Semantic Shopping: A Literature Study

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Abstract

The digitalization of the economy and society overall has a significant impact on customers' shopping behavior. After being conditioned by experiences in entertainment or simple Internet search, customers increasingly expect that a smart shopping assistant understands his/her shopping intentions and transfers these to shopping recommendations. Thus, the emerging opportunity in this context is to facilitate an intention-based shopping experience similar to the way semantic search engines provide responses to enquiries. In order to progress this new area, we differentiate alternative types of shopping intentions to provide the first set of conversation patterns. Grounded in the Speech Act Theory and a structured literature review, semantic shopping is defined and different types of shopping intentions are deduced.

1. Introduction

Before the first online-shops emerged, traditional brick-and-mortar retailers were only able to gather information on the customer's tastes, preferences, previous purchases, the current situation, and other information about their local context because of the close contact of shopkeepers to their customers. Additionally, they had knowledge about the current product availability and how products can subsidize and complement each other. All this information is useful to personalize the customer interaction [16]. Thus, shopkeepers are trained in grasping the demands of their customers [55].

Today, this personalization has not only been mirrored but in many cases exceeded in the area of e-commerce through sophisticated, often artificial intelligence-enabled engines supporting product search, comparison and recommendation [16, 30, 31, 51]. Examples are Amazon's flexible suggestions interface [44] and other smart shopping assistants such as honey (https://www.joinhoney.com/) or piggy (https://www.joinpiggy.de/) [e.g. 40].

Smart shopping assistants and new digital technologies such as robotics, artificial intelligence and the Internet of Things and their integrated use have led to a fast-growing design space in terms of possible new shopping experiences. This development is grounded in a data-rich environment, which facilitates advanced data analytics and results in fine-granular, real-time insights about the customer shopping behavior and a detailed classification of products to purchase. Thus, the automatic understanding of customer's needs by an assessment of his/her shopping behavior, emotions and intentions has become a topic of high interest. In particular, it is becoming possible to either allow the customer to simply purchase based on directly articulated intentions ('I like to buy an easy to cook fish') or based on intentions indirectly inferred based on complementary data [38, 41, 43, 44].

The emerging opportunity in this context is to facilitate a more convenient intention-based shopping experience similar to the experience offered by semantic search engines that return responses matching the searcher's intentions [e.g. 20, 23]. An understanding of the customer's shopping intention would facilitate a more convenient [19] shopping experience for the customer as it releases him/her from the task of converting the intention into actual products on his/her own or with the help of a physical shopkeeper or shop assistant as it is the case in traditional, stationary shopping environments.

Thus, obtaining an understanding of a customer's shopping intention in order to support the act of shopping is the most critical task in semantic shopping. Semantic shopping aims at providing information and executing workflows based on the customer's shopping intention to support the creation and purchase of a shopping basket containing items of the retailers' product portfolio (see Section 4). Thus, semantic shopping systems are more than just context-aware recommender systems [e.g. 33].

We argue that smart personal assistants (SPA) enable to offer semantic shopping in the physical surroundings of the customer. In general, SPAs are autonomous software agents that interact with the user to understand his/her intentions from natural spoken or written language as well as from contextual information to adapt to his/her preferences and assist

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him/her through the execution of personalized services or tasks [5, 46, 54]. Examples of prominent SPAs are Cortana, Siri, Alexa, and Google Assistant [28]. However, trials have shown that existing SPAs only support the act of shopping to a limited extent. Yet, SPAs have the potential to realize semantic shopping and embed it into the daily lives of the customers, no matter if they are at home, in a mall or in a retail store.

At this stage, theory-guided frameworks or guidance on how semantic shopping could be designed or implemented in SPAs are missing. In light of this, we address the following two research questions: (1) *What is semantic shopping?* (2) *How can shopping intentions be classified?* In order to answer the questions, we derived a semantic shopping concept that classifies different intention types. They have been deduced through a structured literature review and converted into an overall concept for semantic shopping using patterns of conversion types based on the Speech Act Theory [39].

In the remainder of this paper, we first introduce the research method in section 2 followed by the theoretical background in section 3. In section 4, we introduce the notion of semantic shopping. The theory-guided intention types are presented by explaining the related conversation patterns in section 5. In section 6, we discuss our outcomes, the limitations, and the possibility of future evaluations. The paper concludes with a summary, and the theoretical as well as managerial contributions.

2. Research Method

In order to build and deduce the semantic shopping concept, a structured literature review based on the approaches of Webster and Watson [53] and vom Brocke et al. [11] has been performed. The aim was to identify typical characteristics and application examples of semantic shopping to define semantic shopping and to deduce different intention types.

Before performing the structured literature review, a preliminary search has been carried out on Google Scholar to get an overview of the related research areas. This investigation showed that promising results related to semantic shopping can be identified by searching for semantic retail and related terms such as semantic web and technologies. However, terms such as intention-based shopping and retail have not yet been discussed in the literature. The insights from this first search were then utilized to determine the search strings for the structured literature review based on a keyword search. Different keywords have been used to define a search string with different combinations of the keywords. Exemplary keywords are 'semantic shopping', 'semantic retail', 'semantic web', 'semantic technology', and 'semantic search'. The search strings were used for gathering the literature on the databases EBSCO, Scopus, and AISeL. Based on the preliminary search and the structured literature search, a total of 158 publications have been identified (EBSCO (6), Scopus (142), AISeL (2), and Scholar (8)). After filtering for duplicates, analyzing titles and abstracts and including forward and backward search, the remaining 39 publications have been identified as relevant for the purpose of the paper and build the foundation to answer the research questions. These publications were investigated in detail.

Using the insights from this literature review, two main categories (intention and potential outcome) have been identified as most promising in order to structure semantic shopping. Thus, as a post-processing step, the resulting publications have been coded to the intention and the outcome category. This coding scheme built the foundation to perform the further analysis of the publications and to classify them in a concept matrix. A concept matrix synthesizes the identified literature results in logically developed groups and classifies the key concepts to those groups [53]. Afterward, the insights from these publications and the concept matrix were used for deducing a semantic shopping concept and identifying intention types. This has been achieved by synthesizing the insights from literature, which were iteratively integrated by merging, adjusting, and adding elements to the concept in an abductive manner through a series of consensus-seeking discussions within the research team [14]. To define the different intention types, the Speech Act Theory of Möschler [39] has been applied as it helped to structure conversation patterns for each shopping intention type.

3. Theoretical Background

3.1. Semantic Web

The semantic web aims at reducing the information overload by supporting users in finding the objects or information of interest and, thus, support their decision-making [16, 30, 35]. It relies on linked machine-usable content (e.g. ontologies) and logic with rules. This allows systems to understand what the web content means, infer the meaning of new content, and grasp how it can be used [18, 32, 35, 40, 52].

One well-known implementation of the semantic web is semantic search. Semantic search takes advantage of the available semantic information to generate more precise or augmented search results [20, 36]. An example is the capability to infer that using a search query such as 'Albert Einstein' means looking for a person [20]. To achieve precise or augmented search results, the scope of the search, the activity a user wants to perform, and the search context to infer the user's intentions or preferences are analyzed [20, 23]. With this understanding, semantic search tries to support the user in finding the objects of interest (e.g. products) or additional information about the search object [20]. Prominent examples of semantic search are search engines such as Google and Bing.

One significant application area, where the semantic web can help to support users, is the retail sector. Here, semantic technologies can be utilized to support the act of shopping – called semantic shopping (described in section 4).

3.2. Speech Act Theory

The Speech Act Theory by Austin [4] has been developed to understand the performative usage of language. "Speech acts are not isolated moves in communication: they appear in more global units of communication, defined as conversations or discourses" [39:240]. That is why the theory has been extended by Moeschler [39] to support the analysis of conversations. According to this theory, a conversation consists of several speech acts in a sequence whereby at least two speakers are in a verbal interaction [45]. Two dimensions can be distinguished to structure a conversation: (i) principle of functional composition and (ii) a procedure of interpretation assignment [39]. The principles of functional composition (i) describe that components might have illocutionary functions (initiative, reactive, and reactive-initiative), and/or interactive functions (directive, and subordinate). The procedure of interpretation assignment (ii) aims at defining a semantic, which can be used to assign it to the hierarchical-functional structure in order to be able to interpret the functions of each speech act [39].

This rigor of identifying structured patterns of conversation provided the theoretical lens we used when identifying and structuring different intention types of semantic shopping.

4. Introduction to Semantic Shopping

As stated above, understanding the meaning of the customer's shopping intention and using it to support the act of shopping is the most critical task in semantic shopping. An intention is "a relationship between some object … and an actor's internal mind state – desire, belief, goal, purpose" [22:5]. The actor is the customer in the sense of a buyer and the object is a product or a service. Intentions can be distinguished in intention-as-wants (describing a specific plan of an actor what he/she wants to do or know), intention-as-plans (describing individual's propositions about his or her future's behavior), and intention-as-expectations (describing the individual's expectation how likely a particular behavior is to occur) [49]. An example of intention-as-wants is "I want to buy vegetables in the afternoon", which describes a concrete envisaged activity of the shopper. Typically for intention-as-plans are statements such as "I am planning to buy a house during the next five years", which just states a proposition of the shopper. Lastly, an example of intention-as-expectations is such as "it is likely that I am going to use a semantic shopping assistant in the future", which describes how likely it is to do something particular. In this paper, shopping intentions are understood as intentions-as-wants, i.e. wishes or desired end states [49] of a customer motivating him/her to get in touch with a retailer in order to get further information about a product or a service. The most clearly articulated shopping intention would be a specific item on a customer's shopping list (e.g., soya sauce) [21]. In contrast, an unclearly articulated intention could be an expressed desire to cook a specific type of food (e.g. a Thai dinner). A way to articulate a shopping intention is a spoken [e.g. 12] or textual query [e.g. 2, 18, 40, 56].

An understanding of the different types of shopping intentions is important to guide the design and implementation of a semantic shopping assistant. However, explicit shopping intentions are often not investigated in detail.

Up to now, scholars present technical architectures to explain the semantic shopping system components to guide the implementation of such systems [e.g. 2, 16, 25, 31, 40, 55]. Other scholars discuss product interfaces considering natural language communication [25], the utilization of semantic product memories [26], and the opportunities of a semantic or smart retail store setting [7, 44], but with limited relation to the customer's shopping intentions.

Other scholars consider a conceptual view on the topic of semantic shopping, presenting input and output mechanisms or processes as a way to structure the semantic shopping system [2, 21, 40, 43]. However, again, these tend to provide little details about the possible types of shopping intentions that can serve as input data and as such do not provide a holistic overview of the semantic shopping concept.

Many scholars focus on semantic shopping systems using the shopping context (e.g., time of the day, weather) as a factor influencing the system's response [33, 37]. Situational data relevant to shopping can be differentiated into customer's current behavior [27, 40, 43, 44, 55], location [18, 21, 25, 27, 32, 33, 41, 55], current situation [16, 33, 55] and other environmental factors [16, 21, 32] related to the customer's shopping encounter. Two examples to capture such context information are the tracking of the users' navigation behavior on websites [55], and the use of video analysis in in-store environments [43].

A number of scholars have discussed the use of customer data, to analyze the customers' long-term interests [21]. For this purpose, these studies suggest using data such as information from customer profiles [7, 21, 32, 33, 40], past purchases [1, 16, 41, 44, 55], previous behavior [16, 32, 44], social media information [7, 32], information about similar customers [32, 44] or other user-generated content such as reviews [32, 40]. Examples for long-term interests could be special dietary preferences [7], the preference for a specific brand [21] or simply information about products or devices [7, 32].

While context information such as situational data and long-term interests can help to infer a customer's current shopping intention, this inference is only an indirect way to interpret the intention correctly. It would be easier if the intention is directly articulated.

Only a few scholars focus on the customer's articulated shopping intentions more closely [21, 25, 31, 37, 40, 43]. The majority of those focus on the development of a personalization architecture using ontologies [21], a dialog system [24], dynamic product interfaces [37], a meta-search framework [31], or a smart shopping assistant for an online-shop [40] in order to enhance the access to further product information. Moreover, Popa et al. [43] developed a multi-level framework to analyze the customers' shopping behavior based on a Hidden Markov model. All of these scholars consider the shopping intentions of the customers. However, none of the scholars holistically investigate the specific types or conversation patterns of different customers' intentions in relation to the act of shopping. More specifically, we lack an understanding of semantic shopping itself and its related intention types. To the best of our knowledge no approach exists that provides a conceptual view on semantic shopping to understand the intention types and to structure the related conversations.

We aim to address this gap by placing a specific emphasis on the customers' intentions. Thereby and in contrast to the abovementioned scholars, we accentuate the customers' intentions when defining semantic shopping. Thus, we define semantic shopping as the transfer of articulated and contextualized intentions of a buyer to products, services, information, and workflow assistance in order to support the act of shopping. "The act of shopping can be considered as a single act or a set of interrelated unit acts" [15:292]. A single act is e.g. to buy a product such as a pair of shoes and a set of interrelated unit acts would be gathering information through different channels about a specific product [15]. For both, the object of interest for the customer might be a product, or a service. Consequently, the concept of semantic shopping consists of an object of interest as input and an output such as the requested information or the execution of workflows, both supporting the creation or purchase of a shopping basket containing items of the retailers' product portfolio when a product is considered as an object of interest. To transfer intentions into the expected output, intentions need to be analyzed, interpreted in a given context and mapped against items of the retailers' product portfolio. This processing step can make use of context information. As this processing step is not part of the scope of this paper, it is visualized as a black-box in Figure 1.

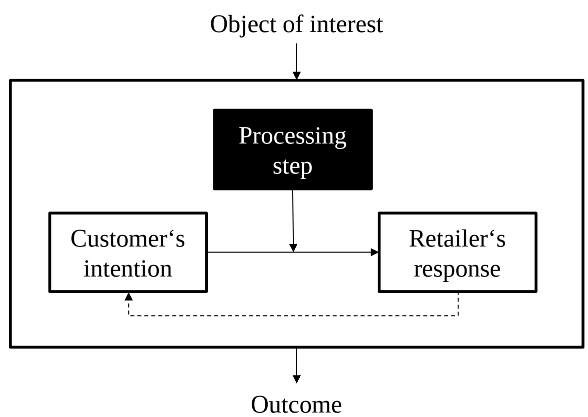

Figure 1: Concept of semantic shopping

In the end, the conversion of intentions into products or services is the core of the semantic shopping concept. Thus, two different types of semantic shopping related to the object of interest can be distinguished: product-related, and service-related semantic shopping. In this article, we focus on product-related semantic shopping. Service-related semantic shopping is out of scope and will be investigated in future research.

5. Types of Shopping Intentions

5.1. Overview of Intention Types

Semantic shopping aims for an improved customer convenience by providing information, service and product recommendations aligned with the customer's current goals and desires [38, 40, 41, 44]. Through the analysis of the literature, three different intention types have been identified: informational, transactional, and explorative. Each of these types is discussed in the following and enriched by considering the fictive running example of Paul, who wants to organize a BBQ for his friends.

Each intention of a buyer has a specific goal. The goal of the intention represents the reason, a customer queries a semantic shopping assistant. The goal depends on a customer's expected shopping value, which can either be utilitarian or hedonic. While utilitarian shopping value "can be considered a cognitive and non-emotional outcome of shopping", "hedonic shopping value refers to the value received from the multisensory, fantasy, and emotive aspects of the shopping experience" [9:101]. These shopping values are "a key element in predicting consumers' shopping intentions" [9:101]. Here, we focus on intentions following a utilitarian shopping value. To support the act of utilitarian shopping, the literature talks about what we have defined as *informational*, *transactional*, and *explorative* reasons to query a semantic shopping assistant. For each of these intention types, the conversation pattern varies. Thus, we use the Speech Act Theory by Moeschler [39] to define the conversation pattern of each shopping intention type in order to classify the different types.

5.2. Informational Intention

An *informational intention* is a request motivated by an information search problem [e.g., 10], i.e. the customer *wants* to query the system to receive the desired information [1, 17, 24, 37, 48, 55].

In the running example, Paul just scheduled a BBQ with his friends and is now looking for a bottle of red wine for his guests. However, Paul only drinks beer and has no knowledge, which wine he should buy. The only important decision criteria for Paul is that the wine should be cheap. Thus, he queries his smart personal assistant (SPA): "Hey SPA! What is the cheapest red wine that goes with a BBQ dinner?" The SPA responds with the requested information: "Merlot of the brand XYZ". By doing so, he requested a recommendation of a product from a specific product category [16, 21, 40]. Besides, Paul could have requested information about the availability of certain products [1, 25, 29] or the characteristics of these [e.g. 26]. Connected to this, semantic shopping can support Paul by providing information for the evaluation and comparison of products according to his demands [26, 31, 35, 42, 56]. The buyer's informational intentions could also be supported by augmenting the shopping environment with requested additional information [24, 29, 40]. Examples discussed in the literature are the augmentation of shopping lists, in-store touchpoints [24, 26, 40, 44], and product pages with the product information [3, 55]. In sum, informational intentions can be satisfied by different means easing information search and, thus, supporting the customer's current act of shopping.

Functional Composition			Speaker	Interpretation Assignment
E	M1	dA	Paul	Question
	M2	dA	SPA	Answer

Figure 2: Conversation pattern of informational intentions

Due to the availability of semantic information and an understanding of the shopping intention, the item search can be improved. Additionally, the pattern of the conversation can further support the understanding of the intention type. Following the Speech Act Theory based on the principles of functional composition [39], the example represents a conversational exchange (E) with two directive acts (dA) whereby the first move (M) of Paul is an initiative move and the second move is reactive. The first move is always an initiative one [39]. The second dimension of Speech Act Theory interprets the functional structure (procedure of interpretation assignment) [39]. Here, the speech act of Paul is a question to which the SPA provides an answer. The *informational intention* of Paul concentrates on an informational search problem. Thus, the described conversation pattern is typical for each informational intention-guided conversation (see Figure 2). It is a conversation of different directive acts, which typically, but not necessarily, consists out of just two acts. However, it always requests concrete information and is directly articulated. Thus, it always consists of a pair of directive acts – a question directly requesting information and an answer. The resulting response of the SPA is, thus, a direct response as this type the intention is articulated specifically enough.

5.3. Transactional Intention

A *transactional intention* is a request expecting workflow assistance [e.g., 50], i.e. the customer *wants* the system to execute a sequence of scripted steps required to achieve his desired outcome. In the running example, Paul wants to order and cook a fish. As Paul is not an expert when it comes to fish dishes, he asks his SPA for help (see Table 1).

Table 1: Exemplary transactional intention-guided conversation

Paul	I am not the best cook and we decided to grill fish. What is an easy to cook fish for eight persons open for new things?
SPA	I would suggest to grill salmon.
Paul	Okay. What steps should be taken to avoid a dry fish?
SPA	You need lemons, herbal, salt, and pepper. Put a piece of salmon together with the other ingredients in aluminum foil.
Paul	And what do I have to do afterwards?
SPA	Heat up the barbeque and grill it.
Paul	Ok, thanks. Can you order everything for me?
SPA	Sure.

Such a request is considered a *transactional* intention as a sequence of interrelated interactions belonging to a specific workflow or the automation of the subsequent steps through the SPA (e.g. add all ingredients to the shopping basket, confirm shipping address, and effect the payment) are required to handle it. In other words, Paul's reason to query the semantic shopping assistant was to support his act of shopping with a specific sequence of scripted steps [e.g. 42]. Indeed, there are numerous possible workflows connected to the act of shopping, which could be automated by a semantic shopping assistant. Besides, the avenues for the automation of subsequent steps include but are not limited to the processing of order requests as well as automatic or improved checkout procedures [26]. For example, Paul's act of shopping could also be supported by providing him means to request transactional information such as facts about his previous purchases (transactions) [55] in order to repurchase certain items. Furthermore, the SPA could even allow to add requested items to a shopping list or interact with a smart fridge to automatically add required items to it [26]. Additionally, the SPA could afford to request the call of a shop assistant [43], the delivery of a product through a shop assistant [25] or reminders for products on the shopping list [26].

An overview of a related conversation pattern is provided in Figure 3. The exchange of the conversation between Paul and his SPA consists of several directive speech acts. Directive moves (dM), which "contain the act from which the move receives its illocutionary function" [39:246], are included to guide the conversation. The functional interpretation (see Figure 3) of the conversation between Paul and his SPA are: <<Question, Answer>, <Follow-up Question, Answer>, <Follow-up Question, Answer>, <Follow-up Question, Answer>>. The last directive act of Paul requests the automation of the remaining workflow, which is the order of the demanded products. The SPA concludes the conversation by confirming the request.

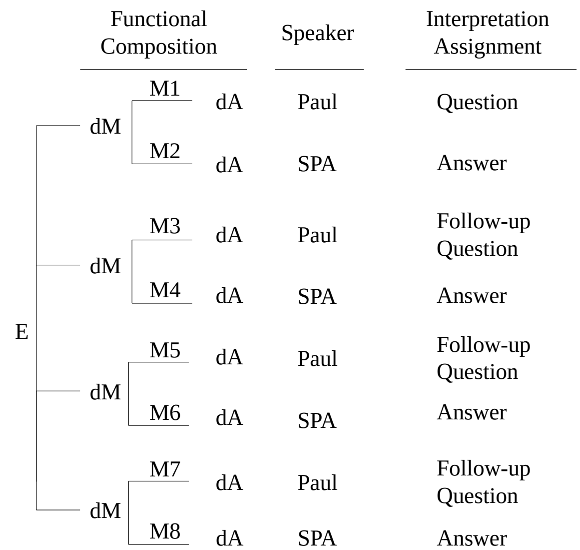

Figure 3: Conversation pattern for transactional intentions

This pattern represents a typical conversation for a *transactional intention*. In the example, Paul asks several questions, which are related to the same topic and build on each other. Therefore, the resulting conversation pattern comprises questions and answers for several directive acts. However, not all workflows, which could be supported by the SPA, do necessarily require a sequence of questions and answers. Also, the conversation of a *transactional intention* does not always have to be concluded with a request to automate the subsequent steps as described in the example. However, one of these transaction-related options needs to be present to be considered as a conversation supporting a *transactional intention*.

5.4. Explorative Intention

An *explorative intention* of a buyer is a conversational problem, i.e. how to design an interactive conversation with an initial lack of clarity [40] regarding the desired outcome in an agile manner [6]. For our example, this means, that Paul does not know what he wants to grill for his guests and he asks his SPA for its opinion (see Table 2).

Table 2: Exemplary explorative intention-guided conversation

Paul	In the light of the items in my fridge and my cooking skills, I require suggestions for what to grill today?
SPA	For how many persons do you want to cook?
Paul	Eight.
SPA	Do you need to consider particular dietaries?
Paul	No.
SPA	What would you prefer? Fish or meat?
Paul	Meat.
SPA	What is about a typical Brazilian barbeque?
Paul	Perfect!
SPA	Then you should buy chicken hearts, beef and sausages.

Such a request is considered an *explorative intention* as the conversation begins with a question of the buyer with an initial lack of clarity [40]. Thus, the system might, for instance, require additional information about the desired product characteristics (e.g. particular dietary requirements). Therefore, a question in return of the SPA immediately follows the initial question and an answer of the buyer is expected since the intention of the buyer is not clear. This process is repeated as long as the customer's intention is not clear. The conversation is concluded by an answer of the SPA to the initial question. Shopping intentions of this type might be implicitly articulated (e.g. a proactive response to an intention inferred from the context information), processed proactively, and/or informed by contextualized intentions [1, 21, 25, 32, 44]. In order to interpret the *explorative intention* correctly, different mechanisms can be utilized. For example, though filtering mechanisms [21, 24, 40], the SPA could return a list of most relevant items [16, 21, 31, 40].

An overview of a related conversation pattern is provided in Figure 4. The exchange of the conversation between Paul and his SPA again consists of several speech acts. However, between the initial and concluding directive act, only subordinate acts (sA) are included. Within these acts, the SPA asks for more details in order to understand or clarify the intention and expects answers. Thus, during the subordinate exchanges (sE), the roles of the buyer and the SPA are interchanged: The buyer is the respondent and the SPA the questioner. During the conversation, subordinate acts can be canceled. However, they support the initial directive act by giving further meaning to the superordinate [39]. Thus, if they would be canceled, the SPA would possibly give a wrong answer since the intention of the buyer was not understood completely. The functional interpretation (see Figure 4) of the conversation between Paul and his SPA are: <Question, <Question in return, Answer>, <Question in return, Answer>, <Question in return, Answer>, <Question in return, Answer>, Answer>. The last directive act of the SPA delivers a proposed response to the initial question of Paul.

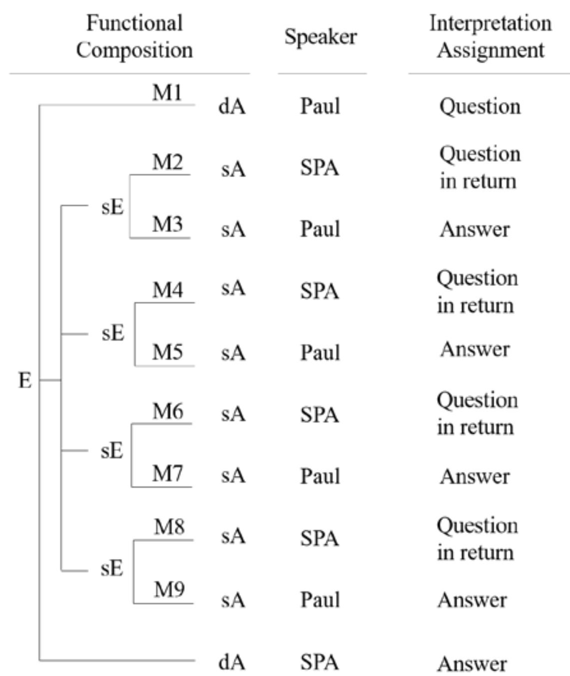

Figure 4: Conversational pattern for explorative intentions

This pattern represents a typical conversation for an *explorative intention*. In the example, the SPA asks four questions to request more information from Paul. Therefore, the resulting conversation pattern comprises questions and answers in several subordinate exchanges. These were required to understand the customer's intention, which was initially vaguely articulated. While the amount of subordinate exchanges required to collaboratively refine the intention is not fixed, the SPA always concludes the conversation with a proposed response.

6. Discussion

A SPA considering these intention types can be compared to a situation-specific and self-learning chatbot supporting the different activities of a customer, which are related to the act of shopping. The most important aspects with respect to the three intention types can be summarized as follows: (1) Informational intentions describe an information search problem of the buyer who directly articulates the information request. The related conversation pattern always consists of a pair of directive acts – a question directly requesting information and an answer. (2) Transactional intentions result in requests of the buyers expecting workflow assistance. Hence, the conversation pattern is uniquely represented by a sequence of interrelated directive acts in order to drive the workflow-related support needed by the customers or a request to support and automate specific subsequent steps supporting the act of shopping. (3) Explorative intentions are conversational problems. Here, the SPA has to find out the meaning of the buyers' intentions by asking questions until the semantics of it are understood.

While the intentions discussed above were presented separately, they can be mixed. First, the SPA might propose a transactional intention after finalizing an informational conversation pattern. Furthermore, the SPA could request, if the returned information or suggested workflows tasks meet the customer's intention. If denied by the customer, any conversation could end up in an explorative conversation. By analyzing these corrected conversations with unsupervised machine learning techniques, the SPA could even inductively improve the interaction with specific customers over time [cf. 34].

As the area of semantic shopping is only emerging, this paper is subject to limitations. First, a semantic shopping assistant could support more than product-related and utilitarian intentions of a customer. We focused on the definition and investigation of this semantic shopping type. Besides, also service-related semantic shopping should be investigated. Moreover, we concentrate on intentions following a utilitarian shopping value. By considering hedonic shopping values, further intention types might be uncovered. Such intentions could inquiry "multisensory, fantasy, and emotive aspects of the shopping experience" [9:101]. Thus, the customer would query the system to be entertained. For example, the customer could request an inspirational video showing different BBQ themes [e.g., 24, 25].

Second, the impacts of context information on the conversations have not yet been examined. An example for including context information into semantic shopping could be the request of a deferred transaction execution based on weather conditions. For such an inquiry, the SPA requires access to situational data [21]. Besides, the dialogs of all intention types can be supported and further mixes of them could be enabled by context information. For example, the SPA could use it to sense the need for a transition from one intention to another.

Finally, the article at hand just marks the starting point of a larger Action Design Research [47] endeavor iteratively carried out with practitioners. We focused on the problem formulation and the generation of initial design knowledge. Now, further requirements need to be mutually defined with retailers and customers. Within others, a structured set of possible inquiries for each intention type should be defined. These could then be tested in a first artificial evaluation with the involved stakeholders focusing on the completeness and acceptance of the proposed system. Based on these insights, design principles [13] for a prototype of a semantic shopping assistant can be defined. Starting with a minimum viable product, this prototype can then be refined in several intervention and evaluation steps within a more naturalistic setting.

7. Conclusion

This paper aimed at progressing the notion of semantic shopping by proposing three structured conversation patterns for different intention types. Based on a structured literature review three different intention types have been identified (see section 5): Informational, transactional and explorative intentions. They have been distinguished by their underlying conversation patterns, which were grounded on the Speech Act Theory [39]. Thereby, the main theoretical contributions of this paper are that we structured the concept of semantic shopping from a conceptual viewpoint and that we defined the conversation patterns of each intention type as a starting point to define design principles [13].

The main managerial contributions are that semantic shopping assistants can help retailers to improve customers' shopping convenience since they would provide a service interface to the customers, which allows them to reduce the time and effort required to carry out the act of shopping at a moment and place convenient for them [19]. Besides, by introducing a smart shopping assistant, the capabilities of shopkeepers could be complemented with digital services, which customers are already accustomed to from e-commerce. As efficiency and effectiveness driving services are likely to be adopted by the customers [8], retailers should embrace semantic shopping assistants as a promising future technology to introduce complementary digital service offerings for their customers.

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