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ABSTRACT

In the age of information and knowledge, the role of business companies is not only just to sell products and services, but also to educate their consumers. Educating consumers with extremely diversified backgrounds about technical knowledge is an important part of competitive advantage. To succeed, modern companies need to develop the best education technologies and teaching philosophies. The intelligent agents can play a right role in the personalized education of online consumers, because intelligent agents can learn the consumers' learning preferences and styles and recommend the best learning strategies. Educated and informed consumers are smarter and more confident in their buying decisions. This paper investigates using intelligent agents to support consumer learning and proposes an agent-based consumer learning support framework.

Keywords

Intelligent agent, consumer learning, e-commerce.

INTRODUCTION

Nowadays, Internet based e-commerce is becoming an increasingly common practice in our daily lives. Not only in developed countries; like the United States and European countries; but also in many developing countries; like China and India, more and more people buy items from online stores, like Amazon (www.amazon.com), eBAY (www.ebay.com), and Alibaba (www.alibaba.com). In fact, today's e-commerce is no longer a competitive advantage, but a competitive necessity. Traditional stores, such as Best Buy, Toys "R" Us and Sam's CLUB, also have expanded their business to online. With the development of e–commerce, people's concerns about shopping online have been gradually transferred from basic business issues; like trust, security and payment to higher level issues; the quality of e-commerce itself. Of the many issues affecting the service quality of online commerce, one critical issue is consumers learning quality and features of their selected product. Very often, due to the lack of help or decision support given to consumers, on-line searching and buying can be frustrating (García-Sánchez, Valencia-García and Martínez-Béjar, 2005). The consumer learning issue is becoming more and more important, because many highly complicated knowledge-intensive products are sold and bought online. To serve consumers better, online sellers are developing various online techniques to teach consumers about their products, to demonstrate these performances and features. However, most of these efforts treat diversified consumers as unified without enough consideration for consumers' differences in learning capabilities, learning preferences, and knowledge backgrounds.

In this paper, we analyze existing consumer learning-support technologies and methodologies and discuss problems with these. Finally, we investigate the potential opportunities for improvement and propose an agent-based consumer learning framework. In this paper we do the following: discuss consumer learning and learning styles; review existing consumer learning technologies; propose an agent-based framework of consumer learning support, discuss and draw conclusions.

LEARNING AND LEARNING STYLES OF CONSUMERS

Consumer learning refers to any process that changes consumers memory and behavior as a result of information processing (Arnould, Price and Zinkhan, 2001). Consumer learning is an important phenomenon in the context of online e-commerce; many factors like gender, education level, Internet experience, and age can affect the consumers' learning and their purchase decision (Bhatnagar and Ghose, 2004). Especially when products and services are relatively complex, substantial consumer learning may be involved, and such learning depends on the nature of product features (Green, Krieger and Terry, 1997). Consumer learning is different from student learning in classroom. Some consumers are experts in using a product, but others

know nothing about it. More importantly, companies cannot push consumers to learn to earn a grade. If consumes can't figure out how to use a product, they often just won't buy it. Therefore, the teaching of consumers about products must be offered in an extremely friendly way.

Teaching pedagogy for consumer learning is critical to the survival and success of companies in that consumers are shopping online for evermore complex, technology intensive products—computers, camera, expensive furniture, and/or even automobiles. Different from shopping at the point of sale in person, consumers have no chance to examine products first hand. For those who lack specific knowledge of the product, information mainly is available on sellers' web sites. Of course, existing e-commerce stations give very detailed technical features about their products. However, many consumers lack the knowledge to interpret the information and do not have the ability to learn how to interpret it in order to make the right decision. Teaching consumers what they need to know to make sound buying decisions is important to successful e-commerce. However, different persons have different learning curves. People can be classified into five different categories of adopters according to their different attitude and abilities towards change and innovation; their learning curves; in an increasing order of resistance to change: (1) Innovators (about 2.5%) are the more venturesome. They enjoy learning how to use new innovations when they are first introduced. Often they are not social leaders. (2) Early adopters (about 13.5%) are well integrated into the social group and often have a leadership role. They generally play an important role in initiating the diffusion of the innovation in the group. (3) Early majority (about 34%) have a relatively positive attitude towards innovation but need more time to adopt the innovation. (4) Late majority (about 34%) are more cautious about innovation and typically adopt new technology once the majority of the people already have adopted it. (5) Laggards (about 16%) have the most cautious attitude towards change (Rogers, 1995, p. 262).

Clearly people demonstrate different levels of learning efficiency and effectiveness. Except for the small percentage of innovators who enjoy involvement with new challenging technology and figuring out how it works, most people need help to learn about and how to use new technologies, especially people who are very cautious and resistant towards change. Even some wealthy, well-educated consumers lag behind when it comes to learning how to use new, complex technologies and how to adapt to changes in innovation. If they think learning to use a new product is too difficult, they avoid it and choose other products and/or that don't require them to learn so much. Clearly, companies must make learning to use their products easy.

People learn using different methods. Each person prefers different learning styles and techniques. In deed, we observe that some people prefer to read to learn, and some people prefer to listen. It depends on what is being learned; different kinds of learning require different approaches. Memletics' classification of learning styles is as follows:

- Visual. You prefer using pictures, images, and spatial understanding.
- Aural. You prefer using sound and music.
- Verbal. You prefer using words, both in speech and writing.
- Physical. You prefer using your body, hands and sense of touch.
- Logical. You prefer using logic, reasoning and systems.
- Social. You prefer to learn in groups or with other people.
- Solitary. You prefer to work alone and use self-study

(www.accelerated-learning-online.com/styles/).

According to Memletics' classification, e-commerce companies should prepare their materials in different format and recommend the right format of message based on consumers' preferred styles.

Another important factor that requires the personalized learning strategy in e-commerce is consumers' limited time. The pressures of time affect consumers' buying decision (Oppewal and Holyoake, 2004; Verhoef and Langerak, 2001). In e-commerce, consumers often make decisions under pressured, having insufficient time for thorough examination of provided information (Kocher and Sutter, 2005). For example, during online auctions, consumers need to make difficult decision within a limited time. Such consumers must be taught quickly and correctly how to shop online. If one company can educate consumers more efficiently and effectively than others, they gain the competitive advantage.

Product educated consumers improve their skill level in using a particular product and often require an improved model with more sophisticated features from that company's product line (Herriott, 1992). Therefore, consumer learning is a continuous, progressive process. When offering materials describing products, sellers should consider the differences in potential

consumers' experience with such products. If a consumer is unfamiliar with a product line, the seller must start at the beginning to teach that consumer. Those acquainted with the product need quick, clear information delineates new features and advances over the product's previous generation.

TECHNOLOGIES OF CONSUMER LEARNING SUPPORT

Many online consumer learning support technologies have been developed and used in e-commerce. These technologies were successful supporting consumers' buying decisions. Some consumers well-acquainted with these technologies have gradually developed ways to use them. We might prefer to read product description then to ask friends should we need clarification. The purpose of this paper is to achieve higher success using existing learning support technologies. To this end, we first introduce and explain a few existing consumer learning support technologies.

- Description of Product Specification: Price, delivery, and technical information are offered.
- Frequently Asked Question (FAQ): Companies can classify the most frequently asked questions for later referral. Also, companies can classify these questions into forums; for example, Toshiba creates support bulletins for consumers to view the list of Toshiba Knowledgebase documents of specific models (www.toshiba.com).
- Virtual Reality: Consumers can experience products realistically over the Internet, thereby mitigating problems associated with consumers' lack of physical contact with products (Suh and Lee, 2005).
- Collaborative Filtering: Products are recommended based on consumers' similar purchase interest.
- Online user groups on the message board: Consumers can post their questions and wait for responses from other consumers or technical experts.
- Technical Support: Consumers can ask questions directly of the technical department using E-mail, dialing their 1-800 telephone number or using online chat over the Internet.

Problems with existing consumer support technologies are obvious. Many consumer support technologies and methodologies don't deliver their presentation formats based on different consumers' preferences and backgrounds. Companies scramble all kinds of information in different presentation formats on their web sites and let users choose although some need guidance. Unfortunately, the important information garnered from consumers' previous learning habits is not incorporated into learning support.

A strategy that personalizes a variety of learning approaches would be very helpful to online consumers in e-commerce. Artificial Intelligence based agents can help to identify consumers' learning styles and recommend suitable consumer learning methods and formats, but until now in e-commerce, intelligent agents only have been widely used to identify consumer buying habits and to recommend products based on their preferences (Guan, Chan and Zhu, 2005; Kwak, 2001; Lee and Benbasat, 2005; Lee and Yang, 2003). Despite their narrow application in the past, intelligent agent technology is the best candidate to support personalized consumer learning, and existing intelligent agents applications in the fields of e-commerce and e-learning reveal a great deal about how intelligent agents can be adapted for consumer learning.

AGENT-BASED CONSUMER LEARNING

Intelligent software agents can perform tasks on users' behalf independently of direct control of users themselves (Hostler, Yoon and Guimaraes, 2005). As a vibrant and rapidly expanding field of academic research and business applications, Agent technologies are providing a new paradigm for designing and implementing systems for a complex, dynamic, and distributed environment (Rudowsky, 2004). In the online virtual world, software agents enhance users' "online" experiences by proactively offering personalized assistance and adapting to users' needs over time (Tewari, Youll and Maes, 2002).

In the open and complex information environment, the structure of the system itself is capable of dynamically changing. The pre-defined and fixed software paradigm cannot work properly in this environment. The software agents must be able autonomously adapt through learning about changes in the environment. Therefore, Artificial Intelligence and agent systems are closely related; Artificial intelligence studies components of intelligence like the ability to learn and plan while the study of agents deals with integrating these components (Rudowsky, 2004). In order to achieve the goal of the user, agents can perform the following actions (Reticular, 1999): execute autonomously, communicate with other agents or the user, and monitor the state of their execution environment. Intelligent agents are especially able to exploit significant amounts of domain knowledge, to tolerate errors and unexpected input, to use symbols and abstractions, to adapt to goal-oriented behavior, to learn from the environment, and to operate in real-time (Newell, 1988).

The agent applications alleviate the burden of retrieving and processing information. A just-in-time information retrieval agent proactively retrieves and presents information based on a person's local context in an easily accessible yet non-intrusive manner (Rhodes and Maes, 2000). In the non-intrusive mode, agents continuously watch users' environment and present information without requiring the users to be cognitively involved (Doctor, Hagras and Callaghan, 2005; Rhodes and Maes, 2000). Intelligent agents help online consumers reduce the time spent searching for products, and intelligent agents improve the quality of users' decision making (Hostler et al., 2005). Supporting personalized product recommendations, intelligent agents are used to help online consumers to overcome information overload, which occurs when they are shopping in an Internet marketplace (Cho, Kim and Kim, 2002; Wang and Benbasat, 2005).

Product recommendation and preference tracking systems have been adopted extensively in e-commerce (Guan et al., 2005). The intelligent agent is used to improve accessibility of E-commerce applications and Web sites for visually impaired individuals (Pontelli and Son, 2003). In one agent-based learning support system, agents work collaboratively to enable personalization by recognizing an individual's e-Learning pace and reacting correspondingly to provide an important technology for accomplishing personalization in virtual learning environments (Xu and Wang, 2005).

The agents can manage a learning portfolio of students' e-learning behavior through a web log, and agents can analyze students' learning behavior from the Internet and from the classroom in order to evaluate each student's overall performance then automatically send an e-mail message to teachers and parents who will be better able to guide and assist students with revising their learning attitude (Chen, Yu and Chang, 2005).

Of all the characteristics of intelligent agents, learning from the environment is the most important capability (Urlings, Sioutis, Tweedale, Ichalkaranje and Jain, 2005). In web-based information systems, intelligent agents track users browsing behaviors to learn their activity patterns using machine learning, and agents also can adapt to users' changing interests and preferences (Godoy, Schiaffino and Amandi, 2004; Lee and Yang, 2003). Intelligent agents autonomously learn from repeated human activities to discover consumers' behavior pattern. For example, along with underlying algorithms, a learning agent is designed to discover users' interest areas from user access logs (Cheung, Kao and Lee, 1998). Therefore, the learning capability of intelligent agents can be widely applied in various online recommendation systems. For example, intelligent agent can recommend which movies consumers should buy based on consumers' buying histories; or intelligent agents can recommend personalized newspapers to consumers based on their past preferences (Lee and Yang, 2003).

As has been shown, consumers have different learning styles and learning capabilities which are apparent in consumers' browsing activities: the way consumers best learn can be detected through examining their activity patterns, and intelligent agents can identify such learning patterns.

On an e-commerce station, one company offers various presentations, each on different web pages. For example, page one displays product and related information, mainly using text; page two displays the product and related information using video; page three displays product and related information using 3-D virtual reality technology. The page the consumer consults first and the amount of time spent exploring each subsequent page indicates something about the consumers' learning styles and preferences.

The agent can acquire consumers learning preferences in two ways. To begin, users can explicitly tell intelligent agent their surfing and learning habits. For example, users can tell agent that they prefer a vide demo program of the digital product, the detailed specifications.

Next, the agent can learn users' implicit surfing and learning styles from their practical learning activities then adjust to the agent's self-input learning patterns. Information used in learning might be the times users spend on each web site and/or users' feedback about just what they learned.

Intelligent agent can recommend different learning strategies to consumers based on consumers' preferences and learning styles. Also, the agent must be programmed to consider consumers' familiarity with the product in its line and the time pressures on consumers' making decisions. Accordingly, the key factors agent support must consider for consumer learning are summarized:

- Learning capability: consumers' capability to learn new knowledge.
- Learning style preference: consumers' preferred styles to learn new knowledge.
- Familiarity with the product in its line: consumers' familiarity with previous versions of the product desired or similar products.
- Time pressure: Time available for consumers to make buying decisions.

Considering all the factors so far discussed, we propose an agent-based consumer learning framework. See Figure 1. The intelligent agents acquire consumers' personal information, including personal learning preferences, learning capabilities, familiarity with the product line, and the limited amount of time consumers indicate they have to make a decision (time pressure). Then the agent can recommend the appropriate learning materials for consumers' preferred formats.

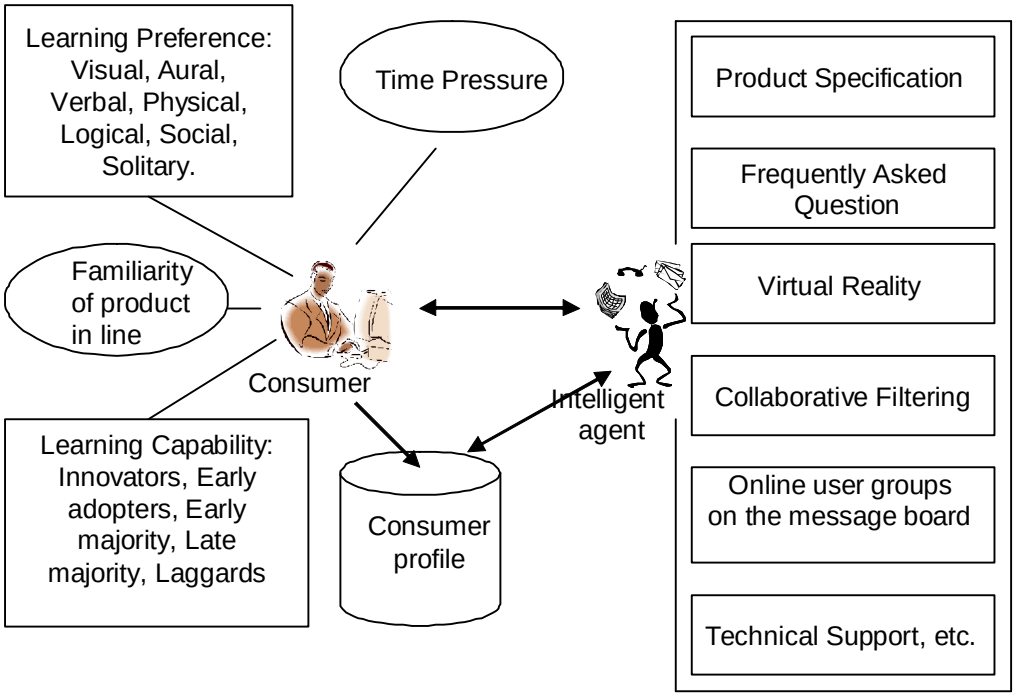

Figure 1. Agent-based Framework of Consumer Learning

DISCUSSION AND CONCLUSION

With built-in, artificial intelligence based, learning functions, intelligent agents can discover and learn the patterns of consumers' online shopping behaviors. Until now, these patterns have been applied widely to help online companies develop successful personalized marketing strategies. However, these agent strategies are used primarily to identify the buying patterns of consumers; e-commerce has not fully realized the significance of consumers' learning patterns in consumers' attempts to understand which product they prefer.

Clearly, current consumer learning support strategies have not considered enough the differences among consumers' learning styles and capabilities. We, therefore, present our framework for agent-based consumer learning to enhance the quality of online consumer service in e-commerce. The primary objective for this framework is to identify consumers' learning patterns in order to help online companies to develop agent-based personalized consumer learning support methodology. Our proposed framework has significant implications for both practice and research of e-commerce applications.

Implications for practice

In the age of knowledge and information, one important competitive advantage of companies is better support of consumers in their attempts to learn about products. Companies that market products and services online must teach product knowledge. The education of consumers is one important approach to gaining a unique competitive advantage. Our proposed framework helps system designers create personalized, consumer learning support systems. Easy access to more information about desired products make consumers confident in buying decisions and builds consumers trust.

Implications for research

Our proposed framework offers a new perspective to researching online consumer learning support. The implementation of our framework integrates research from several areas: artificial intelligence learning methodologies, cognitive theory,

intelligent agents, and online teaching methodology. To successfully implement the framework in e-commerce, challenging but very promising research issues need further investigations:

1) The selection and integration of right agent learning methodologies is crucial to the success of identifying consumer learning pattern. There are many machine leaning methods developed in the area of users' preference recognition (Finton, 2005; Fyfe and Jain, 2005; Godoy et al., 2004; Lee and Yang, 2004). Researchers need to choose the right agent learning method and integrate different agent-learning methods to achieve synergy. For example, we may use case-based reasoning to do the initial pattern matching then the neural network algorithm to adapt changes to users' preferences.

2) The literature of cognitive effort (cost) perspective indicates that cognitive effort is an important factor in the decision-making process (Gregor and Benbasat, 1999). The cognitive cost in adopting the proposed agent framework is also a major concern for both researchers and consumers. If an agent learning method needs consumers' significant cognitive efforts to acquire learning style by answering dozens of quiz questions (e.g., multiple choice questions), this method hasn't much meaning to the practical business scenario. Therefore, agent-based consumer learning methods should adopt a seamless and non-intrusive method to get consumers' learning styles without much effort on the part of consumers.

3) Privacy and security issues concerning consumers' learning styles: security and privacy issues are a common concern when applying intelligent agent systems (Abidi and Manickam 2004; Aron, Sundararajan and Viswanathan, 2006; Norman 1994; Ulieru, Hadzic and Chang, 2006). In our case, consumers' personal learning styles and learning capabilities are private. Indeed, not everyone likes to share personal information. Therefore, when applying agent-based consumer learning support, companies must request approval from consumers and assure them that this information won't be misused and/or transferred to third parties without permission.

4) After implementing the proposed framework, empirical studies need to be done to investigate the usability of the proposed framework. There are many dimensions of the usability. The dimensions of usability from International Organization for Standardization (ISO) are effectiveness, efficiency, and user satisfaction (ISO, 1998). Consumers' learning effectiveness, learning efficiency and satisfaction using the agent-based consumer learning methodology are reasonable measurements of evaluation. Of course, other specific dimensions regarding consumer learning could be developed for evaluation.

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