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# RFID-based Recommender Systems in Stationary Trade

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## ABSTRACT

Recommender Systems have been successfully deployed in a variety of e-Commerce application scenarios. Customer selections of services or standard goods are supported as well as product configuration tasks. Little research has however been done on the application of Recommender Systems outside the virtual domain in real-world stationary trade. This surprises as on a business side, brick-and-mortar stores remain the primary distribution channel for products of daily usage. On a technical side, the growing popularity of RFID-transponders for product identification has laid the foundation for generating both context-aware and user-adaptive product recommendations. This contribution describes approaches and challenges of utilizing concepts from the realm of Recommender Systems in RFID-enabled stationary trade.

## Keywords

Personalized Recommendations, Stationary Trade, RFID-Transponder

## INTRODUCTION

Recommender Systems have been successfully deployed in a variety of e-Commerce application scenarios. Customer selections of services or standard goods are supported as well as product configuration tasks. These application scenarios however share one common denominator: they are all part of the virtual domain. Majority of grocery shoppers in stores and supermarkets thus have never encountered recommender support in their buying processes. The current limitation of Recommender System usage to the virtual domain surprises from both a business and a technological perspective.

On a business side, brick and mortar stores remain the primary distribution channel for products of daily usage. With the demise of mom and pop stores, the average size of supermarkets has significantly increased during the last 10 years. So has the amount of products offered per store on average [3]. As customers are unable to evaluate the utility of each product due to information overload, product recommendations can be used to individually highlight potentially interesting products. Despite its sales increasing potential however, recommending products by other means than non-personalized advertisements does not take place.

On a technical side, the growing popularity of RFID-transponders for product identification has laid the foundation for application of real-time Recommender Systems in physical store settings. Recommendations need to be returned timely to the customer in order to be considered as buying options. Using traditional barcode technology, recommendations could have been generated soonest at time of checkout when product selections were scanned at the cashier. RFID-transponders decrease this time lag and allow for the real-time collection of customer information during his selection process. In the following, we discuss approaches and challenges of generating both context-aware and user-adaptive recommendations outside the virtual domain.

## AUTOMATIC RECOMMENDATIONS IN STATIONARY TRADE

Recommendation services are offered primarily for three reasons:

- The business model consists of offering recommendation services as primary revenue source. Users intentionally access services to receive recommendations. As such they are willing to spend time to interact with the system and to specify their desires [11]. This is the case for example with search engines based on a revenue stream from advertisements.
- Recommendations are added as complimentary, on-demand service for real-time user assistance. Users access the service from within a different context specifically in case of need. This is for example true for product configuration processes, in which the user might not complete the buying process without expert support regarding mandatory design decisions [12, 13].
- Recommendations are delivered without explicit user request. They are ideally context- and user-dependant and therefore of potential relevance for the individual customer [14, 15]. The “better together”-functionality at Amazon is an example for this type of automated product recommendation being targeted at an increase in consumer spending.

In the following, we focus on the latter aspect of automatically generated recommendations. This kind of recommendation has previously been suggested to become core functionality in mobile information devices for usage in large retail stores [4]. Such devices have already been prototypically implemented for user support in physical store environments. They are typically installed at the customer baskets and consist of a tablet-pc for specification and display of user-individual information [8].

For generating automated recommendations outside the virtual domain, we in the following look at RFID-based approaches for real-time data collection in stores. We then analyze how this data can be timely processed and how the recommendation can be returned right into the decision context of the customer. Finally, we look at measuring the success of generated recommendations in regards to customer behaviour.

## RFID-BASED DATA COLLECTION

Optimally, we want to collect and analyze information regarding both context-awareness and user-adaptability for issuing recommendations [1].

Context-awareness in our context is a concept focussed on the understanding of the most current product interests of the customer. More precisely, we would like to know the kind of product the customer thinks about purchasing right that minute when he is about to receive a recommendation. By adjusting the recommendation towards customer’s current decision context, the perceived relevance of the recommendation is increased. In e-Commerce, context-aware information can be easily derived from mouse clicks and product page requests. The customer requests a product presentation for display and therefore reveals his most current product interest. We can then return a recommendation specifically related to the requested product embedded in the product presentation page.

User adaptability is the concept of returning a recommendation that has been generated using individual customer data. Different users are therefore returned different recommendations despite a similar product request. The following information can be used to increase adaptability in e-Commerce:

- Data from the current visit such as other items in the virtual basket and/or user’s clickstreams, i.e. previous product pages viewed.
- Data from previous visits: past transactions or past clickstreams. Access is only possible in case of upfront customer identification at the beginning of customer’s selection process, realized e.g.. through cookies or log-in functionalities.

Outside the virtual domain, data collection and user tracking is considerably more difficult. As substitute for real-time clickstream analysis in e-Commerce, we utilize the concept of RFID-based product identification in real-world stores. Due to its potential of simplifying supply chain logistics, the amount of RFID-tagged products is heavily increasing. Prerequisite for realizing each of the concepts for user tracking listed in table 1 is the RFID-transponder tagging of product instances.

	<b>Intelligent Shelf</b>	<b>Intelligent Basket</b>	<b>Checkpoint</b>
<b>Point-in-Time of Data Collection</b>	Product consideration	Product selection	Time-shifted
<b>Available Data for Recommendation</b>	Selected product	Selected product, previous selections and potentially previous transaction data	Selected product, previous selections and potentially previous transaction data
<b>Degree of Context-Awareness</b>	High	High	Low
<b>Potential Degree of User Adaptability</b>	Low	High	High

**Table 1. RFID-based Concepts for Data Collection in Stationary Trade**

Intelligent Shelves generate information that is comparable to the identification of a product page request in e-Commerce. Our customer selects a product from the shelf and by doing so, moves the attached RFID-transponder outside the range of the reading device installed at the shelf. The reading device records customer action and passes the identification code of the selected product (product ID) wirelessly as input to the central Recommender System. The approach thus secures context-awareness but offers only limited user adaptability: each user selecting a certain product is presented the same recommendation. An evaluation of previous product selections or user profiles for better characterization of the customer does not take place. Recommendations can also only be returned to stationary communication devices such as terminals, as no mapping to individual customers is possible.

Intelligent Baskets follow the concept of virtual baskets in e-Commerce. The RFID-reading device is located inside the basket and records incoming items as well as items within the basket. Item information is transmitted wirelessly in defined intervals to the Recommender System. In addition to Intelligent Shelves, further information about the customer can be submitted. Product selections within the basket can be sent along for recommendation or the customer might have identified himself upfront at his basket [7], thus allowing for access to his customer profile. As such the concept of Intelligent Baskets allows for both context-awareness and a potentially high degree of user adaptability.

Checkpoints are the third potential concept for collecting real-time customer data. Each checkpoint consists of an RFID reading device aimed at scanning products in customer baskets. Checkpoints are however installed locally in the store instead of being placed inside each basket. All basket content passed through a checkpoint is recorded. If several baskets are passed through simultaneously, separation of individual basket content imposes a technological challenge that current RFID-technology is yet unable to solve. Although the concept is user-adaptive, it does not generate information usable for context-aware recommendations, as customer selections are identified with considerable time delay. We assume utilization of Intelligent Baskets in the further discussion, as it is the only concept potentially allowing for both context-awareness and user adaptability. This goes along with observations of prototypical implementations of intelligent baskets for practical usage in store settings [8].

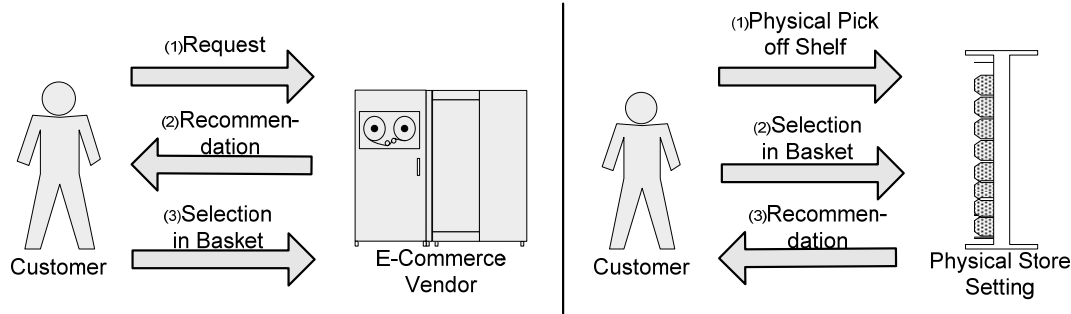
### ***Buying Patterns in e-Commerce and Ubiquitous Commerce***

While we have so far identified ways of collecting data in the physical store, we have not looked at the resulting transactional structures yet. Transactions in e-Commerce and real-world scenarios vary significantly. E-Commerce stores can be considered to be specialized; consecutive online orders of a certain customer usually consist of varying items. Taking Amazon as an example, a certain customer is not likely to order the same media article several times in a row. The amount of orders is rather irregular with a limited amount of items being purchased in each order. This differs in regards to large sized physical retailers carrying items of daily shopping, in which cases product selections are likely to be more uniform. This has the following implications:

- Recommendations in stationary trade have a potentially greater impact on consumption habits. Ideally, recommended products are not only purchased once but regularly in succeeding visits.
- We have to keep track of issued recommendations and learn from the user reactions as we can expect similar recommendation situations for the same user in the future. We therefore need to include knowledge about customer's behaviour after perception of recommendations in addition to traditional transaction structures used for customer description.

## DATA PROCESSING

In e-Commerce, recommendations are perceived by the customer right when preparing for a buying decision. To specify this more closely: the recommendation is returned during the process of selecting a certain product but before a decision on selection has been reached. In brick-and-mortar stores, the point-in-time of perceiving recommendations utilizing intelligent baskets is shifted backwards. Information about a product selection is transmitted to the Recommender System distinctly after the customer has actually decided on the item and has placed it in the basket. Context-aware recommendations are therefore generated and delivered only after the current decision process is successfully completed as illustrated in Figure 1. This has significant consequences on the applicability of concepts for reasoning purposes. It furthermore imposes the rather conceptual question, which kind of product to recommend if the decision context has already passed at time of recommendation generation.



**Figure 1. Recommendation Delivery in e-Commerce and Physical Store Scenarios**

Two major marketing concepts can serve as blueprint for generating automated recommendations.

- Up-selling: recommendations focus on presenting higher-value product alternatives for substitution of a potentially interesting item.
- Cross-selling: recommendations focus on presenting complementary products that the user might be interested in.

For up-selling purposes, first we need to know which kind of product the customer is going to be interested in next. Then using similarity measures, we can identify higher-value goods that could serve well for substitution. With RFID-based product identification, we are able to learn about customer's product interests only after an item has been selected. If the up-selling recommendation is sent anyway, the customer following the recommendation would have to return the previously chosen product and override his decisions. This contradicts the idea of decision support and is likely to decrease user satisfaction.

For cross-selling purposes, the same issue exists to a lesser degree. Recommendations for complimentary items can well be made after a selection is placed in the basket. It needs to be ensured though, that the time span between recommendation delivery and the potential action of selecting the recommended product is minimized. We want the recommendation to be displayed just when the customer has the option of selecting the product from a shelf for two reasons:

- Recommendations have a higher impact, if they are context-aware and highlight a product available for instantaneous selection. This is understood in the tradition of impulse buying being defined as the "sudden [...] urge to buy something immediately" [6]
- Customers might not be willing to accept additional transaction costs i.e. time and effort, if the product is located at the other end of the store, considering an average size per store of more than 48,000 square feet [3].

We will show that this requires modifications of existing reasoning algorithms but does not impose a conceptual challenge. As such, recommendations following the cross-selling concept are more convenient to realize in brick-and mortar-environments than recommendations following up-selling. We want to shortly discuss two concept extensions potentially allowing for up-selling in order to show the considerable raise in complexity:

- If we could predict the next product the customer is planning to purchase, items for substitution could be recommended right before physical product selection. We therefore would have to reason two times in a row. Obviously, this form of inference chaining reduces the quality of recommendations on average by increasing the degree of uncertainty. User-adaptability can be realized under the assumption of upfront customer identification by using past own transactions for sequence prediction. Without, we would have to resort to patterns extracted from the entirety of customers, thus lowering the quality of the predictions and therefore also of the recommendations even further. Considering the ongoing RFID privacy discussion [5], it appears questionable if customers is willing to cooperate with upfront identification by for example having their customer cards scanned when entering the store [7].
- Baskets are equipped with a second RFID reading device. This reading device picks up signals from RFID-tagged products in the shelves. Recommendations are generated but not communicated until the customer passes a product he is likely to purchase. Challenges of this approach include the limited transmission range of about 1-2 meters for passive smart labels currently used for product identification. Smart labels with a higher transmission range would require on-board power supplies and are therefore not cost-effective. A different issue is the need for isolation of customer basket content. Reading devices have to exclude items positioned in other baskets from their scans, requiring baskets to be isolated against incoming or outgoing signals. While these kinds of technological challenges might be resolved in future RFID generations, the approach has to be currently considered to be a future scenario.

Sticking with the more viable approaches, we need to select an inference concept for the realization of cross-selling recommendations. Inference concepts describe the kind of data representation to be used for reasoning. The concept of content-based reasoning uses product attributes, collaborative filtering utilizes user transactions, demographic filtering applies to personal user data and knowledge and utility-based filtering require knowledge-engineered structures [2]. Considering the lack of direct user interaction, possibly no upfront customer identification and on average around 45.000 products per store as contextual requirements, collaborative filtering is best suited for cross-selling purposes. In the tradition of e-Commerce basket analysis, we therefore analyze similar transactions to find recommendation candidates. Recommendation candidates are products identified to appear frequently with products that so far have been chosen by the customer. The process of selecting a product for recommendation from this group of candidates is then adapted towards brick-and-mortar specifics.

### ***Target Parameters and Transaction Structures in Brick-and-Mortar Collaborative Filtering***

Collaborative Filtering is based on the assumption, that people who agree on a set of products might also share further product interests. As customers do not engage in active product ratings, transaction documentations have to be used for defining similarities and generating recommendations.

In e-Commerce, a variety of products can be presented for recommendation at once. The customer then actively selects one or more recommended products he would like additional information about. Without customer interaction, the amount of products to be recommended at a time should be strictly limited. Therefore we look for the single best suitable product from a set of recommendation candidates. The term “best suitable” implies the existence of a measure or target parameter that evaluates the recommendation candidates regarding their suitability for recommendation.

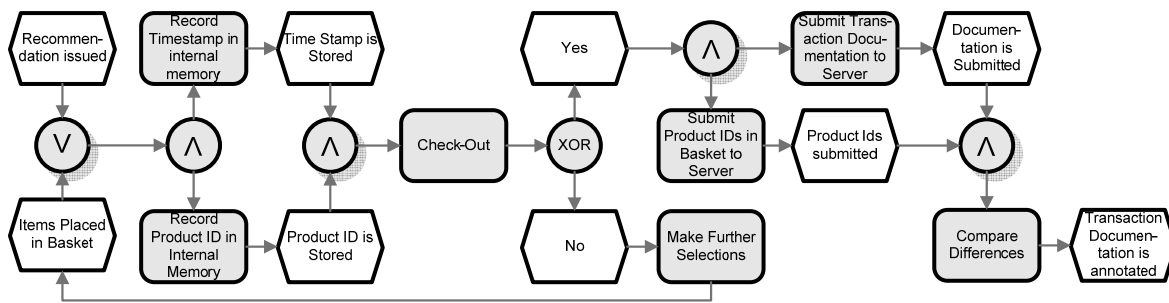
Target parameters traditionally used for this measurement are maximization of the strength of object relation and optimization of financial key ratios. Strength of object relation is a target parameter, in which the product that is most closely associated with one or several input products is returned as recommendation. The product selected for recommendation is expected to match user’s interests best. This parameter is widely used in scientific e-Commerce literature. Optimization of financial key ratios is found especially in practical realizations of Recommender Systems. In this case, the most desirable, i.e. most profitable, product from the vendor’s perspective is returned [9]. As recommendations however are only selected from the group of recommendation candidates, potential relevance for the customer remains secured.

A third parameter exclusively applying to brick-and-mortar scenarios is spacial proximity. Given a large-sized real-world store, transaction costs for taking a product off the shelf vary in regards to the current customer location. We therefore have to minimize the time span between recommendation display and the time it takes to physically select the recommended product from the shelf. In order to do so, either the recommendation has to be returned whenever the customer is physically close to the recommended product or products that are close to the current location of the customer have to be recommended. The first option has been disregarded earlier on in the context of up-selling due to technological issues and the need for a second RFID scanning device on each basket. The second option requires the evaluation of the current user position in regards to the locations of the recommendation candidates.

Assumed the location of each recommendation candidate would already be defined, the position of the customer could then be determined for those points-in-time in which an item is placed into the basket under the likely presumption of a correlation between product location and basket location. The location of products can be modelled following two approaches:

- Coordinate-based definition: the location of each product is documented in regards to its absolute position in the store. The coordinates are then used in mathematical models to determine the proximity between products under specific provision of their actual distance from a customer’s perspective instead of beeline calculation.
- Transaction-based definition: time stamps of past product selections are utilized for proximity calculation. The distance between two products is measured based on the time gap between the average selections of these products. For this purpose, Intelligent Baskets need to be additionally equipped with small amounts of internal memory. This memory stores information about products, their selection order and the time stamps of their past selections.

The second approach causes less manual implementation and maintenance effort. It additionally allows for analysis between complete and finalized transaction documentations with the latter excluding products that were removed from the basket before checkout. Figure 2 illustrates the process of generating and storing time-stamp based transaction documentations in brick-and-mortar settings using a high level Event-Driven Process Chain (EPC).



**Figure 2: EPC-Description of Generating Time-Stamp-Based Transaction Descriptions**

Each product placed in the basket is stored in internal basket memory along with a time stamp of its selection. All displayed recommendations are recorded with an own time stamp as well. At check-out, the Intelligent Basket receives a submission signal and transmits the transaction documentation from internal memory to the central Recommender System. Additionally all product IDs from within the basket are transmitted. Products that were removed before check out are marked in the transaction documentation.

The Recommender System first creates a data structure containing the average difference in time stamps for each product combination, thus allowing for approximation of spacial proximity. Additionally, the system updates a set of key ratios for each transaction on generic as well as –where applicable– customer-specific level as illustrated in table 2.

Customer-Specific-Level		Generic Level	
Key Ratio Description	Information Appended in Customer-Specific Knowledge Structures	Key Ratio Description	Information Appended in Generic Knowledge Structures
Customer-Level Recommendation Success	[Recommended products purchased/ Recommendations sent]	Product- Level Recommendation Success	For each product ID recommended: [Amount of products purchased/ Amount of recommendations sent (usually 1)]
Individual Return-Buyer-Rates (I-RBR)	For each product z purchased in transaction x directly following a recommendation: [defined amount of transactions y subsequently following x/ amount of selections of z in y ]	Global Return-Buyer-Rates (G-RBR)	For each product with an existing I-RBR calculation on customer-specific level: [I-RBR/ Amount of I-RBR]
Recommendation Documentation	Product ID of recommended products, not being selected or not being purchased	Recommendation experience	Rule structure: [(Most recently selected product → Product ID for recommendation); Success]
Deselected Products	Product ID of all deselected products	Transactions with Deselected Products	Transaction structure (for further processing in pattern analysis)

**Table 2. Key Ratios of Experience Knowledge**

These key ratios are understood in form of additional knowledge structures that can be applied for fine adjustment in selecting a product for recommendation from the set of recommendation candidates. We call these ratios experience knowledge, as they contain additional information about past user behaviour derived from time-stamp-based transaction documentations. When searching for the most suitable recommendation candidate, information about for example the global return-buyer-rate (G-RBR) can be of interest. G-RBR describes the frequency, with which customers purchase a previously recommended product over a number of upcoming transactions. Products with high G-RBR values are therefore not only commonly purchased in the transaction, in which the recommendation was issued, but also in subsequent transactions. They therefore introduce a change in consumption habits. Discussion points of G-RBR for recommendations include ethical discussions of blacklisting of addictive products as well as the analysis of substitution effects in the transaction structures over time. For the purpose of maximisation of sales volume, products scoring well on this key ratio are expected to create a potentially high margin in the long run assuming rather uniform transaction structures in brick-and-mortar settings. The G-RBR can therefore also be understood as a long term financial key ratio.

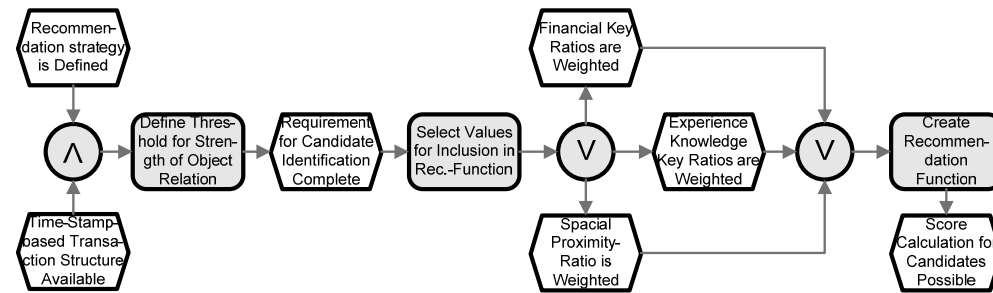
So far, the transaction structure allows for approximating strength of object relation, spacial proximity as well as the creation of additional experience knowledge. What is missing is the consideration of e-Commerce like short-term financial key ratio optimization, such as selecting the most profitable product for the current transaction from the set of candidates. To achieve this, a trade off between performance and redundancy in data storage has to be considered. Either, defined financial key ratios are appended to each transaction structure, leading to redundant information: each product ID within the transactions would have the same financial key ratios assigned. Alternatively, these values could be looked up after selection of recommendation candidates is complete. We prefer the latter approach in order to take potentially changing margins for single products into account, which otherwise would require ex-post modifications of transaction data. For this reason, Figure 2 does not include functions to append the transaction structure regarding short-term financial key ratio optimizations.

The major drawback of using a time-stamped transaction structure for approximating spacial proximity in general is the considerable noise in regards to products being located far from each other. As the measure does not describe actual distances between products but rather the time spans in between product selections, the measure distorts with increasing distance. We do not get to know how soon a product could potentially be selected if the customer was willing to directly approach it. Neither the chosen route in the store, further product selections in between nor social interactions are taken into



consideration. For the purpose of recommending close-by products, this however does not impose an issue. More critical is the definition of what a close-by product really is. We can either define any product to be close-by that is selectable within a given time frame from the current user position. Alternatively, usage of the term can be limited to accessible products in the given time frame that are located in the customer’s direction of movement. While the first definition can be realized using a trivial rule-based definition, the latter requires concept extensions regarding inclusion of a sequence analysis among the most recently selected products.

Before recommendations can be issued, the recommendation strategy and the procedure of calculating recommendation scores need to be manually determined. Recommendation strategy describes the business concept behind offering recommendations, such as focussing on short-term optimizations or defining the time frequency with which recommendations are issued. In order to realize the recommendation strategy, the scores for evaluating each recommendation candidate need to be set as displayed in figure 3.



**Figure 3: High Level Process Description of Calculating Recommendation Scores in Stationary Trade**

Figure 4 summarizes the process of RFID-based recommendation for cross-selling purposes. In a build-time phase, illustrated with dotted lines, the recommendation function is generated using a combination of weighted target parameters.

In the run-time phase, customer then adds a product to the basket. The most recently selected product is wirelessly transmitted to the Recommender System. If the customer has identified himself up-front, user adaptive recommendations are possible by limiting the transaction base for candidate generation to similar transactions. This is displayed in form of a user-specific strength of object relation model. Either the generic or the customer-specific model returns recommendation candidates. These candidates are then evaluated using the recommendation function. The candidate scoring highest is returned as recommendation. After check out, again in build-time, user behaviour is evaluated and the experience knowledge ratios are updated.

In order to highlight the differences between virtual and stationary recommendations, we summarize major aspects in table 3.

	<b>Online Store</b>	<b>Real-World Store</b>
<b>Data source for recommendations</b>	Explicit user ratings, User Transactions, Knowledge Structures	User transactions
<b>Frequency of automated recommendations</b>	Along with each product display	Frequency to be defined via recommendation quality or user acceptance (experience knowledge)
<b>Target parameter to be optimized for recommendation</b>	Strength of object relation, short-term financial key ratio optimization	Additionally: spatial proximity and knowledge structures with long-term-focus
<b>Marketing strategies effectively realizable</b>	Up-Selling and Cross-Selling	Cross-Selling
<b>Point-in-Time of recommendation display</b>	Within decision situation	Before decision situation; time gap between recommendation delivery and decision situation to be minimized
<b>Realization costs</b>	Low: fixed software costs for algorithmic realization of functionality	Additional costs for hardware: RFID-reading devices, wireless network structure; Precondition: RFID-transponders for product identification
<b>Up-Front user identification</b>	Depending on browser setting, identification via cookies automatically without additional user action	Technically identification via customer card possible, Explicit action for Identification required.

**Table 3: Illustration of Differences for Recommendation Generation between E-Commerce and Real-World Stores**

## SUMMARY

With growing brick-and-mortar store sizes and an increase in RFID-tagged products, Recommender Systems will become part of the everyday real-world shopping experience. The key challenge for the application of Recommender Systems outside the virtual domain is to deliver the recommendation right at that moment when the customer is physically able to select the recommended product from the shelf. To realize this kind of context-awareness, we need to extend Recommender System concepts known from the e-Commerce domain to account for the specifics of an in-store setting. First steps are utilizing time-stamp based transaction structures as well as spatial proximity and additional experience knowledge as target parameters. In order to minimize the time span between recommendation perception and physical product selection and further allow for realization of up-selling concepts, we need to even better forecast customer's actions. Upcoming data sources may be accessible from new value-added services such as virtual shopping lists. While we currently have to infer product interests from past transactions, customers might then explicitly specify their planned product selections upfront. This will allow for new recommendation concepts such as based on comparisons between submitted shopping list and actually bought items.

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