e.g. customers, suppliers, distributors. *Business processes* refer to any activity or collection of activities that provide a result that has value to an internal and external customer, e.g. purchasing, sales and logistics. *Transactions* are defined as any activity or collection of activities that involve buying and selling something to external parties. *Electronic data interchange (EDI)* is used as the replacement of paper-based system for electronic transmission of orders, invoices, and remittance information between businesses.

A.1 Intra-organizational e-integration: Volume

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the *number* of

... internal documents that are shared between the business processes via EDI is

A.2 Intra-organizational e-integration: Diversity

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the *varieties* of

... internal documents that are shared between the business processes via EDI is

... internal documents that are processed between the business processes via EDI is

... trade documents that are processed internally via EDI is

A.3 Intra-organizational e-integration: Breadth

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the *number* of

... internal documents that are shared cross-functionally via EDI is

... internal documents that are processed cross-functionally via EDI is

... trade documents that are processed cross-functionally via EDI is

... internal documents that are shared vertically via EDI is

... internal documents that are processed vertically via EDI is

... trade documents that are processed vertically via EDI is

A.4 Intra-organizational e-integration: Depth

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the ***number of business processes*** of our company that

... share internal documents via EDI is
... process internal documents via EDI is
... process trade documents via EDI is

B.1 Inter-organizational e-integration: Volume

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the ***number*** of

... trade documents that are sent to external parties via EDI is ... trade documents that are received from external parties via EDI is

... transactions that are sent to external parties via EDI is ... transactions that are received from external parties via EDI is

B.2 Inter-organizational e-integration: Diversity

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the ***varieties*** of

... trade documents that are sent to external parties via EDI is ... trade documents that are received from external parties via EDI is

... transactions that are sent to external parties via EDI is

... transactions that are received from external parties via EDI is

B.3 Inter-organizational e-integration: Breadth

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the ***number*** of

... external parties that send trade documents to us via EDI is

... external parties that request trade documents from us via EDI is

... external parties that transact with us via EDI is

B.4 Inter-organizational e-integration: Depth

(5-point Likert scale anchored by 1: very low 0–20%; 2: low >20–40%; 3: neither low nor high >40–60%; 4: high >60–80% 5: very high <80–100%)

Within our company, the ***number of business processes*** of our company that

... receive trade documents from external parties via EDI is

... send trade documents to external parties via EDI is
... receive transactions from external parties via EDI is
... send transactions to external parties via EDI is

C.1 Logistics service Performance

(5-point Likert scale anchored by 1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree)

Comparing with our major competitors

... our company receives fewer complaints from trading partners (i.e., suppliers/customers)

... our main trading partners are satisfied with our services

... our main trading partners find our services more reliable (e.g. on-time delivery, error free invoice, on-time payment)

... our service performance is more effective (e.g. close to customer requirements)

... the number of required contact points in our company for trading partners to receive our products/services is fewer

... our response time to trading partners is faster
... our trading partners have more trust with us

C.2 Logistics cost Performance

(5-point Likert scale anchored by 1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree)

Comparing with our major competitors

... our order management cost is lower
... our inventory cost is lower
... our warehouse cost is lower
... our transportation cost is lower
... our logistics administration cost is lower
... our cash-to-cash cycle is shorter
... our net asset turns (i.e., working capital) is better
... our business processes are more efficient
... our utilization of corporate resources (e.g. inventory) is better

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Explaining information technology usage: A test of competing models☆

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Abstract

While much of the prior information technology (IT) research has attempted to explain users' acceptance of new IT, recent research has focused on IT continuance or continued usage. The technology acceptance model (TAM) and the expectation–disconfirmation theory (EDT) are currently the dominant referent theoretical frameworks explaining user acceptance and continuance of IT, respectively. However, no study to date has yet empirically compared the relative ability of the two competing theories in explaining IT continuance intention. This paper fills this gap in the literature by comparing the explanatory ability of the two models via a longitudinal study of computer-based tutorial usage. Our findings confirm that both models have good explanatory power with the TAM providing a better prediction of intention. An integrated model, combining TAM and EDT, provided a marginally better explanatory power.

Keywords: IT usage; Technology acceptance model; Expectation disconfirmation theory; IT adoption

1. Introduction

Information technology (IT) usage has been a major focus of information systems (IS) research for more than two decades. This is so because IT usage has been demonstrated to be a key driver of organizational performance [1]. While most prior IT usage research has focused on initial IT usage or acceptance [2–4], long-term IT usage or continuance has recently gained increased attention among researchers [5,6]. As Bhattacherjee [5] stated, initial acceptance is an important first-step toward realizing IT success; however, IT continuance is more critical toward ensuring long-term viability of IT innovations.

Although both the acceptance and continuance streams of research have evolved from psychology research, they have distinct theoretical foundations. IT acceptance research has been informed primarily by the technology acceptance model (TAM) [2], while IT continuance research has been influenced by expectation–disconfirmation theory (EDT) [7]. TAM is based on the beliefs–attitudes–behavior paradigm of human behavior extended from Fishbein and Ajzen's [8] theory of reasoned action (TRA) in social psychology literature. In contrast, EDT is based on expectation–disconfirmation–satisfaction paradigm

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based on Festinger's [9] prior work on cognitive dissonance theory. TAM is a static model that explains user intention and behavior based on forward-looking or prospective expectations about IT usage, such as perceived usefulness, perceived ease of use, and attitude. EDT, on the other hand, is a process model that explains user intention and behavior based on their backward-looking or retrospective perceptions grounded in actual usage experience, such as performance, disconfirmation, and satisfaction, in addition to initial expectations.

Though TAM is technically a model of IT acceptance, it has also been used to examine post-adoptive usage. For instance, Davis et al. [2] used TAM to examine students' usage of a word processing software (WriteOne) at two points in time—following their initial exposure to the system and then again 14 weeks after initial acceptance—in order to demonstrate model's predictive ability for short-term and long-term (post-adoptive) usage. *Recent longitudinal studies have also employed* TAM to examine post-adoption intention and/or behavior (e.g., [10–12]). In contrast, EDT is designed solely to explain post-adoptive behavior following one's first-hand experience with the target system. Since each theory has distinct roots and is based on a different set of antecedent variables, we contend that they independently provide a partial understanding of users' cognitive processes related to IT usage. It is therefore possible that, when combined, these theories may collectively provide an improved and more comprehensive understanding of the cognitive processes and behaviors related to IT usage, than each theory considered alone.

While prior research have examined TAM and EDT independently in explaining IT usage, to the best of our knowledge, no study has yet theoretically compared or contrasted these two models or empirically compared their explanatory power. Additionally, the potential value and insight that may be derived from an integrated model combining these two theories has also not been examined yet. The primary contributions of this study are its examination of theoretical differences between TAM and EDT in explaining long-term IT usage intention and empirical evaluation of whether a research model integrating the two theories can explain IT usage more than either model considered alone. Findings from this paper may therefore help bridge the extant gap between acceptance and continuance streams of IT usage research.

The next section provides a brief overview of TAM and EDT, as well as the theoretical justification for their integration. Section 3 describes the research methods employed in our empirical study. Section 4 discusses variable operationalization and validation. Section 5 presents data analysis techniques and results. The final section discusses the study's limitations, the significance of its findings, and implications for future research.

2. Theory and research model

2.1. Technology acceptance model

TAM was proposed by Davis et al. [2] to explain IT users' intention and behavior regarding IT usage. TAM identified two salient beliefs, perceived usefulness and ease of use, as the primary predictors of user's attitude or overall affect toward IT usage (see Fig. 1). Perceived usefulness is the extent to which a person believes that using a system will enhance her performance, and perceived ease of use is the extent to which a person believes that using the system will be relatively free of effort. User attitude is posited to influence behavioral intention to use IT, which in turn, influences actual usage behavior. Davis et al. [2] also hypothesized perceived usefulness to have a direct effect on intention, in addition to its indirect effect via attitude, to account for circumstances where utilitarian considerations may dominate users' decision to use IT, over and above any negative attitude toward such usage. Davis et al. [2] also observed a positive association between perceived usefulness and ease of use.

Numerous empirical investigations have established strong empirical support for TAM [3,10–12]. Perceived usefulness has consistently been the predominant predictor of user attitude toward IT usage, though ease of use has had a somewhat inconsistent effect, especially during later stages of usage [3]. Longitudinal studies *suggest that the decreasing effect of EOU over time in*dicates a "wearing out" of users' initial inhibitions concerning ease of use as they gain experience with and become comfortable in using the target system [13]. While perceived usefulness has a consistently strong positive

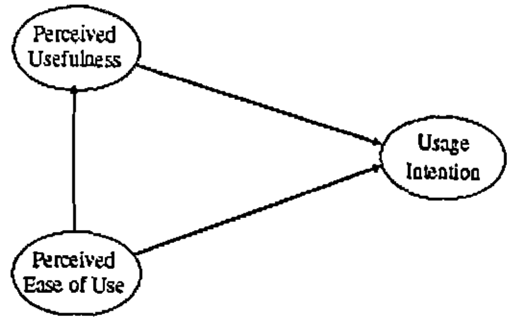

Fig. 1. Simplified technology acceptance model

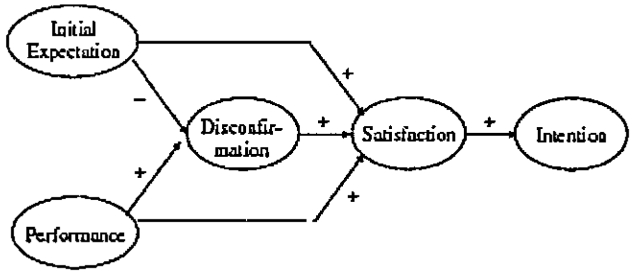

Fig. 2. Expectation–disconfirmation model.

effect of intention, attitude has tended to have a mixed effect, especially when perceived usefulness is included as a predictor of intention [3]. Contrary to TRA, Davis et al. [2] suggested that, in the specific case of IT usage, attitude may only partially mediate the associations between beliefs and intention and that IT usage decisions tend to be more dominated by beliefs such as perceived usefulness than affect such as attitude. This has led many recent TAM studies to drop attitude entirely from their models (e.g., [3,12]).

Among cognitive models, Azjen [14] proposed the TPB as an extension of TRA, to include social influence (subjective norm) and behavioral control as additional determinants of behavioral intention. Some IT usage studies have empirically compared the predictive power of TAM versus TPB (e.g., [4,15]). Taylor and Todd [4] observed that TPB explained 60% of the variance in intention and 36% of IT usage, compared to 52% and 34% for TAM, respectively. Though TPB provides an better understanding of the complex patterns of associations among the antecedents (e.g., beliefs, attitude) of intention, its predictive power is only slightly better than TAM for understanding IT usage intentions, and the parsimony and simplicity of TAM makes it a preferred model for studying IT usage [12]. Hence, consistent with recent TAM studies, a parsimonious model of three variables, consisting of perceived usefulness, perceived ease of use, and IT usage intention is employed as the base model in this study (see Fig. 1).

2.2. *Expectation disconfirmation theory*

EDT was proposed by Oliver [7] in the marketing literature to explain the determinants of consumer satisfaction/dissatisfaction and consequent retention of products and services. Oliver [7] suggested that consumers go though a five-step process in making product or service acquisition and retention decisions (see Fig. 2). First, they form an initial (pre-usage) expectation of the product, based on product information, media reports, feedback from prior users, and the like. Then, they use the product and form a perception of its performance (alternatively viewed as quality) based on their actual product experience. Third, they compare the perceived performance with their initial expectations and determine the extent to which their initial expectations were disconfirmed. Fourth, they establish a satisfaction level, based on their level of disconfirmation and initial expectations. Finally, their satisfaction level influences their intention to repurchase or continue using the product.

EDT posits that consumer satisfaction with actual product or service usage is the primary determinant of their post-purchase intention (see Fig. 2). Satisfied users continue using the product/service, while dissatisfied users stop using it subsequently. Satisfaction, in turn, is based on users' initial expectation from product or service usage and the extent to which this expectation is met during actual usage (disconfirmation). Hence, users can therefore be satisfied in two alternative ways: if they are positively disconfirmed (i.e., experience meeting or exceeding initial expectations), or if they had high expectations to begin with even if such expectations were not met in practice.

Disconfirmation is a function of product or service performance, as perceived by users following their actual usage experience, as well as their initial expectation of the product or service. Initial expectation provides a baseline or reference frame from which performance is evaluated as a deviation in the formation of disconfirmation perceptions. Initial expectation is posited to have both direct and indirect effects on disconfirmation; a negative direct effect since high expectations are most likely to be negatively disconfirmed and a positive indirect effect since high expectations are more likely to lead to higher performance evaluations (halo effect), which in turn, causes greater positive disconfirmation.

Though not included in the original EDT, some researchers have empirically validated performance as an additional determinant of satisfaction (e.g., [16–18]). These studies posit a direct effect of performance on satisfaction, as well as an indirect effect via disconfirmation. However, the relative significance of the two effects vary with product type; high-involvement consumer durables tend to have stronger direct effects than low-involvement products [16].

In IT usage research, EDT was validated by Bhattacherjee [5] in an empirical study of online banking. McKinney et al. [19] found support for EDT in a study of online retailing, separately focusing on users' disconfirmation with the online site and with the quality of information presented on that site. Staples et al. [20] examined the impact of different levels of disconfirmation on perceived system benefits. Bhattacherjee and Premkumar [6] used the core constructs of this theory (i.e., disconfirmation and satisfaction) to explain how users' beliefs and attitude toward IT usage change with time, as the result of their direct experience with IT usage. Across all of these studies, EDT has held up very well as a potent explanation for post-adoptive IT usage.