Personalized training by profiling learners to enhance cognitive flexibility[1]

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Abstract: People need to be cognitively flexible in order to be successful in the dynamic, ever changing society of today. Previous studies found that a carefully designed training program can help people to think and act in a more cognitively flexible fashion, leading to a better performance. This finding asks for more research into the instructional strategies that helps learners to utilize their cognitive flexibility. This paper presents a study investigating whether personalized instruction is more helpful than a standardized instruction. A pattern analysis was conducted on participants' data from our previous training study. Three categories of learners were found: those having difficulty to detect that flexibility is needed; those who found it difficult to decide upon a flexible response; and proficient adapters. These categories were used to specify learner profiles with associated instructional strategies. A study is proposed to investigate the importance of personalizing learning. Implications, challenges and future directions are discussed.

Introduction

The working spaces and learning environments in the 21st century are often complex and rapidly changing due to technological advancements. Learners need to be flexible to quickly adapt to such situations. Studies have focused on how to train learners to become cognitively flexible. Personalized learning might be a potential approach to increase its training effects. This work-in-progress study investigates individual differences of learners' cognitive processes throughout the game-based training to increase cognitive flexibility.

Cognitive flexibility training and learner characteristics

Cognitive flexibility is defined as the individual ability to behave adaptively to novel, uncertain, and changing situations by quickly restructuring one's knowledge (Spiro, Coulson, Feltovich & Anderson, 1988). Cañas et al. (2006) explained the underlying cognitive processes by how individuals adapt and be flexible. First, individuals detect that the situation is new or changed. After correctly assessing and re-planning the given situation, they behave in a flexible and adaptive way. Game-based training is one of the most actively used approaches to train learners to be adaptive and flexible in dynamic environments. Technological advancements allow to create various virtual environments where learners can experience and practice how to deal with such changing circumstances in a situated context (Gee, 2005). A recent study of authors et al. (submitted) reported empirical evidence that the game-based training with changing rules, increases learners' ability to adapt in changing environments.

Few studies discussed learner characteristics in relation to flexible and adaptive behavior. Morgan et al. (2013) proposed four types of learner profiles during the training to be adaptive in multitasking environments. They described that when the difficulty of tasks change, *good adapters* perform all tasks equally well while *poor adapters* fail to perform well on all given tasks. *Attackers* focus only on more difficult tasks while *avoiders* focus only on easier tasks. These learner types help researchers to better understand the differences in learners' adaptiveness, yet the question still remains of how learners differ in their cognitive processes to be adaptive. Although the cognitive processes of Cañas et al. (2006) provide insight for individuals to become cognitively flexible, there might be cognitive differences among individuals in how they follow the process. For instance, some learners may lack the ability to be adaptive because they fail to recognize that circumstances have changed. Others might face difficulties in analyzing or planning to deal with the new situation. Or some learners may feel discomfort towards change.

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Therefore, a systematic analysis is needed to identify possible differences between learners so that training can better accommodate the needs of learners.

Personalized learning for cognitive flexibility training

Personalized learning refers to customization of learning materials, instructional supports, and learning trajectories in response to characteristics, needs, and behaviors of individual learners (Chrysafiadi & Virvou, 2015). Studies on personalized learning reported positive learning effects and learner satistifaction (e.g., Aleven et al., 2016; Wickens, Hutchins, Carolan & Cumming, 2013). Previous studies stated various strategies for personalized learning (e.g., O'Donnell, Lawless, Sharp & Wade, 2015). A learner-centered approach provides learning autonomy to learners, which guides learners to monitor their learning progress, and to select the learning materials or level of difficulty that suits them. In an instructor-centered approach, a human or machine instructor diagnoses learners' learning process and provide tailored instruction or materials. Personal profiling based on learner characteristics is another commonly used approach (e.g., Chrysafiadi & Virvou, 2015). Techniques such as grouping common characters of learners and diagnosing mistakes have been actively used in personalized learning to analyze learner characteristics and to derive patterns of learners for personal profiling.

Based on the positive experiences of personalized learning reported in the literature, we argue that personalizing a game-based training might enhance learners' cognitive flexibility to better deal with changing situations. There are few studies on game-based learning in this topic that applied personalized learning methods. Bell and Kozlowski (2008) study focused on customizing the instructional strategy for learners to explore, tolerate their own mistakes, and control their emotions during their training. Hughes et al. (2013) study allowed learners to select the difficulty of learning materials during the training. In both studies, positive effects of tailored instructional approach was reported on achieving the learning goal of adaptive behaviors. However, personal profiling was not the used approach in either study. Therefore, applying a personal profiling method to personalize training of cognitive flexibility may still yield positive learning gains. As the challenges of identifying learner characteristics have been highlighted, deriving personal profiles by analyzing data, which is collected during a training, might be beneficial. Moreover, modifying a technique to create virtual personas in Human Computer Interaction (e.g., Acuña, Castro & Juristo, 2012) may be useful in deriving learner profiles, due to its systematic process of recognizing meaningful patterns.

The present study

The aim of this study is to investigate whether personalizing reflection feedback on learning process is beneficial to learners during game-based training to enhance cognitive flexibility. In order to achieve our goal, we will first investigate whether there are individual differences on learners' cognitive processes throughout a training. We will examine learner characteristics using participants' data from our previous experiment (Authors et al., submitted). Through the analysis of participants' written reflection on their reasoning process, we will derive learner profiles, if we find sufficient evidence that there is apparent differences on learners' cognitive processes. Our expectation is that there is evident differences in learners' cognitive processes throughout the training.

Method

Material: Game-based learning scenarios

A narrative-rich PC game was used for the training to enhance learners' cognitive flexibility in changing environments (Authors et al., 2017a; 2017b; submitted). The game consists of three scenarios of a robot threat, nanotechnology and border control, respectively. In each scenario, learners need to make the best decisions while the surrounding situation changes. Each scenario consists of three phases (See figure 1) of learning (LP), consolidation (CP) and test (TP). During the LP, learners learn rules to make good decisions. During the CP, learners put the learned rules into practice. At the end of the CP, a major event is introduced (e.g., solar storm) that changes the rules of the underlying game. The learners are not told this. In the subsequent TP, they need to discover these rule changes from the feedback on their actions, and then need to figure out how to adapt their actions to the changed rules. To achieve successful performance during the TP, learners need to follow the cognitive processes of detecting the changed rules, re-planning, and making decisions accordingly.

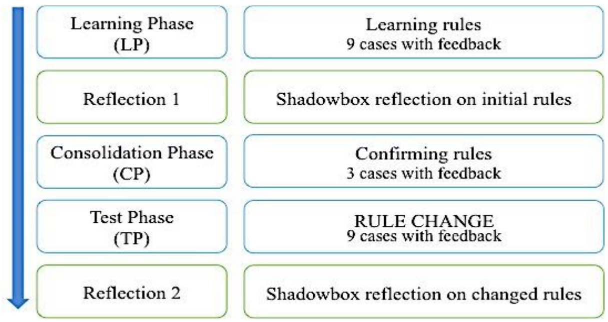

Figure 1: Structure of the game

Material: Shadowbox reflection

Authors et al. (2017b) have argued that game-based training in rule-changing environments should be accompanied with cognitive reflection. The Shadowbox method of cognitive skill training (Klein & Borders, 2016) was used for this reflection. During the Shadowbox reflection, learners check the validity of their assumptions and line of reasoning by comparing their reasoning with those of experts. This method was applied during the game training, once after the initial rule and once after the rule change (See figure 1) for scenario 1 and 2. This was done as follows: during the game-based training scenario, participants (n=49) received an assignment in which they had to prioritize four given possible actions from the most suitable to the least suitable. Then, the participants were asked to write down their argumentation. Subsequently, they were provided with experts' prioritization and argumentations. Participants were then asked to compare both, and to evaluate the underlying reasons for the similarity or differences between solutions.

Analysis method

To analyze the learners' characteristics of their cognitive processes throughout the game-based training, we conducted a pattern analysis on participants' written reflection data. The analysis followed five steps, which is modified from the Personas technique in HCI (Acuña, Castro & Juristo, 2012). The first step was to state the preliminary hypotheses. We hypothesized that there are four types of learners (See figure 2), based on the literature and our experiences with learners from previous experiments. Among the four types of learners, we hypothesized that learners who are unable to detect the change (category 1) cannot recognize that situations have changed. Also, learners who cannot re-plan according to changed situations (category 2) will recognize the changes but will fail to correctly apply new rules to the modified situations. Learners who cannot not respond adaptively (category 3) will properly recognize the changed situations and can re-plan accordingly, yet they will still behave inflexibly. Learners who are adaptive and flexible (category 4) will recognize the changed situations, re-plan accordingly, and behave adaptively. The second step of the pattern analysis was to identify behavioral variables. The variables we selected are: participants' scores on prioritization assignments, correctness of initial and changed rule detection, correctness of applying initial and changed rules, and the four hypothesized learner categories. During the Step 3, we mapped each participant to identified behavioral variables. One approach we took was to map learners by their prioritization assignment scores (See table 1 for the result). Our second approach was to analyze the reasoning of each participant's written reflection based on our hypotheses. During this analysis, we applied a profiling technique to analyze how much participants' reasoning deviated from those of experts (Chrysafiadi & Virvou, 2015). Then, we assigned each participant to hypothesized categories. Step 4 was to identify significant behavioral patterns (See table 2 for the result). During this step, we followed another profiling technique to search for participants' common errors and misconceptions (Chrysafiadi & Virvou, 2015) in detecting, and applying the initial and changed rules correctly. Lastly, step 5 was to identify all inclusion criteria per pattern. In particular, we verified whether identified patterns matched per hypothesized category, and then we concluded the derived patterns.

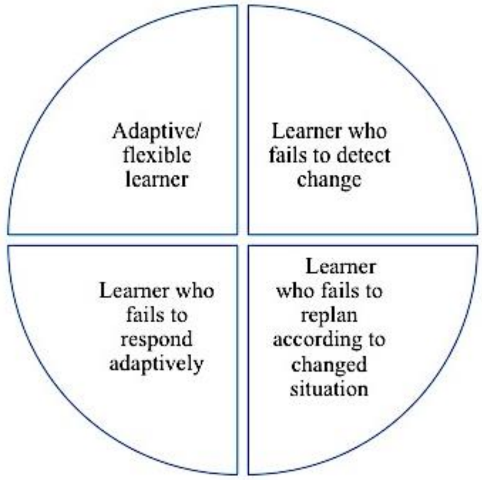

Figure 2: Hypothesized learner profiles on cognitive processes

Result

Table 1 shows an example of learner categorization based on the participants' prioritization assignment scores. This result derived from the analysis in step 3. Table 2 is the result of the analysis in step 4, an established pattern based on the four categories hypothesized. The comparison between the results of table 1 and 2 reveals that not all participants who scored high on the assignment wrote correct reasoning during the reflection. Also, the pattern analysis revealed that we were able to assign the majority of participants into the four hypothesized categories. However, some placements for category 2 and 3 were open to interpretation due to the analysis required of the reasons why these participants failed to adapt. This result is inconclusive because of the difficulty in analyzing whether some participants failed to adapt due to bad planning, or they failed not due to planning but due to the decision not to execute their plans. Therefore, we adjusted the learner profiles (See figure 4), based on the conclusions made after the analysis. Instead of four categories, we categorized learners into three types: learners who fail to detect change, learners who fail to re-plan and behave adaptive, and adaptive or flexible learners. Another finding was the interference of participants' prior knowledge on rule learning, which negatively affected their cognitive processes. Although we recognized this pattern on less than 15 % of the total participants, the interference occurred throughout the learners in all hypothesized categories. Therefore, this characteristic was not added as a new category when the profiles was established. Instead, we will discuss ways to solve this issue. During the presentation, we will provide more examples and details of the analyzed data, the developed personalized instructions, and learners' evaluation (pilot study) of the personalized training.

Possible answer	Scoring (min 8-max 16)	Per score		Per answer		Participant #
		# (n=49)	%	# (n=49)	%	
Dacb	16	31	63%	31	63%	2, 3, 9, 13, 19, 25, 27, 31, 33, 35, 39, 43, 47, 51, 57, 60, 61, 63, 65, 67, 69, 71, 75, 77, 79, 81, 83, 85, 87, 93, 95
Dabc				4	8%	1, 10, 49, 59
Dcab	14	12	24%	8	16%	17, 21, 23, 37, 41, 53, 73, 89
Adcb				0		-
Dbac				0		-
Dbca				1	2%	8
Dcba				1	2%	11
Cadb	12	5	10%	0		-
Cdab				1	2%	45
Acdb				1	2%	15
Adbc				1	2%	91
Abcd				0		-
Abdc				0		-
Acbd				0		-
Bacd				0		-
Badc	10	1	2%	1	2%	29
Bdac				0		-
Bdca				0		-
Cabd				0		-
Cdba				0		-
Bcad				0		-
Bcda	8	0	0%	0		-
Cbad				0		-
Cbda				0		-

Table 1: Participants' data categorized according to their assignment scores (Step 3)

Hypothesized categories	Participants' prioritization assignment score					
	8	10	12	14	16	Total (%)
1. No detection	0	2	8	12	6	29
2. No re-planning	0	0	2	6	2	10
3. Refuse adapt	0	0	0	6	0	6
4. Adaptive learner	0	0	0	0	55	55
Total (%)	0	2	10	24	63	100

Table 2: Established pattern of learner profiles based on participants' data (Step 4)

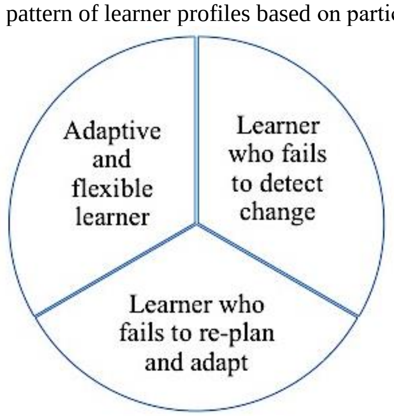

Figure 2: Adjusted learner profiles based on the pattern analysis

Discussion and conclusion

The current work-in-progress study examined whether differences among learners' cognitive processes are apparent throughout the game-based training to increase cognitive flexibility. The empirical findings of the pattern analysis showed that three types of learners were identified based on the participants' cognitive processes. The differences between the learners generally aligned with the underlying cognitive processes of Cañas et al. (2006). However, we found that there were few cases where learners' prior knowledge interfered with the process of rule learning and application regardless of the proposed categories. This was unexpected, as the scenarios were purposely created in a futuristic context to prevent such interference (Authors et al., 2017a; 2017b; submitted). A possible solution is to improve the glossary by providing more details on items that are relevant to initial and changed rules (e.g., tank is type of a land vehicle). Another interesting finding is that some learners did re-plan well but did not always adapt accordingly. Although this type of learners can successfully recognize environmental changes, it is possible that their low confidence in their ability to successfully re-plan stopped them from executing it (Ivancic & Hesketh, 2000). These types of learners need different feedback to become adaptive, compared to learners who need guidance on recognizing the changed situations.

Based on our findings, we conclude that differences in the cognitive processes among learners are evident throughout the training. Also, personalizing the reflection feedback based on our learning profiles could benefit learners and their learning process of increasing their cognitive flexibility. Our contribution to the personalized learning society is that we took a rigorous approach to define learner profiles on the cognitive processes based on the data collected, which could be useful for personalized learning in other domains that involve complex cognitive processes. Furthermore, our study could be helpful for practitioners who want to implement the concept of personalized learning in real-life educational trainings. As this study is in its preliminary phase, there are several challenges. Based on the derived personal profiles, it is important to focus on strategies (e.g., scaffolding) in developing personalized reflection feedback that can efficiently accommodate the needs of each learner. An important issue is how to automate the diagnosis process during the real-time training. Moreover, further investigation is needed to test the effect of the personalized reflection feedback during the game-based training, for the purpose of enhancing cognitive flexibility.

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