Universität Augsburg

Cosima^{B2B}

—

$SalesAutomationforE - Procurement$

Werner Kießling, Stefan Fischer, Sven Döring

Report 2004-2 Januar 2004

Institut für Informatik
D-86135 Augsburg

COSIMA^{B2B} – Sales Automation for E-Procurement

Werner Kießling, Stefan Fischer, Sven Döring
Chair for Databases and Information Systems
University of Augsburg, 86135 Augsburg, Germany
{kiessling, fischer, doering}@forsip.de

Abstract

E-procurement is one of the fastest growing application areas for e-commerce. Though B2B transaction costs could be reduced recently by establishing XML based standards for electronic product catalogs and data interchange, B2B sales costs are still high due to the amount of human interaction. For the first time we present a fully automated electronic sales agent for e-procurement portals. The key technologies for this breakthrough are based on preferences modeled as strict partial orders, enabling a deep personalization of the B2B sales process. The interplay of several novel middleware components achieves to automate skills that so far could be executed only by a human vendor. As personalized search engine for XML based e-catalogs we use *Preference XPath*; the *Preference Presenter* implements a smart and sales psychology based presentation of search results, supporting various human sales strategies; the *Preference Repository* provides the management of situated long-term preferences; the flexible *Personalized Price Offer* and the multi-objective *Preference Bargainer* provide a personalized price determination and the opportunity to bargain about the price of an entire product bundle, applying up/cross and down selling techniques. Our prototype COSIMA^{B2B}, supported by industrial partners, has been demonstrated already successfully at a large computer fair.

1. Introduction

Nowadays the sales process in e-procurement is still a business with lots of human interaction. The misery starts already with the product search. Often B2B customers are forced to manually scroll through huge electronic product catalogs, being a time-intensive and costly task. Obviously, a preferable way would be to employ an e-procurement portal with a more intuitive user interface like B2C portals do, e.g. Ebay.com. But the problem in large-scale B2B e-procurement is even worse because of the complexity and variety of the products on sale. Frequently, commercial search engines simply interpret the customer's search conditions as hard constraints, resulting in the embarrassing 'empty result effect' ([8]). A popular, but failing solution attempt is to interpret the search constraints as 'or'-conditions, e.g. see the B2B portal B2B-perfect.com, causing the 'flooding effect' ([8]). Another attempt is parametric search ([1]) that iteratively asks the customer to soften his or her search criterions, being a tedious and time-consuming process. Offering a full-text search like many B2C e-shops do is no remedy either, because B2B product search is basically an attribute based search, if modern e-catalog standards are in place. Due to these problems many e-procurement portals do not even provide a search engine and only support customers who exactly know what to buy. For instance, Hilti (www.hilti.com), the world market leader for construction technology, only provides a plain hierarchical interface (see Figure 1, label 1), where a customer must traverse top-down through the e-catalog. During this process he does neither know, whether there is a desired product nor whether the one he has located is the best matching result with respect to his search preferences. Only if the customer knows exactly about the existence of a desired product and its item number, he gets it by one click (see Figure 1, label 2). On top of this, in case he needs any help, then he only can get instructions via phone (see Figure 1, label 3). Thus state-of-the-art approaches to find products are not enough for the B2B customer (see also [15]). In fact a good B2B product search demands a search engine that can handle attribute-rich e-catalog data, that can be personalized to the customer's wishes, roles and situations, and that fully automatically delivers best alternatives when there is no perfect match.

But much more is necessary to provide a similarly good sales service as competent human vendors can offer. Current e-procurement platforms do very little or nothing to implement well-established principles of sales psychology ([12]) when presenting the search results. In the old economy's B2B transactions a human vendor has to find a clever way to satisfy as good as possible both his own sales preferences as well as the preferences of his customer, which is a very challenging act. As stated by established models of customer choice behavior ([7], [3]) within sales scenarios, a major factor in convincing the customer is to intelligently argue about the quality of the presented products with respect to his search preferences. Some of today's search engines can compute alternatives in case of a missing perfect match, but are not able to provide semantic explanations about the quality of the search result. Moreover, little or no information about product coherences is provided, i.e. what are mandatory articles fitting to selected products. As a good sales practice, known as cross selling, a knowledgeable human vendor can provide the customer with additional information about useful accessories to the considered products. In addition, an advanced e-procurement portal should be able to apply down selling or up selling techniques, when it recognizes that the selected products are too expensive or too cheap, respectively, for the customer. Such an intelligent behavior, of course, requires a deep personalization of the whole e-procurement process.

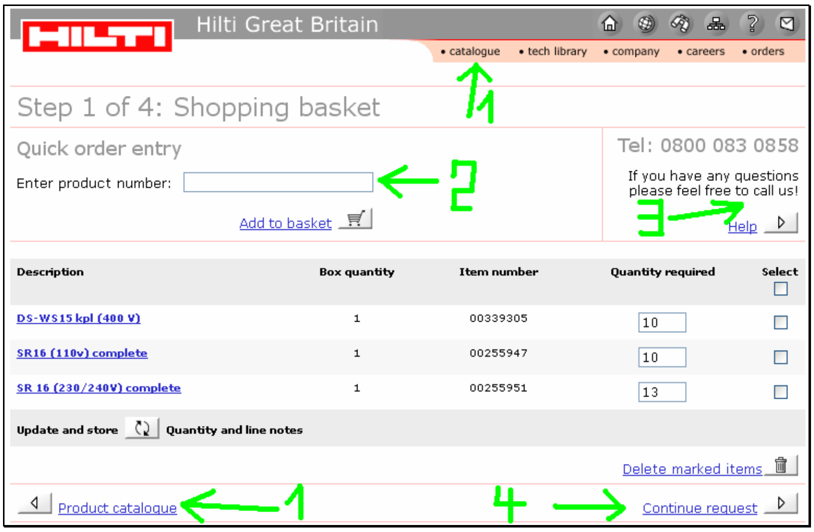

Figure 1: Not personalized e-procurement

Inadequate product search and bad product presentation are two big obstacles that to date prevented a fully automated, effective and cost-efficient electronic sales agent for e-procurement. A third challenge is that current e-procurement portals either are not able to tell a price for the content of the shopping cart or only summarize list prices for the concerning goods. For example, at Hilti the customer has to send his selected shopping cart via e-mail to get an offline calculated offer (see Figure 1, label 4). In contrast, in sales transactions in the old economy a customer is treated individually regarding to his price preferences and other personal conditions, expecting also personalized discounts according to his prior business relationships. Depending on the customer's buying pattern an advanced e-procurement portal should also provide the opportunity for interactive price negotiations.

This necessity for bargaining has been already recognized e.g. by [10], but restricted to the simple one-dimensional case. Customer preferences must be respected, but solely relying on numerical ranking (see e.g. [1], [14]) is not advisable. Approaches based on collaborative filtering or case-based reasoning (see e.g. [15], [13]) fail at the point which search result to present or to recommend, because there is too little intuitive semantics behind this crucial sales decision: When valuating the search results only numerical distances are computed, yielding an intuitively hard to comprehend similarity measure. Thus a holistic novel effort is necessary to make an electronic B2B sales agent no longer a pie in the sky. Due to the high costs of human vendors the return on investment for such effective e-procurement automation can be reached quickly. Both vendor and customer party would profit from such a technology.

The rest of this paper is now organized as follows. Building on the powerful and intuitive preference model introduced in [8] (see also [2]) in section 2 we present the innovative middleware components that are required to implement a fully automated sales agent for e-procurement, using widely spread XML based e-catalog standards like BMEcat and eCl@ss. In section 3 we take the reader onto an e-shopping tour with COSIMA[B2B], our sophisticated prototype with multimodal human-computer interaction capabilities. As a crucial functionality for the e-procurement provider we introduce our novel personalization manager. Section 4 will summarize our results and give a short outlook.

2. Preference Technology Enabling a Personalized Sales Automation

In this section we will introduce our detailed model of an e-procurement process for searching and purchasing products supporting a fully automated offer composition, followed by our novel approach to solve the problems described above.

2.1 Business Model for an Automated E-Procurement Process

As described in [11] an e-procurement process for the customer consists of four steps: searching through catalogs for desired products, pricing and ordering, delivery, and payment and controlling. To build up an automated offer composition in e-procurement applications we modeled the first two steps in detail as illustrated in Figure 2. Firstly, the shopping cart will be filled step by step with desired products and corresponding quantities. This process includes the product search, a presentation of the search results and the decision, whether to put one or more results into the shopping cart. Secondly, the price for the shopping cart as a whole will be determined. According to the customer's practice he will bargain about the price. At last, the customer has the choice whether to accept the offer or to get an open offer valid for a specific period. Of course, the individual steps in that process are not bound to a linear sequence of actions. It is possible and reasonable to reiterate some steps, e.g. to change the shopping cart after a first price fixing.

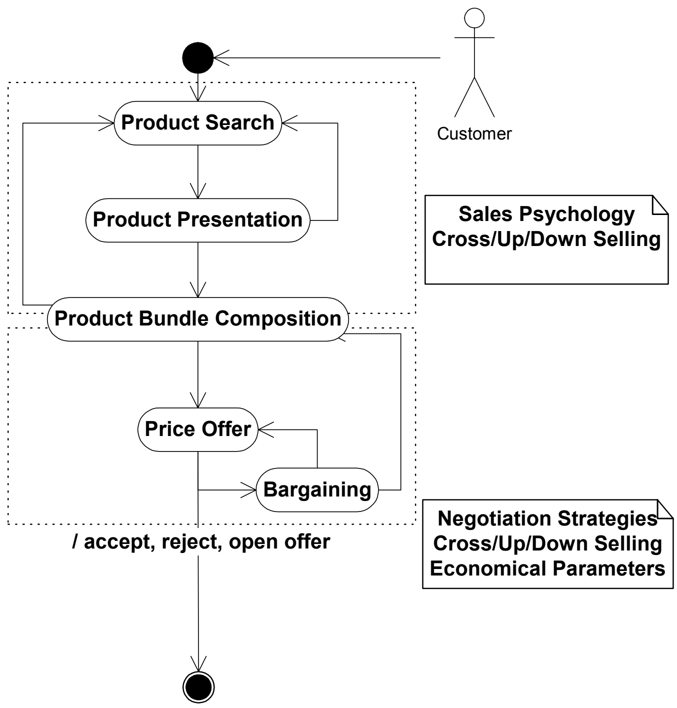

Figure 2: Automatic offer composition

As stated before, advanced e-procurement requires a high level of personalization and situation awareness to provide custom-tailored product recommendations and price offers. Based on preferences modeled as strict partial orders ([8], [2]) the following middleware components will enable the implementation of deeply personalized and situated e-procurement applications:

- The Preference XPath search engine
- The Preference Repository
- The Preference Presenter
- The Personalized Price Offer and the Preference Bargainer

2.2 The Preference XPath Search Engine

Preference based search engines like Preference SQL ([9]) or Preference XPath, mentioned in [8], avoid the annoying empty result effect and reduce the flooding effect with lots of irrelevant results. The underlying query model delivers best matches only (BMO) wrt. the given search constraints. Since e-procurement standards for product catalogs are mostly XML based, we use Preference XPath technology.

As an extension of the standard query language XPath, all functionality of XPath including hard selection constraints is available. In addition, the full preference model as described in [8] is supported in our most recent release, including the following preference constructor functionality:

- *Base* preference constructors like e.g. AROUND (see Figure 3 below)
- Available *complex* preference constructors are:
    - *Pareto* construction to model *equal importance* amongst several preferences.
    - *Prioritization* to model *ordered importance* amongst several preferences.
    - *Numerical ranking* to model *weighted importance* amongst several preferences.

Preferences are treated as *soft* selection conditions. Thus all tuples in the BMO result set of a Preference XPath query satisfy all hard constraints exactly and satisfy all preferences as good as possible. For illustration let's assume that a guy called Homer is a notebook vendor for resellers. In Table 1 all available notebooks of his storehouse with the according purchase quantity are listed.

	Make	Type	CPU_GHz	MB_RAM	Quantity	Price_per_unit (€)
t_1	Elitegroup	Eli8	2.0	256	40	1450.--
t_2	Gerion	Geri 5	2.0	374	50	1199.--
t_3	Gerion	Geri 4	2.0	374	50	1150.--
t_4	HP	NX7000	2.2	512	50	1249.--
t_5	Toshiba	Satellite	2.4	768	40	1378.--
t_6	Toshiba	Tecra	1.8	512	40	1200.--

Table 1: Homer's product database

His customer Marge calls him in the afternoon and tells Homer her interests. Note, the subsequent natural language statement carefully differentiates between hard constraints ("must") and preferences ("should"):

*"I am interested in notebooks. The clock frequency **must** be **at least** 2 GHz.* // A1
*The order quantity **should** be **around** 40. **Equally important** is that the main memory capacity **should** be at least 512 MB-RAM, and the price **should** be **at most** 1200.-- €."* // A2

Homer as an attentive salesman knows that Marge has *situated long-term* preferences, too:

*"Whenever Marge calls up in the afternoon, her **favorite** manufacturers are Toshiba and Hewlett Packard, which is **equally important** to what Marge will express explicitly."* // B

Naturally, Homer has his own *vendor* preferences:

*"I want to **maximize** my turnover. But since I am a fair dealer, all customer preferences are **more important** than this."* // C

With Preference XPath these rather complex criteria can be expressed declaratively within one query statement. Note that hard conditions are syntactically framed by "[…]", whereas preferences are scoped by "#[…]#". Pareto preference construction is denoted by "and", prioritization by "prior to".

```
/Notebook [CPU_GHz >= 2.0]                 // explicit hard customer constraint   A1
  #[(Quantity around 40 and                // explicit customer preferences       A2
     MB_RAM at least 512 and
     Price_per_unit at most 1200 and
     Make in ('Toshiba', 'HP'))            // long-term customer preference       B
     prior to
     Price_per_unit highest]#              // vendor preference                   C
```

Figure 3: Sample Preference XPath query

Given the database in Table 1 there would be no perfect match, if all search preferences were interpreted as hard conditions, triggering the empty result effect. In contrast, the BMO query semantics yields the result of Table 2. Please note that tuple t_3 is not included in the BMO result set, because it is dominated by t_2 due to vendor preference C, whereas tuple t_6 fails to meet the hard constraint exactly. t_1 is dominated by t_5, because t_5 is better according to make, MB_RAM, and price and has the same order quantity.

	Make	Type	CPU_GHz	MB_RAM	Quantity	Price_per_unit (€)
t_2	Gerion	Geri 5	2.0	374	50	1199.--
t_4	HP	NX7000	2.2	512	50	1249.--
t_5	Toshiba	Satellite	2.4	768	40	1378.--

Table 2: Homer's BMO result set for Marge's complex wish

2.3 The Preference Repository

In the example above Homer knew Marge's long-term preferences, which can be automatically gained by preference mining algorithms (see [6]). But how about administering such preferences? Our *Preference Repository* supports the XML based storage structure for preferences and the underlying situations. Moreover, relevant meta information about preferences can be managed, e.g. a situation which consists of personal characteristics of the customer, time and local attributes, as well as influences of other persons and surrounding influences. The situational context is almost as important as the preference itself. For example, in the morning Marge usually is very busy due to customer calls. But in the afternoon she often works in her office, e.g. arranging a forthcoming sales promotion. For her sales promotions she always prefers notebooks from Toshiba or HP (see Figure 4a). The interplay of the Preference XPath search engine and the Preference Repository within a deeply personalized product composition (upper box in Figure 2) is illustrated in Figure 4b. Moreover, this interplay can also be used by Homer, e.g. when he wants to know all customers having a POS preference for the make Sony. Otherwise he would accept customers preferring Toshiba. Using Preference XPath over the Preference Repository would amongst others deliver Marge as a result, if there is no customer with a POS(make, {Sony}) preference.

```
<PreferenceRepository>
 <UserIdentifier>
   <Name xml:lang="en">Marge</Name>
 </UserIdentifier>
 <PreferenceData name="color">
  <Situation>
  <Condition key="TimeOfDay" value="pm"/>
  </Situation>
  <Preference>
   <POS att="Make">
     <Value val="HP"/>
     <Value val="Toshiba"/>
   </POS>
  </Preference>
 </PreferenceData>
 …
</PreferenceRepository>
```

Figure 4a: Preference Repository excerpt

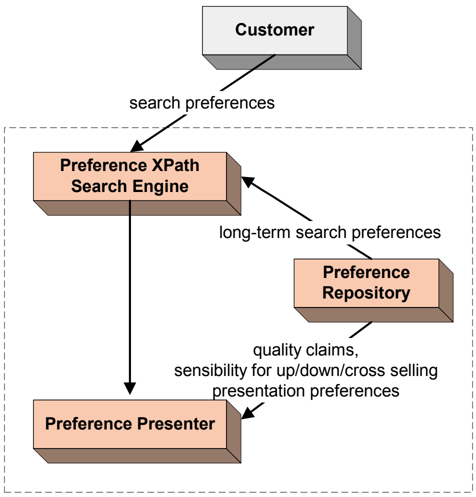

Figure 4b: Product composition components

2.4 The Preference Presenter

A product search engine typically only provides a *pre*-selection to initiate the sales process. An advanced personalized search technology like Preference XPath can accomplish this pre-selection step efficiently and can ensure that it includes exactly the best available candidates. The quality of a search result is known to be a major factor for a promising sales dialog ([7], [3]). But moreover, for a successful deal a clever product presentation of the pre-selected items is a decisive factor. At this point a smart human vendor would start a sales psychology based dialog by choosing a first product and valuate its quality wrt. customer preferences. Our novel *Preference Presenter* component fully automates this complex task. It can deliver presentation arguments for each single preference as well as a situated and personalized overall valuation of the quality of each tuple in the BMO result set. Since this novel technology and its underlying theory will be published in a forthcoming doctoral thesis, for the purpose of this paper we only give a short impression of some features. In contrast to approaches like [15], which only compute mathematical similarity measures with little semantic information, the Preference Presenter can provide intuitively comprehensible quality information for the search result in terms of the customer preferences.

Using the formalism of [8], let a preference P be modeled as $P = (A, <_P)$, where A denotes a set of attributes $\{A_1, \ldots, A_k\}$ with associated domains $dom(A_i)$, $i \in \{1, \ldots, k\}$. The preference order $<_P$ is then a strict partial order on dom(A). A preference can be defined by a base preference constructor (like e.g. 'AROUND') or inductively by complex preference constructors. Given a preference query with soft constraints characterized by P, for each result tuple t we want to valuate the *quality of t* depending on a given *situation* s. Instead of using numerical scores we claim that using linguistic terms [16] is an appropriate choice. Empirical psychological studies support that an ordered linguistic domain with about five terms is a reasonable way for many applications[1]. For the scope of B2B sales we decided on this choice and their respective ordering:

'other values' < 'acceptable' < 'good' < 'nearly perfect' < 'perfect'

Given a base preference P, a situation s and a result tuple t we now can define a *quality function* $QUAL_{P,s}(t)$ as follows: Let $C(s) = \{C_1(s), \ldots, C_5(s)\}$ be a partition of dom(A) and let t[A] denote the projection of t to A, then:

$$QUAL_{P,s}(t) := \begin{cases} \text{'perfect'} , & \text{if} \quad t[A] \in C_1(s) \\ \text{'nearly perfect'}, & \text{if} \quad t[A] \in C_2(s) \\ \text{'good'} , & \text{if} \quad t[A] \in C_3(s) \\ \text{'acceptable'} , & \text{if} \quad t[A] \in C_4(s) \\ \text{'other values'} , & \text{if} \quad t[A] \in C_5(s) \end{cases}$$

For instance, a numerical base preference P := AROUND(A, z) delivers best matching alternatives nearest to a preferred value z if there is no tuple t with t[A] = z. The quality function of P can be defined as follows:

$$QUAL_{P,s}(t) := \begin{cases} \text{'perfect'} , & t[A] = z \\ \text{'nearly perfect'}, & z - b_1(s) \leq t[A] < z \vee z < t[A] \leq z + b_1(s) \\ \text{'good'} , & z - b_2(s) \leq t[A] < z - b_1(s) \vee z + b_1(s) < t[A] \leq z + b_2(s) \\ \text{'acceptable'} , & z - b_3(s) \leq t[A] < z - b_2(s) \vee z + b_2(s) < t[A] \leq z + b_3(s) \\ \text{'other values'} , & t[A] < z - b_3(s) \vee z + b_3(s) < t[A] \end{cases}$$

How to define C(s) depends on the particular situation. In case of Marge's notebook request, the partition for the valuation of the order quantity could be done e.g. by setting $b_1(s) = 5$, $b_2(s) = 11$, $b_3(s) = 15$.

Quality functions for a complex preference P can be defined recursively in terms of the quality functions of the involved base preferences. It turns out that there are several degrees of freedom to choose such a function, depending on psychological aspects. However, to be accepted by the customer as a correct and intuitive quality measure, the following postulate given a database relation R must be met:

---

[1] E.g. the customers' reviews for books are rated up to 5 stars at Amazon.com. Indeed, the research association ACM uses five different categories for valuating the search results of their online library (see portal.acm.org). Yet, this search result valuation is neither intuitive nor easily comprehensible.

$\forall$ tuples t, t´ $\in$ R: t $<_P$ t´ $\Rightarrow$ $QUAL_{P,s}(t) \leq QUAL_{P,s}(t')$

That means that if tuple t' is preferred over t by P, then the situated valuation of t' must be at least as good as that of t. Given a BMO result set, the Preference Presenter now can adorn each result tuple t with its quality function. At this point the decision can be made, which tuple to present first to the customer. Several psychologically founded strategies for this delicate task are known in the literature ([12]). Thereafter the vendor must try to convince the customer about the quality of the selected product.
Let's reconsider our running example and the results of Table 2. Without going into more details here, let's assume that the calculated qualities for each result tuple for the customer's view are as follows:

	Make	MB_RAM	Quantity	Price_per_unit (€)		Overall quality
t_2	'other values'	'good'	'good'	'perfect'		'good'
t_4	'perfect'	'perfect'	'good'	'nearly perfect'		'nearly perfect'
t_5	'perfect'	'perfect'	'perfect'	'acceptable'		'nearly perfect'

Table 3: Search result qualities for Marge's view

Applying the popular 'most perfect arguments' strategy, an electronic sales agent would pick tuple t_5 to start the presentation. Knowing the detailed quality information for t_5, the Preference Presenter can fully automatically generate the following natural language dialog:

> *"There are three best matches with respect to your preferences. I recommend the Toshiba notebook. Overall it **nearly perfectly** fits your preferences, because it **perfectly** hits your favored manufacturer, it **perfectly** fulfills your desired order quantity, and has **even** 256 MB **more** RAM than you wished. Thus, I think that the moderately higher price is **acceptable** for this high-quality product."*

2.5 Personalized Price Offer and the Preference Bargainer

In common, e-procurement prices ought to be personalized for every customer. For the price determination first the product discounts and the differential prices, respectively, will be applied to the list prices personalized for each customer and accumulated for the product bundle. Afterwards, discounts regarding the complete product bundle will be subtracted. We modeled a framework for the flexible definition of each kind of discount, because there is no standardization yet. Conditions can be modeled as constraints e.g. for a volume discount of orders higher than 10,000 €. Also different calculation levels and the choice between absolute and relative discounts are supported.
Depending on customer's practice he might be offered to bargain about the price. Therefore we extended the *Preference Bargainer* that has been presented in a first prototype version already in [5]. Besides the ability for multi-objective bargaining, this technology also provides techniques like cross, up and down selling. Proactively, alternative or additional products and services are offered regarding the customer's preferences and the corresponding situations stored in the Preference Repository. There are several types of bargaining strategies like progressive, 'tit for tat' or random strategies in order to be unpredictable. Moreover, the bargaining component learns about the customer's behavior and adjusts its own bargaining strategies. After the optional bargaining the customer has to decide whether to accept the offer immediately or to take an open offer for a specified period of time. The components' interplay for a personalized price composition (lower box in Figure 2) is illustrated in Figure 5a.

2.6 Implementation Aspects

BMEcat (www.bmecat.com) is an XML based product description standard for electronic data interchange (EDI). This standard in connection with the article feature standard **eCl@ss** (www.eclass-online.com) is a powerful instrument to exchange or import product catalogs. Moreover, BMEcat allows the specification of relations between articles, e.g. additional or alternative products. Therefore, when using BMEcat/eCl@ss we gain lots of helpful semantic information for an effective offer composition. Also economical data about the product prices, product discounts and differential product prices are inte-

grated. By means of BMEcat the price composition described above could easily be realized as illustrated in Figure 5b. First, the price of the accumulated products regarding personalized and situated individual product discounts is determined. In the following the discounts of the product bundle are calculated and the total price is possibly determined by the Preference Bargainer, finally.
Our middleware for sales automation in e-procurement was developed using the standard enterprise technologies J2EE and XML. The components are implemented as Enterprise JavaBeans running on the open source solution JBoss application server (www.jboss.org). Since we used only the specified functionality of J2EE our components are compatible to e.g. IBM Websphere, BEA Weblogic and Oracle Application Server. Our components are based on the theoretical model of [8] and are therefore interoperable and of course can also be used stand-alone.

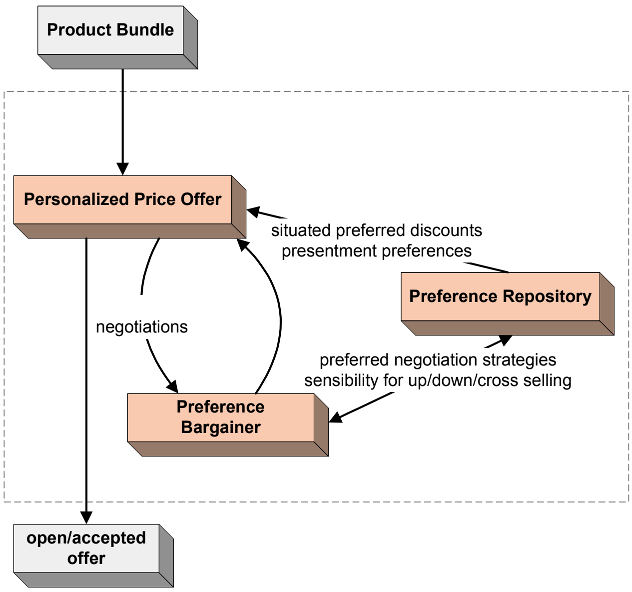

Figure 5a: Pricing components

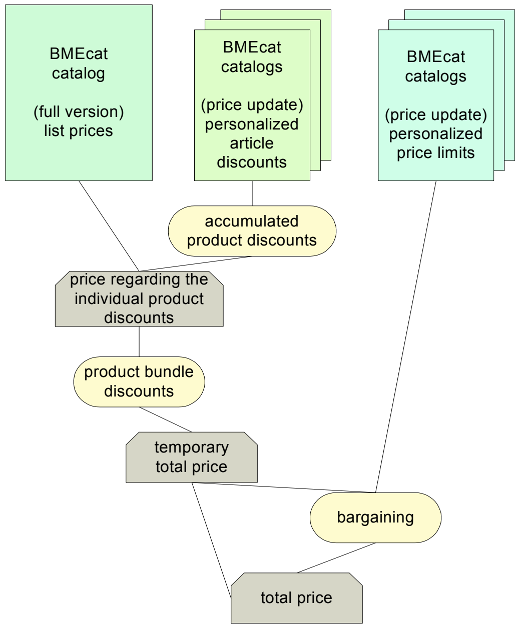

Figure 5b: Price fixing with BMEcat

3. COSIMA^{B2B} – The Fully Automated Sales Agent

In this section we will describe our prototype COSIMA^{B2B}, implementing a fully automated sales agent.

3.1 The Use Case

COSIMA^{B2B} is able to automate a cost intensive e-procurement process. With our industrial partners SSI Schäfer (www.ssi-schaefer.de) and MAN Roland Druckmaschinen AG (www.man-roland.de) we modeled a typical B2B use case scenario. Our product domain comprises boxes, in particular storage, transport, and waste container according to the domain of our industry partners. Insertion and adaptation of our industry partner's product catalog was easily achievable using the XML based BMEcat respectively eCl@ss standard. On the client side we equipped our customer interface with some optional features. A female embodied character agent named COSIMA embodies our electronic sales agent. She does a very emotional job when presenting the search results or bargaining with the customer. Moreover, she talks to the customer via dynamic speech output in real time. With the agent based FIPA-OS platform we integrated a further high level facility for the communication to e.g. technologies for an improved human-computer interaction like speech or mimic recognition ([4]). Meanwhile, the source code counts more than 100.000 lines.

3.2 A Sample Shopping Tour

When entering COSIMA^{B2B} the friendly embodied character agent welcomes the customer. Then the customer iteratively composes the content of his shopping cart by searching the product database. In our example the customer is searching for a red storage container made of polyethylene with a volume of about 3 liter and a width of 100 till 150 millimeter (see Figure 6). Actually, there is no perfect match for these search preferences in the product database, thus *best alternatives are offered*. As shown in Figure 7 COSIMA does a smart and psychology based presentation of the search results. Following a given personalized sales strategy COSIMA *points out a special result,* and presents the article with most perfectly fulfilled base preferences, which provides a lot of single sales arguments. In this example she especially emphasizes the perfectly matched red color and fairly mentions the nearly matched volume of 2.7 liter. Because the width is perfectly in the customer's preferred range and also the material is exactly the desired COSIMA completes her arguing by emphasizing the 'perfect' overall quality. Finally, COSIMA proactively leads the customer's attention to optional accessories (*cross selling*).

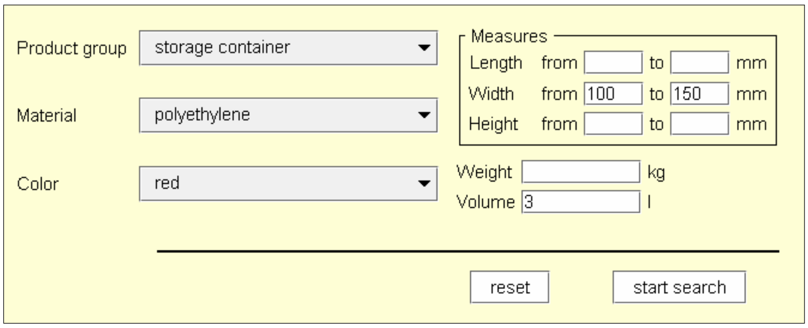

Figure 6: Sample customer's search preferences

After finishing the product bundle composition a personalized and situated price will be offered to the customer. Depending on the customer's practice COSIMA offers the opportunity for *further price discussions***.** During the bargaining process COSIMA makes usage of techniques like *up/cross and down selling*, regarding the customer's and seller's preferences as well as the situational context.

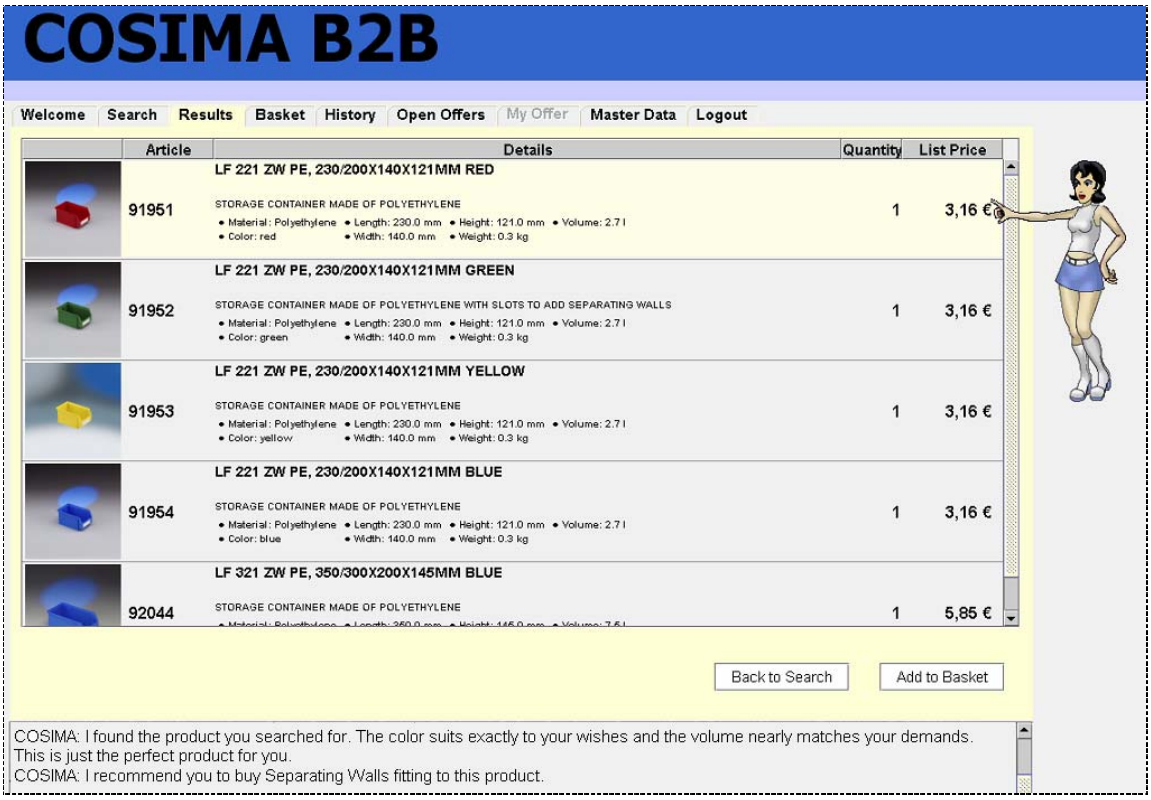

Figure 7: Sales psychology based search result presentation

Besides this, of course COSIMA also provides services to manage the done orders and open offers as well as the possibility for the customer to give feedback about reasons for a failed open offer.

3.3 The Personalization Manager

Like for a smart human vendor, the behavior of our electronic sales agent is driven by quite a lot of personalized and situated parameters. If the sales strategy is changed by marketing and sales management, then human vendors must be informed and trained to adapt their selling style to this new situation, which can be quite costly and time-consuming. A similar process is necessary for an electronic sales agent, but with the difference that it can be achieved faster. To this purpose we developed a sophisticated sales management tool called the *Personalization Manager*, offering an easy and intuitive interface to adapt the various parameters that drive the whole sales process. Let's highlight some of its functionality.

• *Management of product search and presentation parameters*: As depicted in the screenshot in Figure 8, the importance of customer preferences gained from the search mask can be adjusted. As shown the material is set to be more important than the color, which is more important than all the equally important other features. Via various parameters the valuation of the quality of the search results can be adjusted for every customer, e.g. a deviation up to 10% from the originally required volume should be regarded as 'nearly perfect'. Even the most promising sales strategy as decided by marketing and sales management can be selected from a pull-down menu. In our example the popular 'second highest price' strategy has been chosen. Using this strategy ensures that customers will not be embarrassed by admitting the price is too high while it shows respect to the customer's financial strength.

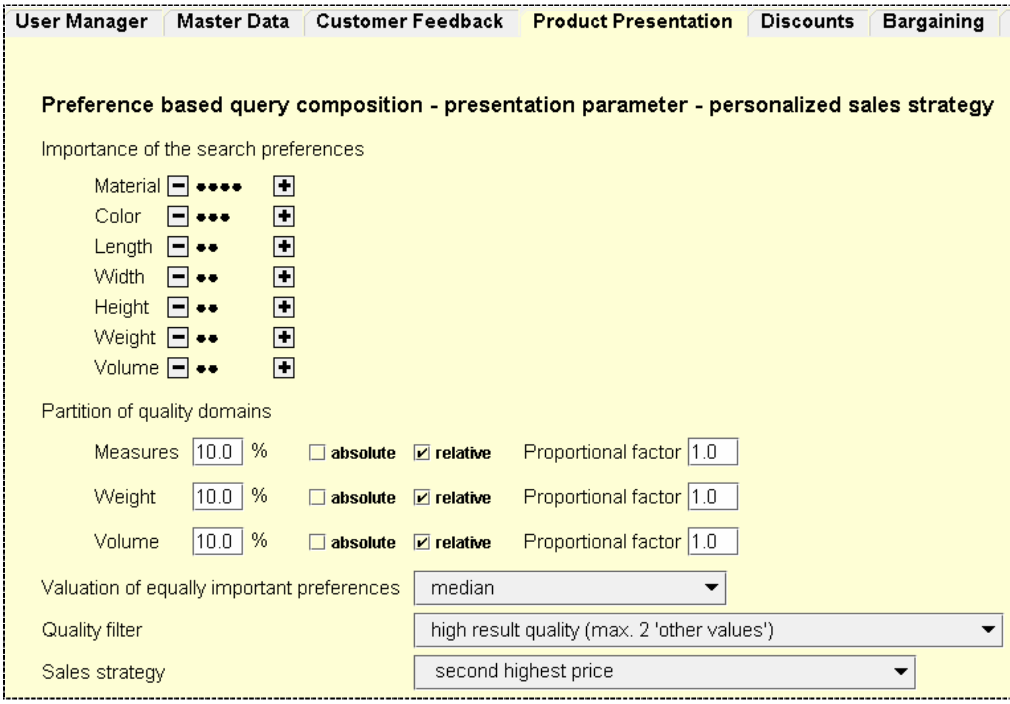

Figure 8: Product search and presentation settings

• *Management of situated long-term preferences*: For each customer the situated long-term preferences stored in the Preference Repository can be managed manually. Algorithms for preference mining like [6] can be integrated to automate this potentially expensive process.

• *Management of price policies*: In order to adapt to changing price policies, discounts can be adjusted on a personalized and situated basis, enabling the fully automated price fixing. Thereby flexible conditions can be specified, when and how to apply relative or absolute discounts.

• *Management of the bargaining policies*: As depicted in the screenshot in Figure 9, parameters like the probability of up/cross and down selling can be set. From a pull-down menu the overall bargaining strategy can be selected. These parameters can be adjusted individually for each customer. Moreover, if the overall sales situation requires it, then they can be set globally to apply for all customers, e.g. to give more vouchers at Christmas.

All these personalization information is persistently managed by the Preference Repository.

3.4 Evaluation

We run several evaluations with test persons for the different technologies and scenarios while COSIMA^{B2B} was presented to a large professional audience at the computer fair SYSTEMS 2003. There we shot a video of each customer and made a sociological analysis (see [4]). Here we want to focus on more technical aspects. The performance evaluation was done on an Intel Pentium 4, 2.4 GHz and 512 MB RAM computer running with Windows XP. Using Preference XPath we queried real product data provided by our industrial partner. This XML based data of 1.5 MB size included about 1000 products with the full product specification in BMEcat, including the full feature description in eCl@ss. Almost independent from the number of search results the Preference XPath search averages a little less than 2 seconds. Naturally, the effort for the presentation calculations rises with the number of results. But only little more than two seconds on the average are necessary for our advanced search and presentation. A more detailed performance analysis for the presentation component is shown in Figure 10.

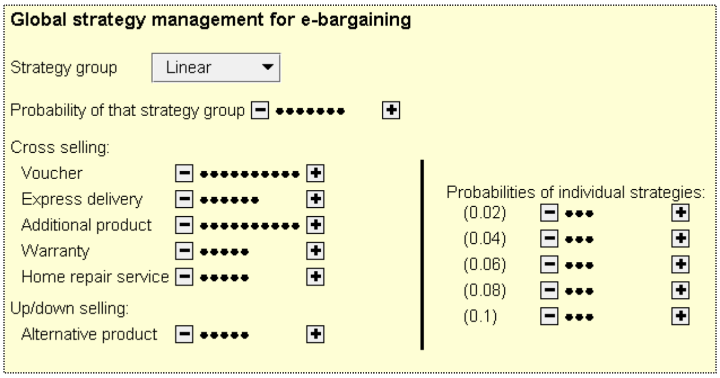

Figure 9: Global bargaining adjustments

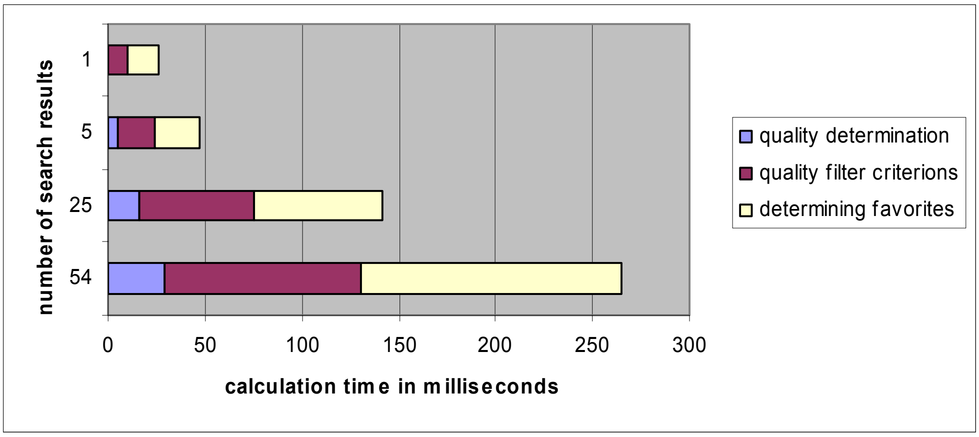

Figure 10: Time effort of the Preference Presenter

4. Summary and Outlook

We have presented several novel middleware components for sales automation in e-procurement, whose sophisticated interplay achieves to automate skills that so far could be executed only by human vendors. Installing a fully automated sales agent at an e-procurement portal promises to bring a rapid return on investment for the provider, because expensive and scarce human sales resources can be utilized more efficiently. Also B2B customers should benefit substantially from it, because personalized purchases can be made around the clock without long waits for getting individual price offers.

The key technologies for this breakthrough are built on a preference model based on strict partial orders, enabling a deep personalization of the whole B2B sales process. In particular, being compatible with XML based product catalog standards like e.g. BMEcat and eCl@ss, we presented the personalized search *Preference XPath*, the *Preference Presenter* implementing a sales psychology based presentation of search results, the *Preference Repository* responsible for the management of situated long-term preferences, the

flexible *Personalized Price Offer* and the multi-objective *Preference Bargainer*. All these components are generic in the sense that they can be customized for different application scenarios. As one use case we presented our advanced prototype COSIMA^{B2B}, which on top of these components offers speech input and output with an embodied character agent, visualizing the electronic sales agent. As another valuable component for the e-procurement provider we presented the *Personalization Manager* of COSIMA^{B2B}.
Our research and development for personalization applications will continue along various topics. As one next step we will automate as much as possible the sales process for the B2B customer side. Preference mining, being the automatic detection of user buying preferences from web or application server logs, is one important issue. As a second large use case we currently build a deeply personalized notification system for MPEG7 libraries, using our middleware components. Last but not least, as a visionary interdisciplinary research project within COSIMA^{B2B} the interplay of our automated sales technologies with dynamic emotion recognition of the B2B customer from his mimics and gestures and with emotional speech synthesis for our embodied character agent is investigated ([4]). In the long run this aims to achieve a more human-like behavior of automated sales agents in many respects.

References

[1] R. Agrawal, E. Wimmers: *A Framework for Expressing and Combining Preferences*. 2000 ACM SIGMOD International Conference on Management of Data, pages 297-306, Dallas, TX, USA, 2000.

[2] J. Chomicki: *Preference formulas in relational queries*. ACM Transactions on Database Systems (TODS), volume 28, issue 4, pages 427-466, 2003.

[3] J. F. Engel, Roger D. Blackwell, David T. Kollat: *Consumer Behavior*. Dryden Press, USA, 1978.

[4] S. Fischer, S. Döring, M. Wimmer, A. Krummheuer: *Experiences with an Emotional Sales Agent.* Technical Report 2003-19, University of Augsburg, December 2003.

[5] S. Fischer, W. Kießling, S. Holland, M. Fleder: *The COSIMA Prototype for Multi-Objective Bargaining*. 1st International Joint Conference on Autonomous Agents & Multiagent Systems (AAMAS 2002), pages 1364-1371, Bologna, Italy, July 2002.

[6] S. Holland, M. Ester, W. Kießling: *Preference Mining: A Novel Approach on Mining User Preferences for Personalized Applications*. 7th European Conference on Principles and Practice of Knowledge Discovery in Databases (PKDD ’03), pages 204 - 216, Dubrovnik, Croatia, 2003.

[7] J. A. Howard, J. N. Sheth: *The Theory of Buyer Behaviour*. John Wiley and Sons Inc, USA, 1969.

[8] W. Kießling: *Foundations of Preferences in Database Systems*. 28th International Conference on Very Large Data Bases (VLDB 2002), pages 311-322, Hong Kong, China, 2002.

[9] W. Kießling, G. Köstler: *Preference SQL - Design, Implementation, Experiences*. 28th International Conference on Very Large Data Bases (VLDB 2002), pages 990-1001, Hong Kong, China, 2002.

[10] T.-P. Liang, H.-S. Doong: *Effect of bargaining in electronic commerce*. International Workshop on Advanced Issues of E-Commerce and Web-Based Information Systems (WECWIS 1999), pages 174-181, Santa Clara, CA, USA, 1999.

[11] H. Österle, E. Fleisch, R. Alt: *Business Networking – Shaping Collaborations between Enterprises*. Springer Verlag, Berlin, 2001.

[12] N. Rackham: *Major Account Sales Strategy*. McGraw-Hill Trade, 1989.

[13] F. Ricci, B. Arslan, N. Mirzadeh, A. Venturini: *ITR: a Case-Based Travel Advisory System*. 6th European Conference on Case Based Reasoning (ECCBR 2002), pages 613-627, Scotland, 2002.

[14] M. Wang, Y.-C. Chang, S. Padmanabhan: *Supporting Efficient Parametric Search of E-Commerce Data: a Loosely-Coupled Solution*. 8th International Conference on Extending Database Technology (EDBT 2002), pages 409-426, Prague, Czech Republic, 2002.

[15] B. Xiao, E. Aïmeur, J. M. Fernandez: *PCFinder: An Intelligent Product Recommendation Agent for E-Commerce*. 2003 IEEE International Conference on Electronic Commerce (CEC 2003), pages 181-190, Newport Beach, CA, USA, 2003.

[16] L. A. Zadeh: *The Concept of a linguistic variable and its application to approximate reasoning.* Elsevier Pub. Co., New York, 1973.