Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2017 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

Summer 2017

Investigating Mutual Adaptation Process between Users and E-Learning System: A Knowledge Access Efficiency Approach

Bingcong Zeng
Hewlett-Packard Enterprise, anson.zeng@hpe.com

Investigating Mutual Adaptation Process between Users and E-Learning System: A Knowledge Access Efficiency Approach

Research-in-Progress

Bingcong Zeng
Hewlett-Packard Enterprise, HK SAR Limited
City Plaza One, 1111 King's Road, Taikoo Shing, Hong Kong
anson.zeng@hpe.com

Abstract

For its advantages in being able to provide rapid and comprehensive access to knowledge, e-learning system has been widely adopted in education to improve learning processes. However, such IT-mediated processes involving both users and system are subject to changes. There exists adjustment in browsing behavior on user side and web structure refinement on system side. It would impose uncertainty and influence on learning quality and thus create a strong need for rapid adaptation between users and the e-learning system. Focusing upon knowledge organization in terms of web structure management, this study intends to find out an effective way to speed up the adaptation process. It consists of two stages. In the first stage, we would like to study the general adapting behaviors of e-learners, and analyze how they are affected by the web structure. Through analytical modeling, Knowledge Access Efficiency (KAE), which is capable of reflecting the quality of adaptation, is conceptualized mathematically. In the second stage, the dynamics of KAE during the whole adaptation process will be carefully investigated. It is hoped that this study can give us useful clues regarding knowledge organization of e-learning system, and by improving web structure management it can elicit better performance of e-learners.

Keywords: Knowledge Access Efficiency, User-System Adaptation, e-Learning

Introduction

With dramatic development, e-learning system today has been widely accepted as an indispensable tool for our education. Not just confined in providing convenient access to knowledge, it is now able to facilitate and enhance the interactivity in learning processes. Doubtless e-learning system will assume greater importance in the future and its potential in education is apparently unlimited.

Evolving from a role as simple learning aid to a highly interactive and immersive learning environment, e-learning system is confronted with lots of challenges. A significant one is regarding how to make the system be used more effectively. There are multiple factors associated with effective use of information systems in general. Like user acceptance (Lee et al. 1995) , interface design (Shneiderman 1998) and user training (Santhanam and Sein 1994) , they have received sufficient attention and been frequently discussed in numerous studies. Specific to e-learning systems, learners' technical competency and learner-to-learner interaction are found able to influence the efficiency of system use (Selim 2007). In addition, service quality, e-learning system quality, perceived usefulness and perceived ease of use could impact users' satisfaction, and then affect the system use indirectly (Roca et al. 2006). While too much focus is placed upon the factors in technology adoption phase, another critical process which concerns learners' adaptation to e-learning system has been overlooked for a long time (McGill and Klobas 2009). Following the general paradigm of IS adoption, adaptation and then diffusion, it is known that adaptation is a crucial and indispensable step just after adoption. It is normally referred to a series of activities new users and system are engaging in either to make the system better fit users or to change users' habit for better use of the system (Barki et al. 2007). It is a mutual interactive game between users and information system. The process will proceed iteratively until a state of equilibrium is arrived at or it will continue all along if the stable balance fails to achieve. The importance of adaptation process has been early identified in 1980s and 1990s. Gasser (1986) pointed out that the use of computer system in organizations involves not just computing work, but also adaptation work in the form of "Fitting, Augmenting, and Working Around". Saga and Zmud (1994) suggested that adaptation activities should be taken into account in measuring the use of IS. Nevertheless, under e-learning context the research on e-learners' adapting behaviors is still at the initial stage, and the understanding of adaptation process, for example what activities it is comprised of, which factor can speed up the adaptation process, and what effect it will bring to the effective use of e-learning system and even to e-learners' learning performance, those remain unclear.

Motivated by attempting to bridge those gaps and echo to the problems, this study would like to deeply investigate general adapting behaviors of e-learners, explore the impact of knowledge organization on adaptation quality, and propose a model able to reflect the dynamics of the whole adaptation process under the changes from both user side and system side. Within our understanding, e-learning system as the middle layer mediates the interaction between e-learners and the knowledge content, making the knowledge transmission proceeding more effectively (See Figure 1). The argument holds on a critical assumption that the interaction between users and system should be efficient. When e-learners have difficulty in using the system or the system cannot fit with e-learners' learning preference, a large amount of time will be wasted on ineffective adaptation process and e-learners will fail to engage in learning and training activities. Given that, a smooth and quick adaptation process is demanded, and a good user-system fit formed in adaptation can greatly foster the effective use of the system and allows e-learners more concentrated on the actual learning activities. Therefore, the model to be constructed should allow us to analyze the factors contributing to the smoothness of adaptation, and hope some managerial insight would be found after a series of comprehensive analysis. Given that, below in concise statements with point form, the research objectives are formally stated. The study seeks to: 1) Understand the mutual adaptation between users and e-learning system through the view of knowledge access efficiency; 2) Explore the role of knowledge organization in knowledge access, and conceptualize it into a model that is able to depict the dynamics of the whole adaptation process; 3) Identify and analyze the contributing factors to the smoothness of adaptation, and make significant suggestions that can improve the effective use of e-learning system.

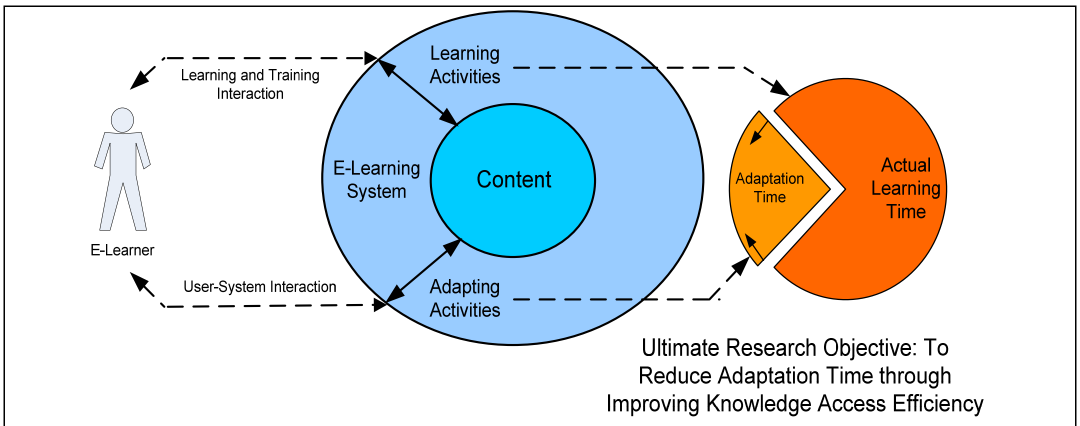

Figure 1. eLearner-Content Interactions and Ultimate Research Objective

E-Learning Adaptation Process and User-System Fit

It is not hard to find that nearly most of e-learning systems nowadays are web-based. Although integrating with rich functions, essentially speaking from users' perspective they are all websites that present knowledge. A general adaptation process within it actually involves two key phases: initial technical adaptation phase and content-structure adaptation phase. In initial technical adaptation phase, when first visiting a new e-learning website, e-learners will probably travel around and spend some "play time" in trying out the functions the site provides. They are more inclined to accommodate themselves to the technical aspect of the virtual learning environment. Being familiar with the functions and knowing where and how to use them are the major concerns in the first meet (Vandenbosch and Higgins 1996). The time length of such technical adaptation will be largely depended on the IT skill of the e-learners (Selim 2007). They usually need to pay a couple of revisits to complete the adaptation. The process would be very painful for certain e-learners with relatively insufficient IT knowledge. If serious, it might frustrate their intention to continuously use the e-learning system in the future (Roca et al. 2006). But if high-quality of training about the system is provided in advance, then the occurrence of this bad situation would be prevented to a great extent and the adaptation time could be shortened tremendously.

Content-structure adaptation, the major part of adaptation process, starts generally after or sometimes during initial technical adaptation. In this phase, e-learners browse the website with aim to acquire knowledge or resource they desire. No doubt, one of the major functions of an e-learning website is to present and share knowledge in a well-structured way. The "well-structured" here is referred to not only clear knowledge content shown in each page but also efficient links arranged among web pages. In order to obtain the information or knowledge needed, e-learners are required to go through some paths and reach certain web pages. It is equivalent to assign them search tasks in the website. The performance of search tasks should be highly correlated with the organization of web content and the design of web structure, according to cognitive fit theory which believes that the task performance for individual users will be enhanced if there is a cognitive match between task and information presentation format (Vessey 1991). In other words, if the web content and structure can be organized in high correspondence with the search tasks, then e-learners will complete the tasks efficiently and capture the knowledge they want effectively. Goodhue and Thompson (1995) first identified the importance of the fit between information organization and task requirements, and conceptualized it as task-technology-fit (TTF). Barki et al. (2007) applied TTF in the study of IS-use related activities and claimed that there exists a degree of fit between users and system which has tremendous impact on the system use. Adopting the similar notion, user-system fit (U-S fit) in this study, is defined as the extent of match of IS properties and users' preference. It directly determines the effectiveness of e-learners' browsing actions, thus influencing the effective use of e-learning system. In content-structure adaptation, users and e-learning system mutually adapt to each other to pursue higher degree of U-S fit. On system side, the content and web structure are not static. System designers keep reviewing and modifying them to enhance system fit to users. Moreover, many e-learning systems have already adopted dynamic web technology (e.g. PHP and JSP), and they are able to adjust links among web pages to fit the preference of e-learners. On user side, through repeated interaction with the system, e-learners become familiar with the content and structure, and they know which paths can lead them to their targeted pages more quickly. As a result, the paths with more efficiency will gain more clickstream and the ones with less will gain less. It will eventually result in a stable information access pattern. At the end e-learners will follow their preferred fixed paths to complete tasks. A smooth and rapid adaptation implies a good match between users and system. In this case, e-learners do not need to spend too much time in adaptation. So they can concentrate more on the learning activities. It is not difficult to infer that web structure would have impact on the time length of adaptation process. Under e-learning context, the web structure to some extent reflects the knowledge organization in e-learning system, and it determines the accessibility of the knowledge presented in web pages. A good designed web structure should be the one with high efficiency in making e-learners access their information quickly. Therefore, web structure optimization essentially is to improve the knowledge organization by making the web pages more accessible by e-learners. In terms of adaptation, an efficient web structure can make the adaptation process smoother and thus shorter. If a web structure is in high efficiency, e-learners will rapidly adapt to it and access the knowledge they want in an easy way. Hence it will lead to more effective use of the system.

A General Model of Access Efficiency

It is known that not limited in e-learning context but applicable in general IS adaptation also, with users gaining more knowledge about web structure and system adjusting its structure to accommodate users' preference, the access to destination pages becomes more efficient. Users are inclined to use easier way more frequently and thereby shorter path should attract more clickstream traffic. The model of Access Efficiency (*AE*) introduced in this section is to trace this trend and check whether users and IS are well adapted to each other regarding access efficiency. *AE* incorporates the factors of both system side and user side. On system side, the easiness to be accessed contributed by web structure design is modeled through "accessibility". Accessibility of a webpage refers to how easy the page can be reached. Obviously, if the webpage has more inlinks, which means more links are pointing to it, it will be more convenient for e-learners to visit. Therefore the number of inlinks should be regarded as an important factor for webpage accessibility. A model proposed by Yen (2007) suggested that the impact of each inlink on the accessibility is jointly determined by the attractiveness of the inlink and the level of its source page. Based on that, the accessibility A_j of destination page j can be modeled by the total summation of the impacts from all inlinks:

$$A_j = \sum_{i=1}^{n} I_{i,j} = \sum_{i=1}^{n} \left(\alpha_{i,j} \times L(d_i) \right) \qquad (1)$$

With:

- $I_{i,j}$ is the inlink$(i\ j)$'s impact on accessibility of destination page j, and n is the total number of inlinks pointing to page j
- d_i, the depth of page i is defined as the minimum number of links to follow in order to travel from root page to page i. The level function $L(d_i)$ reflects the effect of depth on page's accessibility. It should be a decreasing function of d_i, showing that the accessibility declines with its depth going deeper. For simplicity, $L(d_i)=0.5^{d_i}$ is suggested.
- α_{ij} reflects inlink (i,j)'s attractiveness in source page i. When e-learners browse to page i, due to some reason, e.g. the link (i,j) is highlighted or they have experience in traveling link (i,j) and know the destination page j has the information they want , it will attract the e-learners to choose this link. In our model, higher α_{ij} implies more attention the inlink receives from the source page.

During adaptation, dynamic links are established among web pages, and web structure is periodically revised by designers. As the result of those system-side adaptation activities, A_j the accessibility of webpage is changing in order to fit with users' preference. Meanwhile on user side, users are holding a subjective evaluation regarding the importance of each link. The more important they think the link is, the more likely they will travel through that link. For every webpage there are multiple inlinks by which it can be accessed. Thereby for each inlink it is associated with a probability to be chosen which reflects users' preference on it. For each visit, a specific inlink will be chosen. Given that, the actual impact of inlink on accessibility of page j under user's judge for a visit can be regarded as a random variable, which is denoted as AI_j in the model. It follows a multinomial distribution with values $\{I_{1,j}, I_{2,j}, \ldots I_{n,j}\}$ by their respective probability $\{p_{1,j}, p_{2,j}, \ldots p_{n,j}\}$. The expected value of AI_j is:

$$E(AI_j) = \sum_{i=1}^{n} I_{i,j}\, p_{i,j} = \sum_{i=1}^{n} \left(\alpha_{i,j} \times L(d_i)\right) \cdot p_{i,j} \qquad (2)$$

With: $p_{i,j}$ is probability of inlink(i,j) to chosen by e-learners to access the destination page j. $\sum_{i=1}^{n} p_{i,j} = 1$ and n is the total number of inlinks. $p_{i,j}$ can be measured by the usage rate of the inlink, which is equal to the clicks of inlink (i, j) divided by the sum of clicks of total inlinks.

$E(AI_j)$ is the synergy of system-side and user-side adaptation. It shows the actual effective accessibility of page j. Mathematically $E(AI_j)$ should fall in the interval bounded by the minimum and maximum value of the set$\{I_{1,j}, I_{2,j}, \ldots I_{n,j}\}$. It varies in a spectrum when users update their preference on the inlinks. Assume the inlinks have the same attractiveness (α_{ij} is the same). When $E(AI_j)$ is close to the lower bound of the spectrum, it indicates that users are more often using longer paths to access the destination page since more probability is assigned to the inlinks which source pages are in deeper level. With $E(AI_j)$ increasing and moving towards the upper bound of the spectrum, it implies that users have better knowledge in accessing the page. They know how to go through shorter paths and prefer to use them more frequently. The position of $E(AI_j)$ in the spectrum therefore reflects the efficiency of users to access the page. It can be computed as follows:

$$AE_j = \frac{E(AI_j) - Min(SI_j)}{Max(SI_j) - Min(SI_j)} \quad \text{where } SI_j = \{I_{1,j}, I_{2,j}, \ldots I_{n,j}\} \qquad (3)$$

Access Efficiency AE_j measures the performance of users in choosing the paths to access webpage j. When users and IS become more fitted in the adaptation process, users are able to take more efficient way in information access. Since more efficient paths are selected, AE_j in general will be increased monotonically when adaptation proceeds. By using AE, practitioners can easily identify the problematic web pages which are being inefficiently accessed. It offers a quick and useful state indicator to gauge the quality of on-going adaptation process.

Research Plan and Methodology

The overall aim of the study is to radically advance the effective use of e-learning system through enhancing the access efficiency of knowledge during adaptation. The general model of *AE* will be extended to Knowledge Access Efficiency (*KAE*) model and applied under the context of e-learning. *KAE* will be built with intention to trace the mutual adaptation process between e-learners and e-learning system and be capable of judging the adaptation quality. It is known that the traditional e-learning practices are based primarily on the information transfer paradigm, which focuses upon content and information delivery. The "teacher-centered learning" can find its perfect technical mirror in such "page oriented approach" in e-learning system design where the goal is to produce more and better static pages for knowledge consumption of interested students. Currently, with "constructivism" and "student-centered learning" prevailed, significant shift occurs, emphasizing more on providing flexible and appropriate educational materials to fit with student's individual demand (Beldarrain 2006). In student-centered learning environments, e-learners are encouraged to take the initiatives in learning and construct their own knowledge with the help of e-learning systems. Adapting support from the system side thereby is of importance. To facilitate e-learning activities, initially the system may offers a learning space as wide as possible, applying only some restrictions (e.g. limiting the number of outlinks) to protect e-learners from information overload. Then, it will add or remove restrictions according to e-learners' progress. In all, the adjustment in web structure is the main way of system-side adaptation. On the user side, e-learners will adapt themselves to fit with the dynamic e-learning environment. They will keep updating their preference on the links they travelled. A successful adaptation is expected to result in a stable pattern regarding knowledge access, in other words, e-learners can access the knowledge they need through the most efficient way at the end. Although the general model of AE is able to reflect the preference of e-learners in using the system, it more or less confines itself in general inclination in path selection. More factors specific to e-learning activities should be involved in the model of *KAE*. In this research, the properties of links will be investigated deeply. The links will be further differentiated into 5 categories as follow, according to their functions in e-learning: 1) Navigation link; 2) Knowledge-gained link; 3) Glossary link; 4) Problem link; 5) Parallel concept link. The impact they make on e-learners' preference will be distinguished in *KAE*. Incorporating the factors from both system side and user side, KAE will innovatively connect the inlink properties with e-learners' preference for the first time. With the help of *KAE,* practitioners can easily detect the problematic part of the e-learning system and determine where the inefficient knowledge access exists.

Figure 2 provides a helicopter view of this research. In this study we try to investigate the mutual adaptation between e-learners and e-learning system through Knowledge Access Efficiency. Wholly speaking, it comprises two stages. In the first stage, analytical modeling is adopted to offer a pure quantitative perspective in depicting the interactions among various factors during adaptation; in the second stage, in order to reflect the collective effect of adapting behaviors of e-learners, simulation will be employed, then providing a view more close to the practical world.

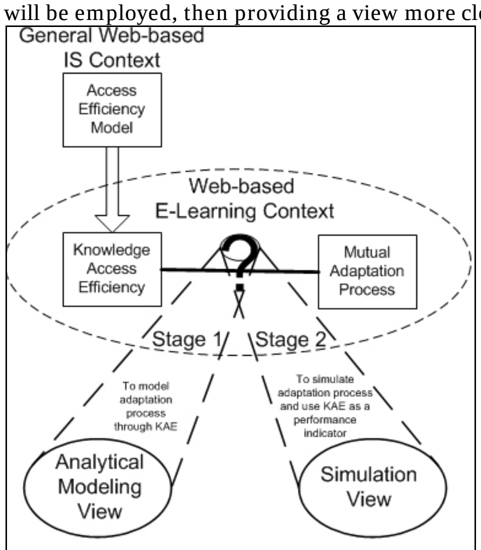

Figure 2. An Overview of Research Plan

As it has been reported in the previous sections in this paper, we have some progress in the first stage. So far, two key phases in adaptation process: initial technical adaptation phase and content-structure adaptation phase have been identified. It is confirmed that web structure is a critical factor in adaptation. When e-learners are performing tasks to acquire knowledge or information, it is the major aspect of the e-learning system users need to adapt to. Given other factors unchanged, if the web structure better fits with e-learners' preference, e-learners can access the knowledge they want more efficiently. Since when adaptation proceeds such fit will be improved, Knowledge Access Efficiency in general will be increased monotonically. Inherited from the general model of *AE*, *KAE* we proposed will probably be modeled at page level also. It will measure the access efficiency of a page at a time point rather than a process. The future extension is considering putting it into matrix form:

$$KAE=\begin{bmatrix} KAE_{11} & KAE_{21} & ... & KAE_{n1} \\ KAE_{12} & KAE_{22} & ... & KAE_{n2} \\ ... & ... & .KAE_{ij}. & ... \\ KAE_{1n} & KAE_{2n} & ... & KAE_{nn} \end{bmatrix} \qquad (4)$$

The KAE matrix above depicts the access efficiency between any two points in the e-learning system, manifesting the knowledge access state at system level. When adaptation goes along, individual *KAE* will increases, and *KAE* in matrix form will gradually converge into a stable state. Linking those converging states with difference equations will constitute a dynamic system with Markov chain property. By studying the converge rate of the Markov chain, we can work out an indicator to measure the speed of the adaptation process. The biggest challenge in this part is to make reasonable assumptions and derive practical implication based on mathematical reasoning.

In the second stage of the research, though our focus will remain on Knowledge Access Efficiency, we would like to further trace back the critical factors that impose significant impact on it. Based on the preliminary findings in the first stage, knowledge organization in terms of web structure is identified as one of the critical factors. We are quite interested in what type of web structure can lead to more efficient knowledge access, and then speed up the adaptation process and shorten the adaptation time. As a matter of fact, it is difficult to keep track with the whole adaptation process in the real life. Knowledge access efficiency will probably increase during adaptation. When a stable state is reached, that means the end of the adaptation. However, the time taken is rather unpredictable, and greatly subjected to individual learners. More importantly, the research requires large sample size in order to make accurate comparison among different web structures. So conducting experiments in this case will be very time consuming. As an alternative, multi-agent simulation (MAS) will be more suitable under this situation. MAS is a technique to utilize computer programs to imitate human operations happened in the real world (Law 2007). It has been widely adopted as an important research method in the fields of management science, information systems research and education studies (Sokolowski and Banks 2009). It is particularly useful in studying how micro-level processes affect macro-level outcome (Weiss 1999). For a general MAS, it involves a number of agents which are programmed to follow certain behavioral rules. They can interact with each other and with the environment to generate collective behavioral patterns. The patterns emerging at the macro-level are not predetermined by the programs. They are the synergic effect by numerous micro-decisions of individual agents. MAS is applicable for both explanatory and exploratory research (Weiss 1999). It is quite fit with our problem context. In stage 2, we would like to explore the impact of web structure on *KAE* during adaptation. The efficiency of knowledge access can be viewed as the macro-level outcome resulting from e-learners' browsing behavior at micro-level. If mapped in MAS, e-learners are the real-world counterparty of agents in the simulation; and web structure is the environment agents can interact with. MAS allows us to construct the scenarios we need. With the help of it, we are able to arrange agents to travel in the web structure we designed, just as e-learners are browsing the e-learning system in the real world. Through simulating the adaptation process under various web structures, we are expected to find out the web structure type which can lead to the most efficient knowledge access and speed up the adaptation process most effectively. Such finding may benefit practitioners and provide useful hints for them in web structure management. Through improving knowledge organization in terms of web structure, it is hoped that the effective use of e-learning system could be fostered and better learning outcome would be generated for e-learners.

References

Barki, H., Titah, R., and Boffo, C. 2007. "Information System Use–Related Activity: An Expanded Behavioral Conceptualization of Individual-Level Information System Use," *Information Systems Research* (18:2), pp 173 - 192.

Beldarrain, Y. 2006. "Distance Education Trends: Integrating New Technologies to Foster Student Interaction and Collaboration," *Distance Education* (27:2), pp 139-153.

Gasser, L. 1986. "The Integration of Computing and Routine Work," *ACM Trans. Office Inform. Systems* (4:3), pp 205–225.

Goodhue, D.L., and Thompson, R.L. 1995. "Task-Technology Fit and Individual Performance," *MIS Quarterly* (19:2), pp 213–236.

Law, A.M. 2007. *Simulation Modeling and Analysis*, (4 th ed.). Boston: McGraw-Hill.

Lee, S.M., Kim, Y.R., and Lee, J. 1995. "An Empirical Study of the Relationships among End-User Information Systems Acceptance, Training, and Effectiveness," *Journal of Management Information Systems* (12:2), pp 189-203.

McGill, T.J., and Klobas, J.E. 2009. "A Task–Technology Fit View of Learning Management System Impact " *Computers & Education* (52:2), pp 496-508.

Roca, J.C., Chiu, C.-M., and Martínez, F.J. 2006. "Understanding E-Learning Continuance Intention: An Extension of the Technology Acceptance Model. ," *International Journal of Human–Computer Studies* (64:8), pp 683–696.

Saga, V.L., and Zmud, R.W. 1994. "The Nature and Determinants of It Acceptance, Routinization, and Infusion.," in: *Diffusion, Transfer, and Implementation of Information Technology.*, L. Levine (ed.). Amsterdam, The Netherlands: Elsevier, pp. 67–86.

Santhanam, R., and Sein, M.K. 1994. "Improving End-User Proficiency: Effects of Conceptual Training and Nature of Interaction," *Information Systems Research* (5:4), pp 378-399.

Selim, H.M. 2007. "Critical Success Factors for E-Learning Acceptance: Confirmatory Factor Models," *Computers & Education* (49:2), pp 396–413.

Shneiderman, B. 1998. *Designing the User Interface : Strategies for Effective Human-Computer-Interaction*, (3rd ed. ed.). Addison Wesley Longman.

Smyth, B. 2009. "Case Studies in Adaptive Information Access: Navigation, Search, and Recommendation," in: *Intelligent User Interfaces : Adaptation and Personalization Systems and Technologies* C. Mourlas and P. Germanakos (eds.). Hershey, PA: Information Science Reference, pp. 35-59.

Sokolowski, J.A., and Banks, C.M. 2009. *Principles of Modeling and Simulation : A Multidisciplinary Approach*. Hoboken, N.J.: John Wiley.

Vandenbosch, B., and Higgins, C.H. 1996. "Information Acquisition and Mental Models: An Investigation into the Relationship between Behavior and Learning," *Information Systems Research* (7:2), pp 198-214.

Vessey, I. 1991. "Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literatures," *Decision Sciences* (22:2), pp 219-240.

Weiss, G. 1999. *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence*. The MIT Press.

Yen, B.P.-C. 2007. "The Design and Evaluation of Accessibility on Web Navigation," *Decision Support Systems* (42:4), pp 2219-2235.