

Agent-mediated Integrative Negotiation for Retail Electronic Commerce

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Abstract

Software agents help automate a variety of tasks including those involved in buying and selling products over the Internet. Although shopping agents provide convenience for consumers and yield more efficient markets, today's first-generation shopping agents are limited to comparing merchant offerings only on price instead of their full range of value. As such, they do a disservice to both consumers and retailers by hiding important merchant value-added services from consumer consideration. Likewise, the increasingly popular online auctions pit sellers against buyers in distributive negotiation tug-of-wars over price. This paper analyzes these approaches from economic, behavioral, and software agent perspectives then proposes integrative negotiation as a more suitable approach to retail electronic commerce. Finally, we identify promising techniques (e.g., multi-attribute utility theory, distributed constraint satisfaction, and conjoint analysis) for implementing agent-mediated integrative negotiation.

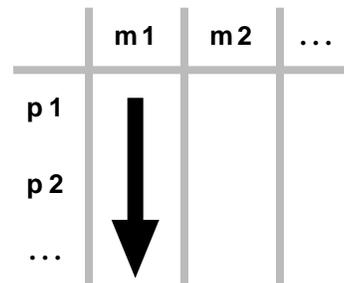
1. Introduction

Online marketplaces are both an opportunity and a threat to retail merchants. They are an opportunity because they offer traditional merchants an additional channel to advertise and sell products to consumers thus potentially *increasing sales*. Forrester Research estimates that online retail sales were at about \$600 million USD in 1996, will exceed \$2 billion USD in 1997, and will reach \$17 billion USD by 2001 [1]. In addition, online markets are more efficient than their physical-world counterparts thus *lowering transaction costs* for both merchants and consumers. For example, low transaction costs is one reason why Amazon.com [2], a virtual bookstore, can offer a greater selection and lower prices than its physical-world competitors.

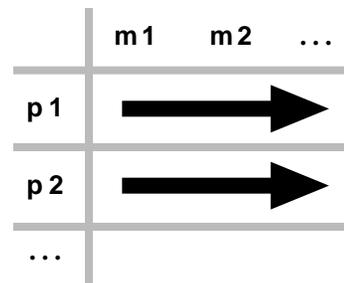
1.1. Cross-Merchant Product Comparisons

As in the physical world, an online merchant prefers to have consumers shop only at its own Web site as

depicted in Figure 1(a). There are an increasing number of software agent tools available to merchants for enhancing and differentiating their product offerings online such as Firefly Network's recommendation system [3, 8] and PersonaLogic's buying guides [4]. These tools help consumers make buying decisions within a specific merchant's site. However, consumers also compare product offerings across merchant boundaries as depicted in Figure 1(b). Due to the lower transaction costs of online marketplaces and with the help of software *shopping agents*, consumers can easily perform cross-merchant product comparisons (whether merchants want this or not).



(a) Within-Merchant Product Comparisons



(b) Cross-Merchant Product Comparisons

Figure 1 - Merchants prefer that consumers shop for products only within their own store (a). However, on the Internet, software shopping agents make it very easy for consumers to cross merchant boundaries and perform cross-merchant product comparisons (b).

1.2. Value-Added, Merchant Differentiation and Market Power

Although cross-merchant product comparisons are a threat to merchant profitability, they are characteristic of the retail marketplace and are here to stay. Knowing this, retailers add value to manufacturers' products to distinguish themselves from their competitors. These *value-added services* include extended warranties, forgiving return policies, wide product selections, brand reputation, extensive service contracts, special gift services, high product availability, superior customer service and support, diverse payment, loan and leasing options, fast delivery times with low costs, promotions and coupons, cross-manufacturer product configurations, etc. Depending on the product, these value-added services can be critical to a consumer's buying decision regardless of the manner of shopping.

Merchant differentiation through added value is necessary for merchants to exercise *market power*, the ability of a merchant to raise the price of a product above its marginal cost. In a fully competitive market, no one has market power forcing prices down to the cost of producing the most expensive (marginal) unit [5]. Therefore, without merchant differentiation, retailers (and other intermediaries) are reduced to competing on marginal costs leaving little room for profit.

Unfortunately for online retailers, all of today's first-generation cross-merchant shopping agents are limited to comparing merchant offerings only on price instead of their full range of value as depicted in Figure 2. This makes it hard (if not impossible) for merchants to effectively differentiate themselves. This results in inappropriately competitive retail markets and forces merchants to compete almost entirely on marginal costs.

This paper suggests a reversal of this problematic trend in cross-merchant shopping agent approaches in order to restore merchant differentiation and thus their market power. With so much money at stake, this

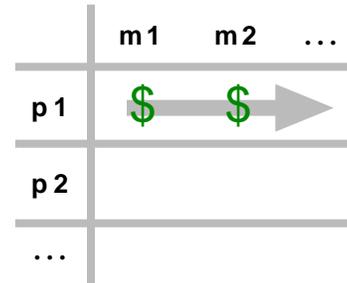


Figure 2 - First-generation Cross-Merchant Shopping Agents

problem warrants attention. Although free markets are inherently “nature red in tooth and claw” [6], this need not be the relationship between retailers and their customers. Rather, we propose that a more cooperative and personalized integrative negotiation approach differentiates retailer's offerings in online markets better than today's limited price-comparison shopping agents and unnecessarily hostile distributive negotiation (e.g., auction) approaches.

1.3. Consumer Buying Behavior Model

Consumer Buying Behavior (CBB) marketing research builds descriptive theories and models for analyzing consumers' actions and decisions involved in buying and using goods and services. Guttman et al augment traditional CBB research with concepts from Software Agents research to accommodate electronic markets [7]. Table 1 lists all six stages of this CBB model and gives representative examples of agent systems that fall within this space.

Briefly, the *Product Brokering* stage comprises the retrieval of information to help determine *what* to buy. This encompasses the evaluation of product alternatives based on consumer-provided criteria. The result of this stage is the “consideration set” of products. The

	Persona Logic	Firefly	Bargain Finder	Jango	Kasbah	Auction Bot	Auction Web
1. Need Identification							
2. Product Brokering	√	√		√			
3. Merchant Brokering			√	√	√		
4. Negotiation					√	√	√
5. Purchase and Delivery							
6. Product Service and Evaluation							

Table 1 - The six stages of the CBB model with representative examples of agent mediators [7].

Merchant Brokering stage combines this “consideration set” with merchant-specific information to help determine *who* to buy from. This includes the evaluation of merchant alternatives based on consumer-provided criteria (e.g., price, warranty, availability, delivery time, reputation, etc.). The *Negotiation* stage is about *how* to determine the terms of the transaction. In traditional retail markets, price and other aspects of the transaction are often fixed leaving no room for negotiation. In other markets (e.g., stocks, automobile, fine art, local markets, etc.), the negotiation of price or other aspects of the deal are integral to product and merchant brokering.

As noted in [7], this analysis of retail electronic commerce represents an approximation and simplification of complex behaviors. CBB stages often overlap and migration from one to another is sometimes nonlinear and iterative.

2. Price-Only Shopping Agents and Distributive Negotiation Agents

There are several types of software shopping agents that assist consumers in making buying decisions. Table 1 gives representative examples of agents that play different roles in mediating online transactions. See [7] for a treatment of agent systems playing in the Product Brokering stage of the CBB model.

2.1. Price-comparison Shopping Agents

After Product Brokering comes Merchant Brokering in the CBB model shown in Table 1. Andersen

Consulting’s **BargainFinder** [9] was the first merchant brokering shopping agent. Given a specific music CD, BargainFinder requests its price (including shipping) from each of nine different online music catalogs using the same requests as a web browser. BargainFinder then presents its results to the consumer. As would be expected from the discussion in section 1, several of the merchants preferred not to participate and blocked all price requests from BargainFinder as shown in Figure 3.

It’s also interesting to note that CDLand initially blocked BargainFinder agents but eventually decided to compete on price. However, a visit to their site indicates that it has been deactivated for the past seven months due to “new management” and “some initial transition difficulties” [10]. We can only presume that a lack of merchant differentiation and market power lead to their demise.

However, is merchant differentiation still relevant for commodity-like and low-price markets such as music CDs? Although there may be less of a need, properly presented merchant differentiation can help consumers make more educated buying decisions even in these markets. For instance, when buying music CDs, consumers may still want to consider product availability, delivery times and costs, gift services, return policies, customer service, as well as promotions and coupons.

Excite’s **Jango** [11, 12] is similar to BargainFinder but with more product features to search across and more shopping categories. The following sidebar describes the limitations of using Excite’s Jango Shopping Agent to buy a specific notebook computer.

BargainFinder Agent

BargainFinder is now searching nine stores for their prices of your album. Clicking on the name of a store will take you directly to your album in that store.

Passion by Peter Gabriel : (Image modified)

\$13.46 [Emusic](#) (Shipping starts at \$1.99 first item, \$0.49 each additional item.)
 \$8.00 (new) [GEMM](#) (Broker service for independent sellers; many used CDs, imports, etc.)
 \$ 12.97 [CD Universe](#) (Shipping starts at \$2.49. World-wide shipping. 30 day returns.)
 \$ 12.47 [CDworld](#) (Variety of shipping options, starting at \$2.74 for first item.)
[CDnow](#) is blocking out our agents. You may want to try browsing there yourself.
[NetMarket](#) is blocking out our agents. You may want to try browsing there yourself.
 I couldn't find it at [Music Connection](#). You may want to try browsing there yourself.
[CDLand](#) was blocking out our agents, but decided not to. You'll see their prices here soon.
[IMM](#) did not respond. You may want to try browsing there yourself.

Figure 3 - BargainFinder requests prices of a given music CD from nine separate merchants and displays them to the consumer for a price comparison. However, three of the nine merchant sites are blocking BargainFinder’s price requests.

An Experience with Excite's Jango Shopping Agent

Product	CPU	RAM	Hard Drive	CD-ROM	Store	Price
MORE PRODUCT INFO					STORE HOMEPAGE	
APPLE PB 3400C/200 2GB 16MB 12X CD	PowerPC 200	16 MB	2.0GB	12X	CDW	\$3579.88 Buy!
PowerBook 3400C/200 16MB/2.0GB/12X CD-ROM	PowerPC 200	16 MB	2.0GB	12X	Micro Warehouse	\$3799.00 Buy!

Above are the results from Excite's Jango of a search for an Apple PowerBook 3400C/200 notebook computer with 16 MB of RAM, a 2.0 GB hard drive, and a 16x CD-ROM drive. Assuming I'm considering buying this computer (and know what these features mean), who do I buy it from? According to Excite's Jango, I can either buy the product from CDW for \$3579.88 or from MicroWarehouse for \$3799.00. All other things being equal (as Jango would have us believe), the rational decision is to buy the product from CDW for \$219 less than from MicroWarehouse. But *are* all other things equal?

After a while of "manual" investigation, I discover that Apple is having a promotion. If I buy this product from MicroWarehouse within the next four weeks, I'll get a free 32MB RAM chip or a free Apple QuickTake Camera! It's not clear whether CDW honors this promotion. Such a differentiation makes the merchant offerings more comparable. Even if CDW also honors the promotion, it would have been useful if Jango informed me of it — perhaps enticing me to buy the product when I may not have otherwise.

More importantly, I also discover during my investigation that both merchants offer a 30 day return policy. However, if I'm unhappy with the product and return it to CDW, I'll be charged a 15% restocking fee. MicroWarehouse doesn't have a restocking fee. The \$219 savings from buying it from CDW instead of from MicroWarehouse would have resulted in an extra \$537 expense. It would have been useful if Jango allowed me to consider this information in my buying decision.

I'm still considering a purchase, but what are the reputations of these merchants? Do they offer extended warranties, service contracts, loan options, or gift services? Is the product even available? If so, how fast can it be delivered? How much will that cost? What other goods and services do I need to configure the product appropriately for my needs? A good sales agent would answer these questions to assist me in making a more educated buying decision and offer more products and options for consideration. Jango is not assisting me in considering any merchant value add in this buying decision.

2.2. Distributive Negotiation

Like the term "agent", there is no consensus on the definition of the term "negotiation." Economists, game theorists, business managers, political scientists, and artificial intelligence researchers each provide unique perspectives on its meaning. The business negotiation literature defines two types of negotiation: distributive negotiation and integrative negotiation [13]. *Distributive negotiation* is the decision-making process of resolving a conflict involving two or more parties over a single mutually exclusive goal. The economics literature describes this more specifically as the effects

on market price of a limited resource given its supply and demand among self-interested parties [5]. The game theory literature describes this situation as a zero-sum game where as the value along a single dimension shifts in either direction, one side is better off and the other is worse off [14].

The benefit of dynamically negotiating a price for a product instead of fixing it is that it relieves the seller from needing to determine the value of the good a priori. Rather, this burden is pushed into the marketplace itself. A resulting benefit of this is that limited resources are allocated fairly — i.e., to those buyers who value them

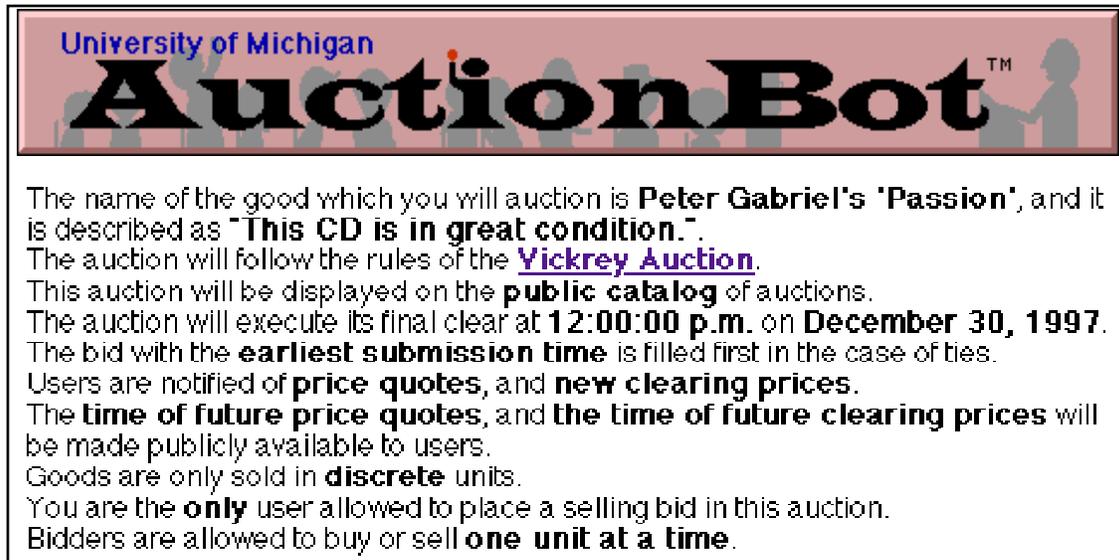


Figure 4 - AuctionBot users create auctions by choosing from a selection of auction types and parameters.

most. As such, distributive negotiation mechanisms are common in a variety of markets including stock markets (e.g., NYSE and NASDAQ), fine art auction houses (e.g., Sotheby's and Christie's), flower auctions (e.g., Aalsmeer, Holland), and various ad-hoc haggling (e.g., automobile dealerships and commission-based electronics stores). More recently, software agents have been taught distributive negotiation skills (e.g., auctioneering and auction bidding skills) to help automate the Negotiation CBB stage of consumer-to-consumer and retail shopping over the Internet.

Kasbah [15, 16] is a Web-based multi-agent classified ad system where users create buying agents and selling agents to help transact goods. These agents automate much of the Merchant Brokering and Negotiation CBB stages for both buyers and sellers. A user wanting to buy or sell a good creates an agent, gives it some strategic direction, and sends it off into a centralized agent marketplace. Kasbah agents proactively seek out potential buyers or sellers and negotiate with them on behalf of their owners. Each agent's goal is to complete an acceptable deal, subject to a set of user-specified constraints such as a desired price, a highest (or lowest) acceptable price, and a date by which to complete the transaction.

Negotiation between buying and selling agents in Kasbah is bilateral, distributive, and straightforward. After buying agents and selling agents are matched, the only valid action in the distributive negotiation protocol is for buying agents to offer a bid to sellers. Selling agents respond with either a binding "yes" or "no". Given this protocol, Kasbah provides buyers with one of three negotiation "strategies": anxious, cool-headed, and

frugal – corresponding to a linear, quadratic, or exponential function respectively for increasing its bid for a product over time. The simplicity of these negotiation heuristics makes it intuitive for users to understand what their agents are doing in the marketplace.¹ This was important for user acceptance as observed in a recent Media Lab experiment [15]. A larger Kasbah experiment is now underway at MIT allowing students to transact books and music [16].

AuctionBot [19, 20] is a general purpose Internet auction server at the University of Michigan. AuctionBot users create new auctions to buy or sell products by choosing from a selection of auction types and specifying its parameters (e.g., clearing times, method for resolving bidding ties, the number of sellers permitted, etc.) as shown in Figure 4. Buyers and sellers can then bid according to the multilateral distributive negotiation protocols of the created auction. In a typical scenario, a seller would bid a reservation price after creating an auction and let AuctionBot manage and enforce buyer bidding according to the auction protocols and parameters.

AuctionBot also provides an application programmable interface (API) for users to create their own software agents to autonomously compete as buyers or sellers in the AuctionBot marketplace. This API permits AuctionBot to enforce auction protocols and provides a semantically sound communication interface

¹ Unlike other multi-agent marketplaces [18], Kasbah does not concern itself with optimal strategies or convergence properties. Rather, Kasbah provides more descriptive strategies that model typical haggling behavior found in classified ad markets.

to the marketplace. However, as with the similar Fishmarket system from the Artificial Intelligence Research Institute in Barcelona [21, 22], it is left to the buyers and sellers to encode their own bidding strategies.²

Agent systems like Kasbah and AuctionBot are useful for building prescriptive theories for coordination among heterogeneous agents with (partially) predictable system-wide dynamics. However, as described next, distributive negotiation auctions are not well-suited for retail markets.

2.3. Auction Fever

Two of the original (non-academic) auction Web sites are OnSale [25] and eBay's **AuctionWeb** [26] and are still very popular. Likely reasons for their popularity include their novelty and entertainment value in negotiating the price of everyday goods, as well as the potential of getting a great deal on a wanted product. In any case, the popularity of OnSale and eBay's AuctionWeb has quickly spawned an already competitive and growing industry. Whereas once auctions were in themselves novel merchant differentiators, with the rapid proliferation of online auctions, this differentiation has waned. Yahoo! lists more than 90 active online auctions today [27]. Forrester Research reports that auctions will be core to making business-to-business transactions more dynamic, open and efficient [28]. online auctions like FastParts [29] and FairMarket [30] are already making this happen in the semiconductor and computer industries.

What's most relevant here is that many online auctions are augmentations to *retail* sites with retailers playing the roles of both auctioneer and seller (i.e., a sales agent). For example, First Auction [31] is a service of Internet Shopping Network, one of the first online retailers. Cendant's membership-driven retail site, netMarket [32], has also recently added auctions to its repertoire of online services. New auction intermediaries such as Z Auction [33] offer their auction services to multiple manufactures and resellers as a new sales channel.

With this much "auction fever," you would think that auctions are a panacea for retail shopping and selling. On the contrary, upon closer look we see that auctions have rather hostile characteristics. For example, although the protocols for the two most prevalent types of online auctions, first-price open-cry English and Yankee [34], are simple to understand and

² Although not currently deployed as a real-world shopping system, Fishmarket has hosted tournaments to compare opponents' hand-crafted bidding strategies [23] along the lines of Axelrod's prisoner's dilemma tournaments [24].

bid, determining the optimal bidding *strategy* is non-trivial³ and, more importantly, can be financially adverse. In fact, in first-price open-cry auctions (i.e., highest bid wins the good for that price), the winning bid is always greater than the product's market valuation. This is commonly known as "winner's curse" as depicted in Figure 5. This problem is exacerbated in retail auctions where buyers' valuations are largely private⁴. Buyers with private valuations tend to (irrationally) skew bids even further above the product's true value.

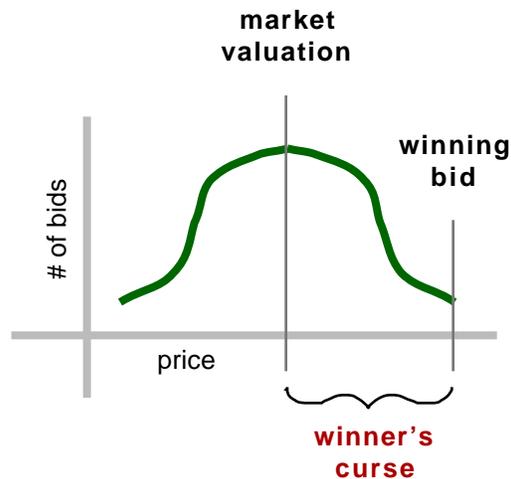


Figure 5 - "Winner's curse" is the paradox that the winning bid in an auction is greater than the product's market valuation. This occurs in all first-price, open-cry auctions – the most prevalent type on the Internet.

Although winner's curse is a short-term financial benefit to retailers, it can be a long-term detriment due to the eventual customer dissatisfaction of paying more than the value of a product. Two universal auction rules that compound this problem are: (1) bids are non-retractable and, worse yet, (2) products are non-returnable. This means that customers could get stuck with products that they're unhappy with and paid too much for. In short, online auctions are less lucrative and far less forgiving than would be expected in retail shopping.

Another customer dissatisfaction problem owing to online auctions is the long delay between the start of the

³ Factors to be considered include information asymmetry, risk aversion, motivation and valuation.

⁴ The motivation of a buyer with private-valuation is to acquire goods for personal consumption (or for gifts). This is in contrast to a buyer with common-valuation (e.g., in stock) where the motivation is to make money through the buying and later reselling of goods which have no other intrinsic value to the buyer.

Negotiation CBB stage and the end of the Purchase and Delivery CBB stage. For example, due to communication latency issues and wanting a critical mass of bidders, the English and Yankee auction protocols as implemented over the Internet extend over several days. This means that after a customer starts bidding on a product, she/he must continuously bid for the product (or have a shopping agent do it as provided by AuctionWeb) up until the auction closes several days later. This does not cater to impatient or time-constrained consumers.⁵ To make matters worse, only the highest bidder(s) of an auction can purchase the auctioned good meaning that the other customers need to wait until the good is auctioned again and then restart the Negotiation CBB stage.⁶ Additionally, since bids are non-retractable and binding, consumers are unable to reconsider earlier brokering decisions during this delayed negotiation stage.

There are other buyer concerns with English and Yankee style auctions such as *shills*. Shills are bidders who are planted by sellers to unfairly manipulate the market valuation of the auctioned good by raising the bid to stimulate the market. Although deemed illegal in all auctions, shills can be hard to detect especially in the virtual world where it is relatively inexpensive to create virtual identities (and thus virtual shills). Also, there is usually no negative consequence to the seller if one of his/her shills (accidentally) wins the auction.

Distributive negotiation auctions in retail markets also pose problems for *merchants*. Although auctions can relieve merchants of the burden of establishing prices for limited resources (e.g., fine art and stocks), this benefit is less realizable for *production goods* as in retail markets. Unlike fine art, for example, it is relatively easy to determine the marginal costs of production goods.⁷ If auctioning these goods, however, it is non-trivial for the merchant to determine the optimal size of the auctioned lots and the frequency of their auction [35]. Such a determination requires an understanding of the demand for the good since it directly affects inventory management and indirectly affects production schedule.⁸ Therefore, retailers are still burdened with determining

⁵ In fact, such delays are the antithesis to *impulse buying*.

⁶ Even in traditional static catalog retail (as well as Continuous Double Auctions), consumers can purchase products immediately.

⁷ Granted, the pricing of retail products can get involved. This is where marketing tactics come into play such as branding, market segmentation, price discrimination, etc.

⁸ This relates directly to the just-in-time (JIT) concept for manufacturing, inventory, and retailing [37]. However, it is not yet clear how best to gauge demand in JIT (e.g., through negotiation or sales).

the value of their goods a priori.

In addition, where sellers may have shills, buyers may collude by forming *coalitions*. A buyer coalition is a group of buyers who agree not to outbid one another. In a discriminatory (i.e., multi-good) auction, the result of this is that the coalition can buy goods for less than if they competed against one another thus unfairly cheating the seller. The coalition can then distribute the spoils amongst themselves (e.g., evenly, by holding a second private auction, etc.). As with shills, collusion through buyer coalitions is also considered illegal. However, as with shills, it can be hard to detect buyer collusion, especially in online markets where bidders are virtual. In fact, Multi-Agent Systems research has developed technologies that can efficiently form coalitions even among previously unknown parties [36] — posing an additional threat to online retail auctions.

As explained, online auctions are unnecessarily hostile to customers and offer no long-term benefits to merchants. Essentially, they pit merchant against customer in price tug-of-wars. This is not the type of relationship merchants prefer to have with their customers [38]. Unlike most consumer-to-consumer and commodity markets, merchants often care less about profit on any given transaction and care more about long-term profitability. This ties directly to customer satisfaction and long-term customer relationships. The more satisfied the customer and intimate the customer-merchant relationship, the greater the opportunity for repeat customer purchases and additional purchases through direct referrals and indirectly through positive reputation.

And as with price-only shopping agents, distributive negotiation auctions focus the consumers' attention solely on a product's price rather than its full range of value. This is a disservice to both consumers and merchants because, as with price-comparison shopping agents, it hides important merchant added value from consumers' consideration.⁹ Also, by only negotiating over price, merchants lose an opportunity to differentiate themselves during the earlier Merchant Brokering and Product Brokering CBB stages. Ultimately, by shortsightedly succumbing to "auction fever," retail merchants may be instrumental in bringing about their own demise. By promoting auctions as appropriate retail negotiation mechanisms, it strips themselves of differentiation and exposes their markets to greater

⁹ For example, Gerry Heller, CEO of FastParts - an online auction for semiconductors, was quoted in a recent Forrester Research report as admitting that even in this commodity-like market "availability is more important than price" when it comes to auctioning semiconductors.

competition thus nullifying their market power and profit.

3. Integrative Negotiation Agents

There is a tremendous amount of literature on how to sell retail products. No one approach is correct as it depends upon a number of factors including the type of product and demographics of its intended audience. Likewise, there is no one correct way to shop. People have different goals, knowledge, preferences, constraints, influences, and attitudes during any given shopping experience. One type of shopping is cross-merchant product comparisons (see section 1.1). It assumes a (partially) rational shopper who is concerned with buying the merchant offering that best meets his/her needs given an invested amount of time and effort.

Cross-merchant product comparisons are conducive to software agent mediation by assisting the shopper in any of the Product Brokering, Merchant Brokering, and Negotiation stages of the Consumer Buying Behavior model. However, some agent-mediation approaches are better than others. We argue in section 2.1 for shopping agents that can perform value-comparisons, not just price-comparisons. In section 2.3, we argue for sales agents that can negotiate over the full range of a merchant's added value rather than just price.

We propose an integrative negotiation approach to cross-merchant product comparisons. This approach promotes negotiation between consumer-owned shopping agents and merchant-owned sales agents across each product's full range of value. The rest of this section discusses integrative negotiation and identifies promising techniques for its implementation.

3.1. Integrative Negotiation

As introduced in section 2.2, the business negotiation literature defines two types of negotiation: distributive negotiation and integrative negotiation. *Integrative negotiation* is the decision-making process of resolving a conflict involving two or more parties over multiple interdependent, but *non*-mutually exclusive goals [13]. The study of how to analyze multi-objective decisions comes from economics research and is called multi-attribute utility theory (MAUT) [40]. The game theory literature describes integrative negotiation as a non-zero-sum game where as the values along multiple dimensions shift in different directions, it is possible for *all* parties to be better off [14].

In essence, integrative negotiation is a win-win type of negotiation. An example of this is depicted in Figure 7. This is in stark contrast to distributive negotiation

which is a win-lose type of negotiation as discussed in section 2.2. Also as discussed, all auctions are forms of distributive negotiation and are therefore win-lose types of negotiation.

Desired retail merchant-customer relationships and interactions can be described in terms of integrative negotiation — the cooperative process of resolving multiple interdependent, but non-mutually exclusive goals. A merchant's primary goals are long-term profitability through selling as many products as possible to as many customers as possible for as much money as possible with as low transaction costs as possible. A customer's primary goals are to have their personal needs satisfied through the purchase of well-suited products from appropriate merchants for as little money and hassle (i.e., transaction costs) as possible. An integrative negotiation through the space of merchant offerings can help maximize both of these sets of goals. From a merchant's perspective, integrative negotiation is about tailoring its offerings to each customer's individual needs resulting in greater customer satisfaction. From a customer's perspective, integrative negotiation is about conversing with retailers to help compare merchant offerings across their full range of value resulting in mutually rewarding and hassle-free shopping experiences.

3.2. Multi-Objective Decision Analysis and Multi-Attribute Utility Theory

Multi-objective decision analysis prescribes theories for quantitatively analyzing important decisions involving multiple, interdependent objectives from the perspective of a single decision-maker [40]. This analysis involves two distinctive features: an uncertainty analysis and a utility (i.e., preference) analysis. Techniques such as bayesian network modeling aid uncertainty analysis. Multi-attribute utility theory (MAUT) analyzes preferences with multiple attributes.

Examples of uncertainty in retail shopping are “will she like this product as a gift?” and “how much do I trust this merchant?” Such uncertainties weighed against other factors play a part in consumers' buying decisions. From a merchant's perspective, analyzing an uncertainty like “what will be the demand for this product?” is vital for pricing products and managing inventory.

Often, decisions have multiple attributes that need to be considered. For example, in retail shopping, the price of a product could be important, but so could its delivery time. What is the relationship and tradeoff between these two? Figure 6 gives a simple example of this.

Multi-objective decision analysis and MAUT can

(and have) been used to tackle many different types of decision problems including electrical power vs. air

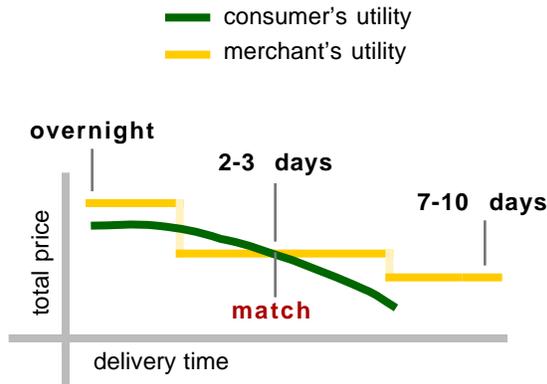


Figure 6 - This graph plots a consumer's and a merchant's multi-attribute utilities for a product's total price vs. delivery time (in days). In this example, the merchant offers three delivery options at different price points of which the "2-3 days" option best matches the consumer's utility profile.

quality, airport location, heroin addiction treatment, medical diagnostic and treatment, business problems, political problems, etc. These theories have also been instantiated in computer systems. The PERSUADER system at Carnegie Mellon University, for example, integrates Case-Base Reasoning and MAUT to resolve conflicts through negotiation in group problem solving settings [39]. Logical Decisions for Windows (LDW) by Logical Decisions, Inc. [41] is a general-purpose decision analysis tool for helping people think about and analyze their problems. Figure 7 shows LDW at work on a retail purchase decision problem.

LDW falls within the Product Brokering stage of our CBB model. However, MAUT tools such as LDW can also be applied to the Merchant Brokering CBB stage by formulating a new problem to analyze merchant value add for the winning product (i.e., considered set) of the Product Brokering stage. If certain pragmatic issues concerning MAUT's appropriateness for real-time Internet-based bilateral negotiations can be allayed, then MAUT techniques are contenders for decision support in agent-mediated integrative negotiation strategies for online retail markets.

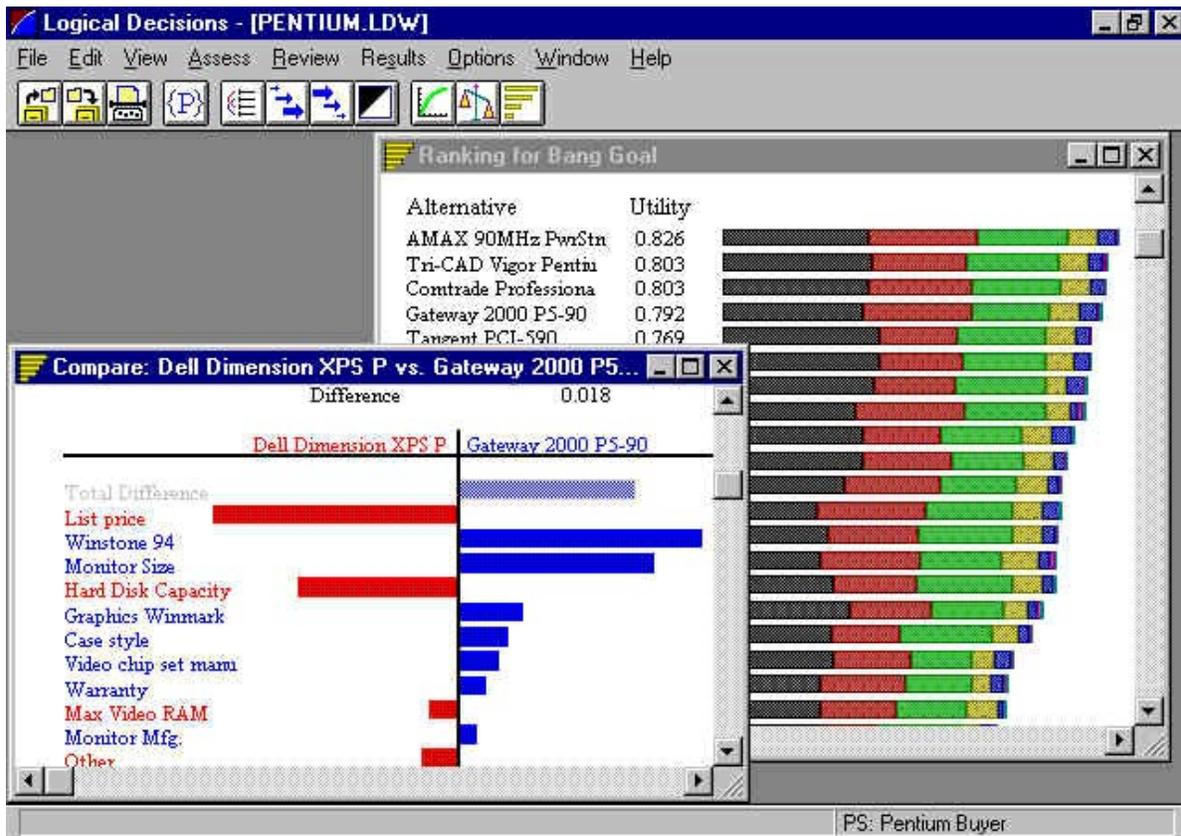


Figure 7 - A screenshot of Logical Decisions for Windows (LDW). This screenshot shows the results of a computer purchase decision after LDW captured the decision-maker's utilities across multiple product attributes. One results window shows the product rankings and the other a side-by-side comparison of two product contenders.

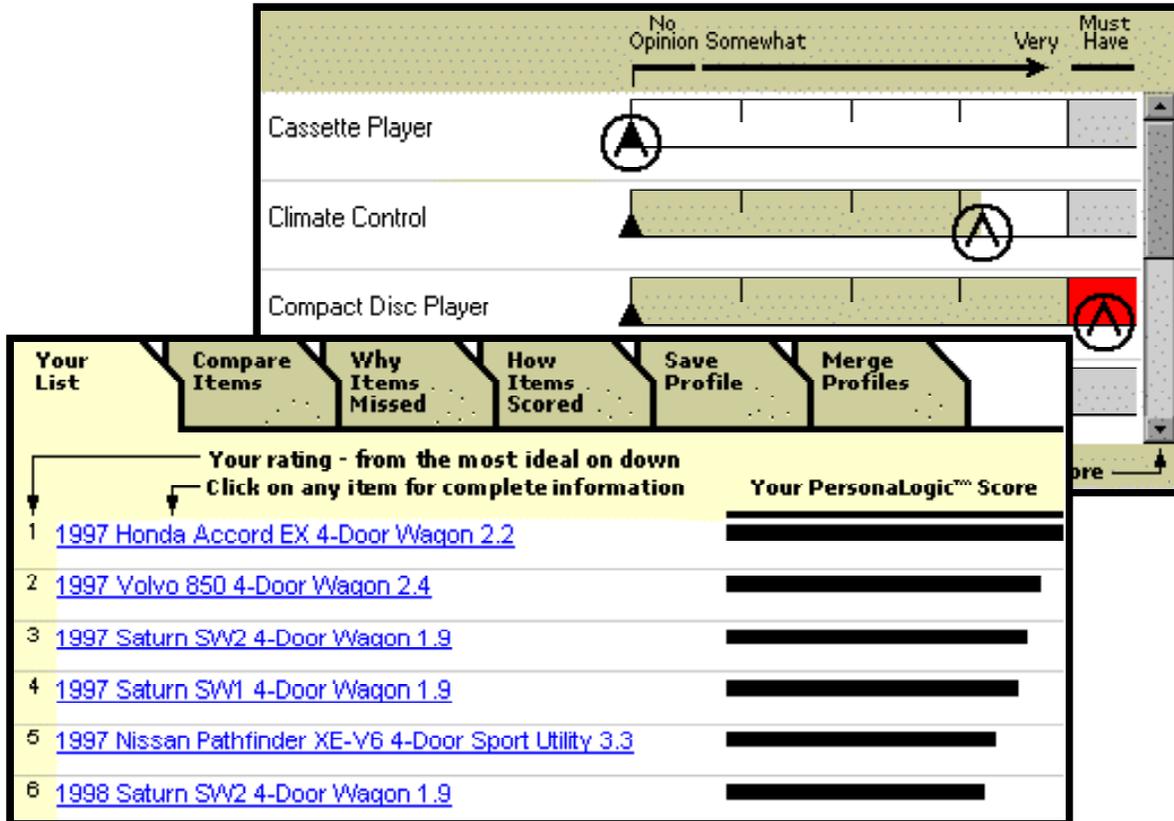


Figure 8 - Screenshots of PersonaLogic assisting a customer select automobile features with results.

3.3. Distributed Constraint Satisfaction

MAUT analyzes decision problems *quantitatively* through utilities. Constraint Satisfaction Problems (CSPs) analyze decision problems more *qualitatively* through constraints. A CSP is formulated in terms of variables, domains, and constraints. Once a decision problem is formulated in this way, a number of general purpose (and powerful) CSP techniques can analyze the problem and find a solution [42].

Finite-domain CSPs are one type of CSP and are composed of three main parts: a finite set of *variables*, each of which is associated with a finite *domain*, and a set of *constraints* that define relationships among variables and restricts the values that the variables can simultaneously take. The task of a CSP engine is to assign a value to each variable while satisfying all of the constraints. A variation of these “hard” constraints is the ability to also define “soft” constraints (of varied importance) which need not be satisfied. The number, scope, and nature of the CSP’s variables, domains, and constraints will determine how constrained the problem is and, for a given CSP engine, how quickly a solution (if any) will be found.

Many problems can be formulated as a CSP such as scheduling, planning, configuration, and machine vision

problems. In retail markets, CSP techniques can be used to encode hard constraints such as “I’m not willing to spend more than \$2,000 for this product,” and soft constraints such as “availability is more important to me than price.” Even constraints such as “I prefer the Gateway 2000 P5-90 over the Dell Dimension XPS P (but I don’t know why)” are legitimate. PersonaLogic (see Figure 8) uses CSP techniques to help shoppers evaluate product alternatives in the Product Brokering stage of our CBB model. Given a set of constraints on product features, PersonaLogic filters products that don’t meet the given hard constraints and prioritizes the remaining products using the given soft constraints. This approach can also be applied to sales configuration systems such as Dell’s “Build Your Own System” [43] and Trilogy’s Selling Chain™ [44].

An important side-benefit of CSPs is that they can clearly explain why they made certain decisions such as removing a product from the results list (e.g., “Product X is not an option because it has only 16 MB of RAM and you specified that the product should have at least 32 MB of RAM.”). This feature is important because it relates to consumer trust. Trust is partially achieved by the shopping agent exhibiting somewhat predictable behavior and being able to explain its decisions.

As with LDW, PersonaLogic can likely be extended into the Merchant Brokering stage of the CBB model. In fact, it may even be possible to extend PersonaLogic into the Negotiation stage by using Distributed Constraint Satisfaction Problem (DCSP) techniques. DCSPs are similar to CSPs except that variables and constraints are distributed among two or more loosely-coupled agents [45]. This appears to map well to the retail case where consumers and merchants each have their respective set of constraints on merchant offerings.

However, DCSPs have been designed for fully cooperative group problem solving situations. Although integrative negotiations are far more cooperative than distributive negotiations, DCSP techniques may require more cooperation than is appropriate for merchant-customer interactions. For example, a customer may not be willing to divulge her reservation value (e.g., a willingness to pay up to \$2,000 for a computer) to a merchant for fear of first-degree price discrimination with the merchant (unfairly) capturing all of the surplus in the market. However, first-degree price discrimination is tenuous in markets with monopolistic competition — i.e., a market with a large number of firms selling similar but differentiated products with no significant barriers to entry — which characterizes most retail markets [5]. This suggests that DCSP techniques may not be overly cooperative for bilateral integrative negotiations in retail markets.¹⁰

3.4. Conjoint Analysis and Machine Learning

Conjoint analysis is a popular marketing tool to help identify and market new product features [46]. The approach involves repeatedly surveying respondents for the preferred product given two or more product choices. This is in contrast to rating products (e.g., in automated collaborative filtering) or specifying requirements on product attributes (e.g., in constraint satisfaction). Rather, respondents jointly consider¹¹ and relatively rank product choices. Conjoint analysis then infers which product attributes are most important to the consumer relieving the consumer of specifying these features explicitly. Also, by being forced to make product decisions, consumers avoid unreasonable product attribute combinations — e.g., the most robust feature set *and* the lowest price. This is a benefit over CSPs which allow consumers to specify unreasonable product attribute combinations resulting in an empty “considered

¹⁰ Full cooperation does not necessitate full disclosure. For example, merchants need not divulge their profit margins. However, full cooperation does assume soundness of trust - i.e., false advertising isn't permitted.

¹¹ Conjoint is a contraction of “consider jointly.”

set” of products.¹²

However, in order to make a product selection, consumers need to identify differences in product attributes. It may be better for a user to just express these attribute preferences rather than spend time making a series of product choices which will (at best) infer the same preferences. Conjoint analysis also suffers from not dealing well with noisy or inconsistent data (which are very common in user surveys), not being conducive to changes in product preferences, and being time-consuming, redundant, and boring for the consumer. As such, although conjoint analysis is appropriate for identifying new product features and segmenting markets, it appears less appropriate as the sole mechanism for extracting utility preferences for integrative negotiations in retail electronic markets.

There are numerous statistical, search, and heuristic approaches that can also learn preferences and patterns of user behavior. In fact, a tenet of artificial intelligence (AI) is learning. Specific AI fields of inquiry include inductive learning, genetic algorithms, classifier systems, case-based reasoning, neural networks, and a variety of other machine learning and adaptive behavior theories and technologies [47, 48].

4. Conclusion

This paper analyzed the state-of-the-art in agent-mediated retail electronic commerce. We first looked at how price-only shopping agents are a disservice to both consumers and retailers by hiding important merchant value add from consumer consideration. We then explored how distributive negotiation techniques (e.g., online auctions) are considerably more hostile to both consumers and merchants than would be expected in retail markets (in spite of their increasing popularity).

Finally, we proposed a new integrative negotiation approach to retail electronic commerce. We described how techniques such as multi-attribute utility theory, distributed constraint satisfaction, and conjoint analysis could be harnessed for allowing consumer's to integratively negotiate over a product's full range of value. From a merchant's perspective, integrative negotiation is about tailoring its offerings to each customer's individual needs resulting in greater customer satisfaction. From a customer's perspective, integrative negotiation is about conversing with retailers to help compare merchant offerings across their full range of value resulting in mutually rewarding and hassle-free shopping experiences.

¹² However, there are CSP techniques to automatically relax constraints in over-constrained problems.

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