Personalization for Specific Users: Designing Decision Support Systems to Support Stimulating Learning Environments

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Abstract. Creating adaptive systems becomes increasingly attractive in the context of specific groups of users, such as agricultural users. This group of users seems to differ with respect to information processing, knowledge management and learning styles. In this work we aim to offer directions toward increasing decision support systems usability, by tailoring toward user learning styles. The results show that decision support systems need to be redesigned toward providing agricultural users with a more efficient time management and study environment, and facilitating group interaction.

1 Introduction

There is an increasing trend of taking into account learning and cognitive styles when personalizing computer systems. Because "one-size-fits-all" approach does not seem to work effectively in practice, the idea of personalizing and creating adaptive systems become increasingly attractive. Research in Adaptive Hypermedia tries to integrate knowledge from hypermedia systems development and user modeling, where educational hypermedia systems and online information systems predominate [1]. Although some early research pointed out that cognitive style based personalization of management information systems (MIS) and decision support systems) DSS is not a relevant issue [2], more recent research show that cognitive and learning styles have a significant effect on technology acceptance and usage [3].

In the context of personalizing for differentiated users, it becomes increasingly important to address specific user groups [4] Agricultural users can be considered as an example of a specific IT user group, which seems to become an important research issue [5]. According to research in the agricultural domain, farmers can be characterized based on their economic characteristics; subsequently different farmer groups can be identified [6]. Moreover, it seems that farmer groups differ also with respect to information processing, knowledge management and learning styles. Also, the usage of agricultural DSSs by farmers has been found unsatisfactory [7].

Nowadays, in all business sectors there is an increasing push towards innovativeness and competitiveness. Agricultural users, as an example of specific users, face many challenges, such as an increasing complexity concerning their farm management,

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the need to address climatologic changes, etc. [6]. In order to support agricultural users, various initiatives emphasize on learning and knowledge transfer. For instance, in the Netherlands, different IT systems such as decision support systems, have been developed. Unfortunately, not all systems are used by agricultural users as intended [6,9].

The proposed approach is an attempt to address the (re)design and personalization aspects of DSS, dedicated to a specific group of users. The problem is the gap that exists between the DSS systems developed by designers, and the low usability of these systems, which emphasizes the importance of the relationship between the DSS developer and the potential user [7]. With our approach we aim to offer an instrument to increase DSS usability, by tailoring DSS design toward user learning styles.

In this research we propose an approach for personalizing decision support systems for specific groups of users, by taking into consideration user's learning style. The redesign and personalization aspects are tackling both the interface (adaptive presentation and adaptive navigation support, in terms of Brusilovsky's terminology), and decision making aspects.

In Section 2, we present the theoretical basis underlying our research, the instruments used and data collection aspects. The third section is dedicated to describing the results, which are further used in Section 4 to provide design guidelines for DSS.

2 Methods and Theoretical Underpinnings

Agricultural users need to be typified corresponding to their leaning styles. To assess the corresponding learning style, two instruments are used: (i) Motivated Strategies for Learning Questionnaire MSLQ [11] and (ii) Kolb's Learning Styles Inventory KLSI [12]. Although criticisms exist concerning the validity and reliability of the KLSI instrument, it is often used for determining persons' learning styles, and for individual profiling in training tasks [13]. We choose MSLQ because we intend to address learning styles not only from an individual, but also from a group perspective.

Based on a selection of constructs from these three instruments, a questionnaire has been sent to 1800 starch potato growers in The Netherlands. The questionnaire was sent out on paper. Of the 1800 questionnaires that have been sent to growers, so far 97 useable questionnaires were returned, which means a response rate of 5%.

An adapted form of the Task-Technology Fit instrument - TTF [8] is used to determine the fit between a DSS, used by farmers and the cultivar selection tasks. As showed in [9], some agricultural users show difficulties in fulfilling the DSS goal, indicating a possible misfit between the DSS design and the tasks to be supported by the DSS. The problematic TTF dimensions determined are then translated into specific personalization actions, depending on the learning style.

The questionnaire consists of a selection of constructs from the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & de Groot, 1990), and Kolb's Learning Styles Inventory [12].

The selection of constructs from the MSLQ follows Pieters' (2005) findings. Pieters' study of learning styles in the agricultural domain in the Northern Netherlands reveals the resource management strategy constructs 'peer learning' (5 items) and 'help seeking' (5 items) to correlate with grower performance (expressed as yield quantity and yield quality). In addition, the MSLQ construct 'management time and study environment' (5 items) has been added. Kolb's Learning Styles Inventory primary scales 'concrete experience' (CE), 'reflective observation' (RO), 'abstract conceptualization' (AC), and 'active experimentation' (AE), as well as the combination scales 'abstractness over concreteness' (AC-CE) and 'action over reflection' (AE-RO) have been included in the questionnaire.

Finally, general questions were posed to typify the agricultural user and his business. Respondents were asked to specify their age, size of the farm, percentage of rented land, etcetera.

The research is organized based on the conceptual model, shown in Figure 1. Following the question concerning the profile of agricultural users in terms of learning styles, we aim to test the following hypotheses:

H1: Learning styles influence task-technology fit.
H2: Learning styles influence decision support systems usage.
H3: Task characteristics influence task-technology fit.
H4: Task-technology fit determines decision support systems usage.

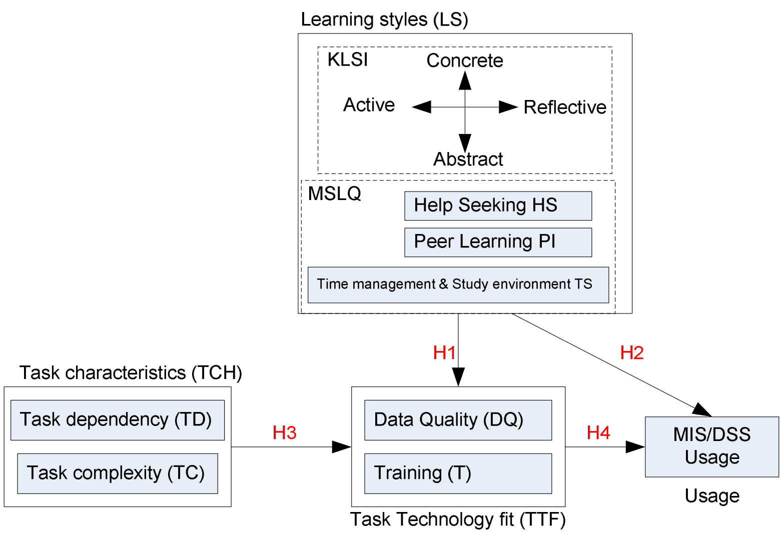

Fig. 1. Conceptual model

3 Results

We distinguish between two types of farming supporting systems, namely Management Information Systems (MIS) and Decision Supporting Systems (DSS). The first group - MIS- consist of MIS_System1, MIS_System2, MIS_System3, MIS_System4, MIS_System5, while the second group –DSS- consist of DSS_System6, DSS_System7, DSS_System8 and DSS_System9[1]. The overview concerning MIS and/or DSS usage, is shown in Table 1. MIS_System3, MIS_System4 and MIS_System5 systems provide

[1] The names of systems remain undisclosed because of confidentiality reasons.

Table 1. Usage of ICT support

ICT support		N	Percent
Management Information Systems Use	MIS_System1_Use	23	26.4%
	MIS_System2_Use	19	21.8%
	MIS_System3_Use	30	34.5%
	MIS_System4_Use	7	8.0%
	MIS_System5_Use	8	9.2%
Total MIS use		87	100.0%
DSS Use	**DSS_System6_Use**	4	15.4%
	DSS_System7_Use	1	3.8%
	DSS_System8_Use	1	3.8%
	DSS_System9_Use	20	76.9%
Total DSS use		26	100.0%

also advising modules, which can be considered as modules used for decision making activities. Therefore, we classify further MIS into MIS including decision making modules (MISwithDMM), and MIS excluding decision making modules, which will be further disregarded. In our analysis we select responses corresponding to those users who use (i) MISwithDMM and/or (ii) DSS.

It is worthwhile to remark that MIS are more used than DSS; a possible explanation is they have been available for a longer period of time than DSS. In case of MIS, the maximum amount of years of availability is 35, while for DSS is 8 years.

3.1 Reliability of Constructs

Task characteristics are measured by means of two concepts: task dependency (2 indicators) and task complexity (3 indicators). For the measurement of task technology fit (TTF), two constructs are used, namely data quality and training. Because not all indicators are reliable, data quality is constructed as an aggregation of 8 indicators, and training is measured by four indicators. Finally, an aggregated measure for TTF is obtained.

Table 2. Reliability of used constructs - Cronbach α scores

Constructs		**No of items**	**Reliability (Cronbach α)**
Task characteristics	Task dependency	2	.705
	Task complexity	3	.793
	Task characteristics (aggregated)	2	.581
TTF	Data Quality	8	.608
	Training	4	.601
	TTF (aggregated)	2	.521
Learning Styles	Time management & study environment	6	.792
	Help Seeking	5	.606
	Peer Learning	3	.856

Finally, the construct Usage is measured as one cumulative counts, system use. In Table 2 are provided the reliability measures for the used constructs. Apart from the aggregated constructs Task characteristics and TTF, all the other constructs show reliability values above the threshold of 6.

3.2 Learning Styles Based on Kolb's Method

Kolb learning styles 'converger' (high scores on AC and AE), 'diverger' (high scores on CE and RO), 'assimilator' (high scores on RO and AC), and 'accommodator' (high scores on CE and AE) could have been ascribed to 45 of the respondents, using the respondents' reports on Kolb's dimensions CE, RO AC, and AE. Table 3 provides an overview of Kolb learning styles in the sample regarding growers' age, farm size, percentage of land rented, and participation to starch potato, sugar beet, consumer potato, and seed potato growths.

Table 3. Grower characteristics per Kolb learning style

Kolb learning style	**Converger**		**Diverger**		**Assimilator**		**Accommodator**	
N	13		8		17		6	
	mean	sd.	mean	sd.	mean	sd.	mean	sd.
Age	48.9	11.2	44.9	10.0	48.1	10.3	39.8	12.7
Total area	99.5	110.7	78.0	49.4	88.4	45.4	63.0	22.6
Percentage rented	52.0	33.0	15.0	20.2	31.1	34.9	54.2	32.6
Area starch potato growth	39.2	51.0	29.9	25.1	32.3	22.8	30.7	15.0
Area sugar beet growth	12.1	6.9	10.9	15.3	12.5	10.6	10.5	9.2
Area consumer potato growth	4.2	11.5	.0	.0	.3	1.2	3.5	8.6
Area seed potato growth	3.2	7.5	.0	.0	.8	1.9	.0	.0

In our sample the group of convergers (AC-AE) is the oldest group, and has the largest mean area in their business. This group also has the highest mean area dedicated to starch potato, consumer potato, and seed potato growth. Assimilators (RO-AC) assign the largest area to sugar beet growth. These differences are not significant but indicative. The percentage of land that is rented shows differences between the learning styles ($F(3, 40) = 3.002$, $p < .05$). The accommodator (CE-AE) and converger group report significantly more area as rented than the diverger (CE-RO) and assimilator groups. The accommodator and converger groups focus stronger on active experimentation. The found result might be an indication that the type of land is a factor these groups vary in their experiments.

3.3 Learning Styles and Task Technology Fit (H1)

A regression model is build in order to identify those learning styles dimensions impacting task technology fit. Two approaches are used, namely first, the task technology fit measure is used as a dependent variable, and second, the components of the TTF construct are used separately (e.g. data quality and training) as dependent variable.

The best regression model turns out to be the one with training as the dependent variable. The independent variables are learning styles dimensions, namely time management & study environment, peer learning and help seeking. At an α level of 5%, the model is significant ($F(3, 44) = 10.67$, p-value <.01) and explains 42,1% of the variance. Time management & study environment is the only significant factor (t = 5.158, p-value <.01) in the regression model, therefore the following model is proposed.

$$\text{Estimation of Training} = 1.558+.777*\text{time management \& study environment} \quad (1)$$

The interpretation of this model is the following: the better one manages the time and study environment, the more knowledge and skills to use DSS will develop.

3.4 Learning Styles and Usage (H2)

In order to assess the influence of learning styles in terms of MSLQ dimensions, a regression model has been developed. The dependent variable is the cumulative count of systems used, and the independent variables are learning styles MSLQ dimensions. At an α level of 5%, the model is significant ($F(3, 57) = 4.04$, p-value <.05), and explains 17,5% of the variance. Help seeking (t = -2.272, p-value <.05), and time management & study environment (t = 2.289, p-value <.05) are significant factors in the regression model (α level of 5%), therefore the following model is proposed:

$$\begin{aligned}\text{Estimation of Usage} = .622 - .338*\text{help seeking} + .367 * \text{time management}\\ \&\text{study environment}\end{aligned} \quad (2)$$

We notice that help seeking has a negative effect on system usage, while time management & study environment has a positive effect, however quite comparable in absolute magnitude. Thus, the better one manages his/her time and study environment and depends less on the help of others, the more systems s/he will use.

3.5 Task Characteristics and Task Technology Fit (H3)

ANOVA testing of the relation between task characteristics and task-technology fit shows no effects, using task complexity and task dependency split at their means as dependent variables. No differences are found between high and low task complexity and task-technology fit ($F(1,48) = 1.238$, p = .271) and between high and low task dependency and task technology fit ($F(1,46) = 1.123$, p = .295). Within the investigated agricultural domain, the results provide no indication that the task characteristics complexity and dependency are predictors for the task-technology fit of available decision support systems.

3.6 Task Technology Fit and Usage (H4)

Task-technology fit shows a relation with the number of years decision support systems are used. A higher reported task-technology fit corresponds with a longer period of use of decision support systems ($F(1,48) = .3.435$, $p < .10$). This relation is mainly influenced by the number of years management information systems that are equipped with decision support modules are used ($F(1,48) = 3.852$, $p < .10$). In contrast, the task-technology fit is no predictor for the amount of decision support systems that are used by a grower ($F(1,48) = .720$, $p = .400$). These results lead to the conclusion that decision support systems that provide good support for specific tasks of a farmer lead to usage over a longer period, particularly in case the decision support is provided by specific modules from the agricultural users' management systems. Furthermore, agricultural users are selective in their choice of decision support. Decision support systems are only used if they provide support for tasks for which an agricultural user desires support; a decision support system's availability and a high task-technology fit will not lead to it being used.

4 Conclusions

This study provides some footholds for the redesign of decision support systems for support of tasks in the agricultural domain, providing personalized decision support to growers. Personalization of decision support systems is realized through altering the presentation of the system, and changing the system's interface. Additionally, personalization can be achieved by changing the decision support focus of the system. The latter form of personalization relates to changing the target of the decision support process, for instance by changing optimization criteria. Changes to a decision support system affect the task-technology fit of the system, which in its turn should affect the system's use.

Based on Kolb's learning style approach, we profiled agricultural users in four categories: 'converger', 'diverger', 'assimilator', and 'accommodator'. More research is needed in order to find out how to use this approach for DSS redesign purposes.

Based on the MSLQ approach, we found relations between learning styles and task technology fit at one hand, and use of decision support systems on the other hand. They provide indicators for redesign not only at a technical level, but also on the level of the context in which these systems are used.

Our first hypothesis leads to the development of a regression model. According to this model, it seems that learning styles dimensions affect task-technology fit (more specifically the training dimension). Therefore, more efforts should be spent on redesigning DSS to facilitate efficient time management and study environment in case of agricultural users.

The second hypothesis was confirmed also based on a regression model. The first regression factor -help seeking- provides an indication that decision support systems are used by agricultural users that learn in solitude. The investigated decision support systems connect to this orientation of agricultural users; existing decision support systems focus on supporting individual agricultural users. In order to increase use of these systems, an orientation towards supporting groups of agricultural users might be considered. A way to provide support within groups is to facilitate discussions between group members as part of the decision support system. The second regression factor operates at the level of use context of decision support systems. Only if agricultural users organize their time and study environment will they be inclined to use these systems. Therefore, to support usage of decision support systems, some incentive needs to be installed to convince agricultural users to use it. The exact form of such an incentive depends on the motivation of agricultural users to learn. Additional information is required about the motivation, intrinsic or extrinsic, of agricultural users to learn in relation to the use of decision support systems.

The results presented in the previous section provide no support towards changing available decision support systems or management information systems that have a decision support module. No relations have been found between task characteristics and task-technology fit (the third hypothesis), or between task-technology fit and usage of these systems (the third hypothesis). Hence, the results provide no indication of the effects of changing the interface or the decision support focus of the systems.

As possible limitations, the results reported in this work can be considered as preliminary (only 5% of the questionnaires have been filled in). Therefore, more data should be collected and analyzed, in order to come with a complete picture concerning learning styles.

This research connects with other learning-based initiatives that aim to support agricultural users, with currently under development by Gielen (see [6]), namely "Stimulating & Inspiring Learning Environment", where 12 learning environments are developed for agricultural entrepreneurs: (1) masterclass, (2) clinic, (3) workshop, (4) lab, (5) academia, (6) general repetition, (7) entrepreneur café, (8) boksring, (9) kitchen table, (10) utopia, (11) study club, and (12) expedition.

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