The Influence of Students’ Cognitive and Motivational Characteristics on Differences in Use and Learning Gain in an E-Learning Environment

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Abstract: Differences in use of e-learning components can be influenced by student-related characteristics. In this study, an e-learning environment was developed in line with the four component instructional design (4C/ID) model. The four components consist of authentic problem-based tasks (i.e., learning tasks), various support (i.e., supportive and procedural information) and additional drill-and practice exercises (i.e., part-task practice). This study firstly investigates the influence of students’ prior knowledge, task value and self-efficacy on students’ use of the components. Secondly, it examines the influence of students’ use of the components on their learning gain, taking into account their characteristics. Results of 161 students reveal a significantly negative influence of prior knowledge on students’ use of learning tasks and part-task-practice, whereas task value has a significantly positive influence on use of learning tasks and supportive information. Furthermore, use of learning tasks, procedural information and students’ prior knowledge significantly contribute to students’ learning gain.

Keywords: instructional design, e-learning, distance education, prior knowledge, motivation

Introduction

Advances in e-learning, such as virtual and asynchronous self-paced approaches, have increased learners’ autonomy. Consequently, e-learners can control when, what and how to study, and accordingly students have to self-direct their learning (Joo, Lim & Kim, 2013). An instructional design model that amplifies self-directed learning is the 4C/ID-model (van Merriënboer & Sluijsmans, 2009). A 4C/ID-based learning environment contains four different components: (1) concrete, authentic, problem-based, whole-task experiences (i.e., *learning tasks*), (2) additional drill-and-practice- exercises (i.e., *part-task practice*) and two categories of support such as (3) background theory (i.e., *supportive information*) and (4) just-in-time information (i.e., *procedural information*). In this study, an e-learning environment was developed in line with the 4C/ID-model. The additional exercises and various support were non-embedded. More specifically, this implies that on the learner’s initiative, additional part-task practice and/or support could be selected. Learning tasks were less optional, since students were strongly encouraged to consult them. Nevertheless, solving all of them or making various attempts to solve a learning task was optional. Consequently, we expected that one student would quickly proceed from learning task to learning task, while another student would select part-task practice or consult supportive information. Accordingly, in this context, self-directed learning refers to students taking initiative in diagnosing their learning needs by identifying appropriate resources (i.e., one of the four components), evaluating their outcomes (i.e., scores on learning tasks) and implementing learning strategies (e.g., consulting additional exercises or support in order to improve their results). Furthermore, prior research indicates that using different e-learning components can be influenced by cognitive and motivational characteristics (Greene & Azevedo, 2007; Jiang, Elen & Clarebout, 2009; Rienties, Tempelaar, Van den Bossche, Gijselaers & Segers, 2009). Therefore, the first aim of this study is to investigate the influence of students’ cognitive and motivational characteristics on students’ use of the four components of a 4C/ID-based e-learning environment. In accordance with prior research, students’ cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics are included in the research model. Moreover, the provision of different components that provide the opportunity to consult additional exercises and various support can enhance students’ performance (Lust, Juarez Collazo, Elen & Clarebout, 2012). By specifically looking at the use of each of the four components, more insight can be gained in how students’ use of a specific component contributes to students’ learning gain. Therefore, a second aim of this study is to measure how students’ use of the four components of the 4C/ID model, influence students’ learning gain, taking into account their cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics. Accordingly, to achieve both aims, a structural model is suggested that integrates students’ cognitive and motivational characteristics, the four components of the 4C/ID-model and students' learning gain in order to elucidate the relationships among these variables.

Theoretical background

An instructional design model that stresses integration and transfer of learning is the 4C/ID model elaborated by van Merriënboer (1997). The 4C/ID model is acknowledged as one of the most effective models for designing learning environments that facilitate the acquisition of integrated sets of knowledge, attitudes and skills (Merrill, 2002). The basic concept of the 4C/ID model is that learning environments can be described in terms of four interrelated components: (1) learning tasks, (2) part-task practice, (3) supportive and (4) just-in-time information. The learning tasks are concrete, authentic, problem-based, whole-task experiences. Learning tasks are grouped in task classes and sequenced based on their degree of difficulty in order to prevent cognitive overload for the learners, as this could hamper learning and performance (van Merriënboer & Sluijsmans, 2009). Support is provided in two distinct manners, that is, supportive and procedural information. Supportive information is basically, the theory and therefore supports the learning and performance of the non-recurrent, problem solving and reasoning aspects of learning tasks. It helps learners to link the presented information to existing schemata, that is, to what they already know in order to solve the learning tasks. Procedural information is prerequisite to the learning and performance of recurrent aspects of the learning tasks in each task class. It allows students to complete and learn routine aspects of learning tasks by specifying exactly how to solve the routine aspects of the tasks. It is presented just in time when learners need it. Furthermore, part-task practice supports the more complex whole task learning by providing additional exercises for selected recurrent constituent skills (van Merriënboer, 1997).

A 4C/ID-based e-learning environment is claimed to stimulate self-directed learning by providing different components at the student's disposal (van Merriënboer & Sluijsmans, 2009). Moreover, by giving students control of the use of the different components, differences in use based on the students' learning needs can be possible. Former research indicated that differences in use of e-learning components is influenced by learner-related characteristics (Greene & Azevedo, 2007; Jiang et al., 2009; Rienties et al., 2009). An important learner characteristic that influences differences in use is students' prior knowledge. Cognitive load theory suggests that students with low prior knowledge cannot immediately be confronted with highly difficult learning tasks. Accordingly, students' cognitive load can be reduced by consulting support and guidance (van Merriënboer & Sluijsmans, 2009). This implies that students who find the task difficult, benefit from various support and additional exercises in order to improve their performance. Nevertheless, selecting various support or making additional exercises can be very challenging (Clarebout, Horz, Schnotz & Elen, 2010; Lust et al., 2012). This requires awareness of learning gains, and therefore includes metacognitive monitoring of knowledge and comprehension, which might be difficult to achieve when students experience high cognitive load. As a higher level of prior knowledge reduces cognitive load during e-learning, students with higher prior knowledge might face lower cognitive load and accordingly, are more likely to cope with these metacognitive requirements compared to students with lower prior knowledge. Subsequently, based on cognitive load theory, differences in use can be influenced by the level of students' prior knowledge (Moos & Azevedo, 2008; van Merriënboer & Sluijsmans, 2009). Despite this theoretical claim, several studies that investigated the impact of students' prior knowledge on differences in use did not find any effect. Van Seters, Ossevoort, Tramper and Goedhaert (2011) used e-learning materials to demonstrate how 94 university students work differently based on their prior knowledge. They measured the learning paths students followed when working with adaptive e-learning material. The learning path was determined by average step size chosen, average number of tries, total number of exercises and time needed to finish. They found that differences in students' prior knowledge did not have an effect on students' learning paths. Taub, Azevedo, Bouchet and Khosravifar (2014) studied differences in use of an e-learning environment in relation to their prior knowledge. Results of 112 undergraduates revealed that all students visited similar number of relevant pages regardless of their level of prior knowledge. Jiang et al. (2009) conducted a study where they measured variety in non-embedded (i.e., optional mode) tool use in an e-learning environment (e.g., checklist tool, information list, calculator etc.). Tool use was measured by frequency of tool use and proportional time spent on tools. Results of 58 bachelor students revealed that there was no influence of prior knowledge on the quantitative aspects of tool use. Aforementioned studies seem to confirm that students do not grasp learning opportunities based on their level of prior knowledge (Lust et al., 2012).

In contrast to prior knowledge, empirical evidence revealed that motivational characteristics have an important influence on students' learning behavior in e-learning settings (Chen & Jang, 2010; Rienties et al., 2009). According to expectancy-value theory, self-efficacy and task value are two key components for understanding students' specific use and academic outcomes. Self-efficacy is defined as a learners' ability to execute the required behavior necessary for success (Greene & Azevedo, 2007). There is evidence that self-efficacious students participate more readily, work harder and persist longer when they encounter difficulties than those who are uncertain about their capacities (Zimmerman, 2000). Task value essentially refers to the reason for doing a task. More specifically, students with high task value pursue enjoyment of learning and understanding of new things (Joo et al., 2013). Martens, Gulikers and Bastiaens (2004) investigated the impact of task value on the use of an e-learning environments. The participants were 33 higher education students. Results showed that students with high task value did not do more, but did other things than students with low task value. Analysis of log files showed that students with high levels of task value showed proportionally more explorative study behavior. The explorative pages were defined as pages that students were not explicitly directed to by the external source. Studies also indicate relationships between self-efficacy, task value and performance. Bong (2001) conducted a path analysis to investigate the relationships between task-value, self-efficacy and enrollment intentions i.e., use of the e-learning environment in an online learning context. Results of 168 undergraduate university students showed that task value was linked to course enrollment intentions. However, no influence of self-efficacy on course enrollment intentions was found.

Furthermore, differences in use of e-learning components can also influence students' learning gain. Lust et al. (2012) conducted a literature study which provided empirical evidence for the beneficial influence of differences in tool use i.e., information, processing and scaffold tools, on students' learning gain. In addition, former research indicated that student-related characteristics can directly influence students' learning gain. Song, Kalett and Plass (2016) studied the direct and indirect effects of university students' prior knowledge, task value and self-efficacy on students' learning gain in an e-learning environment. SEM revealed that university students' prior knowledge directly positively affected their learning gain, but no significant effects of task value and self-efficacy on students' learning gain were found. By contrast, Joo et al. (2013) investigated 897 learners in an online university. Using SEM they found significant positive relationships between both task value and self-efficacy on the final grade on the course. These studies indicate, that when we measure the influence of differences in use on students' learning gain, we should control for student-related characteristics. Summarized, based on these aforementioned theoretical and empirical claims we hypothesize that (1) prior knowledge, self-efficacy and task value can have an influence on students' use of the four components and (2) that students' use of the four components can be beneficial for students' learning gain, taking into account student-related characteristics (i.e., prior knowledge, self-efficacy and task value). Consequently, we formulate following research questions:

- RQ1: How do students' cognitive (i.e., prior knowledge) and motivational (i.e., self-efficacy and task value) characteristics influence use of the four components of the 4C/ID-based e-learning environment?
- RQ2: How does differences in use of the four components of a 4C/ID-based e-learning environment influence students' performance, controlled for students' cognitive and motivational characteristics?

Methodology

Measurement instruments

The e-learning environment in the present study focuses on French as a foreign language. It contains four learning tasks and takes about 1 hour and 15 minutes to complete. The level of difficulty was aligned with the level that students in the Flemish part of Belgium are expected to reach at the end of the secondary school, i.e., level B1 of the Common European Framework of Reference. Participants were 161 first year Psychology and Educational Science students. The majority of the students were female (91%). The average participant was 20 years old (*SD* = 2.92). Participation to research is part of the students training program, but French was not a part of their training program.

The administration procedure of the study consisted of two administration sessions. The first administration session started with a pretest, an introduction of the e-learning environment and an additional questionnaire on task value and self-efficacy. Task value and self-efficacy were both measured after the introduction of the e-learning environment to make sure students had sufficient insight into the e-learning content to form an opinion. The students were asked to use the e-learning environment at home during two weeks. As the learning content was not a part of their educational program, they received the instructions that consulting the four components was optional and that there was no strict trajectory to follow, but that consulting the learning tasks was strongly recommended. After the intervention of twee weeks a second administration session took place where students received a posttest.

The learning environment is developed along the instructional design principles of the 4C/ID model. The first component deals with the learning tasks in the e-learning environment. These learning tasks are based on authentic situations for instance, ordering food in a restaurant. The learning tasks were sequenced in an easy-to-difficult order, and were clustered in a task class. At the end of the task class, students must be able to have a fluent conversation at the restaurant. Students receive automatic generated feedback based on their scores. In order to have a fluent conversation, students must master the grammar (e.g., l'article partitif), vocabulary (i.e., food), skills (i.e., listening) and attitudes (i.e., elementary courtesy in a restaurant). Accordingly, during these learning tasks students can click on links to consult one of the other three components of the 4C/ID model. More particularly, students can consult additional exercises i.e., part-task practice (e.g., drill-and-practice exercises to practice food vocabulary) and support, respectively, supportive (e.g., grammar explained by theory) and procedural information (e.g., grammar explained by using keywords). Subsequently, the supportive, procedural information and part-task practice are non-embedded i.e., they are at the disposal of the students but the students can decide whether or not to use them. Learning tasks were partly non-embedded, since students were free to make as many learning tasks (e.g., several attempts) as they wanted. Nevertheless, as aforementioned, they were also partly embedded (i.e., less optional) since students were strongly advised to complete the learning tasks during the first administration session and in addition learning tasks were clustered in a task class (i.e., predefined order).

Measurement instruments

To measure the learning content a quantitative paper-and-pencil instrument on French was used as pretest (i.e., *prior knowledge*) and posttest (i.e., *students' learning gain*). The instrument consists of 60 items and focuses on knowledge (i.e., grammar and vocabulary) and skills (i.e., listening, writing a conversation). The level of difficulty of the test was B1 of the Common European Framework of Reference (Evens, Elen & Depaepe, 2017). The instruments' reliability was explored by calculating internal consistency i.e., Cronbach's α = .90 for the pretest and Cronbach's α = .89 for the posttest (Cuieford, 1965).

Within this study the constructs *self-efficacy* and *task value* were derived from the Motivated Strategies for Learning Questionnaire (MSLQ; Duncan & Mckeachie, 2005). For this study we used the constructs self-efficacy (5 items) e.g., *"I expect to do well in this course",* and task value (6 items) e.g. *"It is important for me to learn the course content"*, of the motivation section. The questionnaire had a 7-point Likert-type response format with values ranging from strongly agree (7) to strongly disagree (1). The questions were translated into Dutch. Construct validity was checked by conducting a confirmatory factor analysis (CFA). The factor loadings from the latent variable constructs were all significant, had standardized values ranging from .74 to .93 and an average variance explained (AVE) of .76 for self-efficacy and .62 for task value. This verifies that the two measurement models of self-efficacy and task value were each measured well in the current data (Khine, 2013). Internal consistency was investigated by measuring the Cronbach's Alpha. The Cronbach's Alpha for self-efficacy was α = . 94 and for task value α = .84, which indicates high reliability (Cuieford, 1965).

Information of students' *use of the four components* of the 4C/ID model was collected by tracking students' activity, i.e., registration of views and interaction by the Moodle learning management system (LMS) during two weeks for each component. All data were collected on an aggregate module level and afterwards merged, based on the use of the different components. All data were anonymized through means of the use of random codes to safeguard the identities of the students.

Results

Students had an average of 50.97% (*SD* = 18.17) on the pretest and an average of 64.59% on the posttest (*SD* = 15.88). The average student replied "neutral" in terms of motivation (*SD* = 1.13) and self-efficacy (*SD* = 1.10). An overview of the distribution of the use of the four components (i.e., activity tracked by Moodle LMS and the amount of students that used the different components) can be found in Figure 1. The average time spent on using the online learning is 66 minutes (*SD* = 27.34, *min*. = 10.44 minutes, *max*. = 151.43 minutes or approximately 2.5 hours).

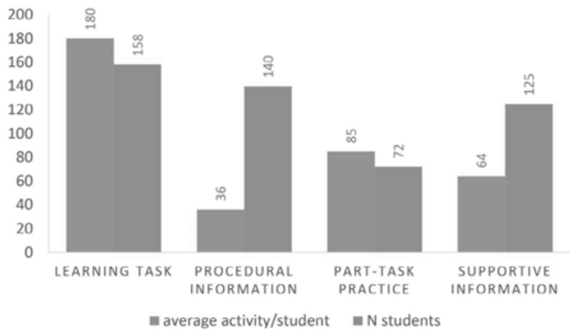

Figure 1. The use of the four components.

Structural equation modeling (SEM; N = 161) was conducted in order to firstly, investigate the influence of students' cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics on the use of the components. And, secondly, to investigate the influence of the use of the components on students' learning gain, controlled for student-related characteristics (i.e., prior knowledge, task value and self-efficacy). For the missing values a two-stage approach was applied. This approach obtains a saturated maximum likelihood (ML) estimate of the population covariance matrix and then uses this estimate in the complete data ML fitting function to obtain parameter estimates (Savelei & Bentler, 2009). Lavaan (Rosseel, 2012) converged normally after 59 iterations. The hypothesized model, provided an adequate fit to the given data [χ^2/df = 155.56/99 = 1.4; SRMR = .05, RMSEA = .06, CFI = .96, TLI = .95]. The χ^2-test indicates the difference between observed and expected covariance matrixes and should be non-significant. However, χ^2-test is highly dependent on sample size and therefore normed χ^2-test is often considered i.e., χ^2-test divided by the degrees of freedom. Values smaller than 2.0 are considered to indicate acceptable fit (Kline, 2013). In addition to χ^2 statistics, the root mean squared residual (SRMR), the root mean squared error of approximation (RMSEA), comparative fit index (CFI) and the Tucker-Lewis Index (TLI) were examined. SRMR is the difference between the observed variance and the predicted variance. A value less than .06 is considered a good fit. RMSEA adjusts for the complexity of the model and the size of the sample. The value for acceptance is >.05. A value of CFI and TLI between > .95 indicates good fit. Assessing all measures and considering the above statements, the original structural model was accepted and considered adequate (Khine, 2013).

Figure 2 gives an overview of the results of the research model. Significant influences of students' characteristics were found on the use of the components, more specifically, students' task value influences the use of learning tasks (β = .21, p <.05) and supportive information (β = .22, p <.05). No significant relationships were observed between students' self-efficacy and the use of the four components of the 4C/ID-model. A significant negative relationship was found between prior knowledge and part-task practice (β = -.21, p <.05). The variance explained for the dependent variables was R^2 =.07 for learning task, R^2 =.03 for part-task practice, R^2=.08 for supportive information and R^2 =.02 for procedural information. RQ2 investigated the influence of students' use of the four components of the 4C/ID model on students' learning gain, controlled for students' prior knowledge, task value and self-efficacy. Results reveal a significant influence of the use of components of the 4C/ID-model on students' learning gain, more specifically, the use of procedural information (β = .08, p <.05) and learning tasks (β = .12, p <.01) have a significant influence on students' learning gain. Prior knowledge had a major influence on students' learning gain (β = .91, p <.001). The variance explained for students' learning gain was R^2 = .79. In conclusion, students' differences in use of the components is influenced by students' task value and prior knowledge. Students' learning gain is influenced by differences in use of learning task and procedural information. Additionally, students' learning gain is mainly influenced by students' prior knowledge.

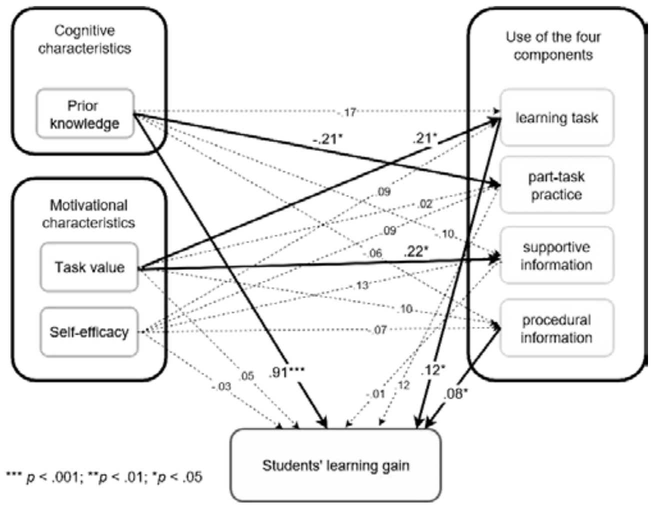

Figure 2. The research model.

Discussion

The current study strived to find evidence (RQ1) for the influence of students' cognitive and motivational characteristics on students' use of the four components and (RQ2) for the influence of differences in use of the four components on students' learning gain, controlled for students' characteristics. All variables were incorporated in one structural research model. Our results are based on data from a pre- and posttest (i.e., prior knowledge, students' learning gain), questionnaires (i.e., task value and self-efficacy) and platform log data from 161 students. Results indicate that prior knowledge and task value induce differences in use of the components of the e-learning environment. More specially, prior knowledge has a significant negative influence on the use of learning tasks (e.g., authentic problem-based exercises) and part-task practices (e.g., drill-and practice exercises). Part-task practices contain additional exercises with more recurrent content in order to prepare students to solve the learning tasks which contain more non-routine content. Accordingly, results indicate that some students seem to be aware that they are lacking routine knowledge to solve the learning tasks. Furthermore, results indicate that students attempted the learning tasks a few times in order to obtain better scores (i.e., differences in activity for the learning tasks). These findings are in contrast to the study of Taub et al. (2014) indicating that there were no significant differences in students' use of the e-learning environment (i.e., defined by the number of relevant pages visited) between lower and higher prior knowledge groups. Results are also different from the study of Jiang et al. (2009) which revealed no association between prior knowledge and the frequency of tool use and/or proportional time spent on tools. A possible explanation for the difference between our results and former studies might be that the uncontrolled setting in our study allows for more self-regulation. The study of Taub et al. (2014) and Jiang et al. (2009) were conducted in a controlled setting i.e., students worked with the e-learning environment under supervision. By controlling the setting students might feel the pressure to complete the tasks in a given time. As consequence students might follow a more traditional linear path. These differences in learner control can have an influence on students' use of different tools. Additionally, results indicate that differences in use are influenced by students' task value. Students' task value seems to have a positive influence on the use of the learning tasks. This could imply that students put more effort in solving the learning tasks qualitatively. Students' task value also has a significant influence on the use of supportive information (i.e., background information and theory in order to understand the content of the learning tasks in its entirety). This corresponds with the study of Martens et al. (2004) who also analyzed log files and found that students with high intrinsic motivation (e.g., task value) showed more explorative study behavior. A difference in the study of Martens et al. (2004) was that the variable exploration was calculated by dividing the number of explorative pages a student had visited by the total number of visited pages. Finally, self-efficacy had no influence on differences in use. These findings are consistent with the study of Bong (2002). A feature of self-efficacious students is that they work harder and persist longer when they encounter difficulties. As there was no influence, this could indicate that the tasks in the e-learning environment were not complex enough for the students to encounter difficulties (Zimmerman, 2000). Findings could also be due to the way in which usage was measured (i.e. course activity and enrollment intentions), as persistence is a feature that it might be possible that the spent time could give more information about this influence.

In this study, RQ2 investigated the influence of students' use of the components on students' learning gain, controlled for cognitive and motivational characteristics. Results indicate that use of the learning tasks and procedural information significantly contributed to students' learning gain. These results imply that the combined use of learning tasks and procedural information influences students' learning gain. The procedural information in this context is just-in-time information. Therefore, consulting this particular support and guidance can prevent learners from paying attention to irrelevant task aspects and subsequently reduce cognitive load, which on its turn can improve their task performance (van Merriënboer & Sluijsmans, 2009). Regardless these results, students' prior knowledge still has a primary significant influence on students' learning gain. This can be related to cognitive load theory, as the online course used rich learning tasks, which are based on real-life situations, these tasks can be highly complex. A risk of this approach is that the cognitive load imposed by the learning tasks is often excessive for students with low prior knowledge and may seriously hamper learning (van Merriënboer & Sluijsmans, 2009). Furthermore, this major influence of students' prior knowledge could also be influenced by the study design, more specifically, the fact that a rather short intervention, spread out over two weeks, is probably not enough to exert a major influence on students' learning gain.

Irrespective of the added value of these findings, some limitations in the current study should be mentioned. Firstly, this study gives information of *what* is used, but little information is provided on *why* students used these specific components. For instance, combining objective information with think-aloud protocols can give more insight in the actual cognitive processes (Winne, 2010). Secondly, by looking at the isolated use of the four components, little is known about *how* the different components are used. By analyzing log-data more in detail (i.e., looking at the sequences of use of the four components), more insight could be given on effective use. A possible example of effective use would be that when a student has an insufficient score, the student decides to consult supportive information. A third important limitation concerns the course design of the e-learning environment. Findings of the current study indicated that the use of learning tasks did not differ based on students' level of prior knowledge. As the learning tasks were sequenced in a simple- to -complex order, were clustered in a task class and had a predefined order, this course design probably influenced these results. It might have been more interesting if students had been able to select learning tasks themselves (e.g., based on their level of difficulty). Follow-up studies should enable students to select their future learning tasks at their option. This would provide more information about the self-directed learning (i.e., evaluating their learning outcomes and selecting learning tasks based on their performance; van Merriënboer & Sluijsmans, 2009).

Conclusion

This study firstly provides more information about the influence of students' motivational and cognitive characteristics on differences in use of the four components in a 4C/ID-based learning environment. Results indicate that students' characteristics do influence differences in use of the four components when students receive a lot of learner control. Moreover, students seem to slightly adapt their behavior based on their specific learning needs and interests. Accordingly, more comprehensive information (e.g., theory) might challenge more motivated students. Additionally, students with lower prior knowledge seem to consult part-task practice to help them to reach a very high level of automaticity for selected recurrent aspects of real-life problem-solving tasks. As a result, findings indicate that the 4C/ID-model is an instructional design model that allows for a lot of learner control and therefore supports self-directed learning, by providing four components containing different information (or a different format of information) that can be consulted freely in an non-linear trajectory. Furthermore, results reveal the importance the combined use of learning tasks and procedural information on students' learning gain, when controlling for students' characteristics. These students' characteristics amongst which prior knowledge, seems to have had a strong impact on learning gain. Therefore, more research should verify the impact of students' characteristics on differences in use and learning gain, using more extensive interventions. Moreover, students' cognitive load should be included to measure the impact of the complexity of the learning tasks. Overall, insight into differences in use based on student-related characteristics is an important step from an instructional design perspective. This could provide important suggestions for intervening and adapting the online learning environment to students' learner-related characteristics and associated learning behavior.

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