The Influence of Students' Cognitive and Motivational Characteristics on Students' Use of a 4C/ID-based Online Learning Environment and Their Learning Gain

Charlotte Larmuseau
ITEC, Imec, CIP&T, KU Leuven
Kortrijk
Belgium
charlotte.larmuseau@kuleuven.be

Jan Elen
CIP&T, KU Leuven
Leuven
Belgium
jan.elen@kuleuven.be

Fien Depaepe
ITEC, Imec, CIP&T, KU Leuven
Kortrijk
Belgium
fien.depaepe@kuleuven.be

ABSTRACT

Research has revealed that the design of online learning environments can influence students' use and performance. In this study, an online learning environment for learning French as a foreign language was developed in line with the four component instructional design (4C/ID) model. While the 4C/ID-model is a well-established instructional design model, little is known about (1) factors impacting students' use of the four components, namely, learning tasks, part-task practice, supportive and procedural information during their learning process as well as about (2) the way in which students' differences in use of the 4C/ID-based online learning environment impacts course performance. The aim of this study is, therefore, twofold. Firstly, it investigates the influence of students' prior knowledge, task value and self-efficacy on students' use of the four different components of the 4C/ID-model. Secondly, it examines the influence of students' use of the components on their learning gain, taking into account their characteristics. The sample consisted of 161 students in higher education. Results, based on structural equation modelling (SEM), indicate that prior knowledge has a negative influence on students' use of learning tasks and part-task practice. Task value has a positive influence on use of learning tasks and supportive information. Additionally, results indicate that use of use of learning tasks, procedural information, controlled for students' prior knowledge significantly contribute to students' learning gain. Results suggest that students' use of the four components is based on their cognitive and motivational characteristics. Furthermore, results reveal the impact of students' use of learning tasks and procedural information on students' learning gain.

LAK'18, March 7–9, 2018, Sydney, NSW, Australia

ACM ISBN 978-1-4503-6400-3/18/03…*$15.00*
https://doi.org/10.1145/3170358.3170363

CCS CONCEPTS

• **Applied computing~E-learning• Applied computing**~Computer-assisted instruction

KEYWORDS

Instructional design, adaptive learning, online learning

ACM Reference format:

C. Larmuseau, J. Elen, and F. Depaepe. 2018. The Influence of Students' Cognitive and Motivational Characteristics on Students' Use of a 4C/ID-based Online Learning Environment and Their Learning Gain. In *LAK'18: International Conference on Learning Analytics and Knowledge, March 7–9, 2018, Sydney, NSW, Australia. ACM, New York, NY, USA*, 10 pages. https://doi.org/10.1145/3170358.3170363

1 INTRODUCTION

Educational research shows that the effectiveness of an online learning environment depends a great deal on its instructional design [1]. Moreover, the instructional design can influence specific behavior and performance of students in online learning environments [2]. An instructional design model that is acknowledged as one of the most effective instructional design models for designing effective learning environments is the four component instructional design model (4C/ID-model) [3]. A 4C/ID-based online learning environment contains four different components, namely, learning tasks, part-task practice, supportive and procedural information, and confronts the learner with the need to assess his or her own performance. Accordingly, on the learner's initiative, additional tasks and support can be selected which implies that learners can choose their own learning trajectory to a smaller or larger degree. Consequently, we expect that one student may quickly proceed from learning task to learning task, while another learner might select part-task practice or consult supportive information [4]. Former research findings indicate that students' use of different components in an online learning environment can differ based on cognitive and motivational characteristics [5-7]. Therefore, the first aim of this study is to investigate the influence of students' cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics on students' use of the four components of a 4C/ID-based online learning environment. Furthermore, the provision of different components can stimulate students' performance since students can consult various support during their learning [8]. By looking at the four components separately, 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 and motivational characteristics. In order to achieve both aims, a theoretical structural model is suggested that integrates students' cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics, the four components of the 4C/ID-model and course performance in order to elucidate the relationships among these variables.

2 THEORETICAL BACKGROUND

2.1 Instructional Design

A learning environment should promote constructive, active, cumulative and self-directed learning [5, 9]. More specifically, well-designed tasks should stimulate students to integrate required skills, knowledge and attitudes and transfer complex cognitive skills to real-world contexts. An instructional design model that stresses integration and transfer of learning is the 4C/ID model elaborated by van Merriënboer [10]. The 4C/ID model is acknowledged as one of the most effective instructional design models for designing effective learning environments that facilitate the acquisition of integrated sets of knowledge, attitudes and skills [3]. When designing an online learning environment the first question to ask is how to develop learning tasks in order to reach the educational objectives and how to organize and sequence these learning tasks [9]. The basic concept of the 4C/ID model is that learning environments can be described in terms of four interrelated blueprint components: (1) learning tasks, (2) part-task practice, (3) supportive and (4) just-in-time information [10, 11]. In a 4C/ID-based learning environment, the learning tasks are the backbone of the design process and are concrete, authentic, problem-based, whole-task experiences. The design of the learning tasks, allows simultaneous practice of domain-specific knowledge and cognitive strategies. 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 [5, 12]. Learners can encounter difficulties while solving learning tasks, consequently adapted learner support should be provided [9]. Support is provided in two distinct manners, that is, supportive and procedural information [10, 11] 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. Accordingly, supportive information provides mental models and cognitive schemata, that allow for multiple use of the same general knowledge for performing different 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. The procedural information may include hints (e.g., summary of theory) or feedback relevant for the specific problem while working on the learning task. A lot of support is given for learning tasks early in a task class, but the support diminishes as learners acquire more expertise. Furthermore, part-task practice (e.g., drill- and practice exercises) supports the more complex whole task learning by providing additional exercises for selected recurrent constituent skills [11]. Learners should be guided during the learning process by giving them summative and formative feedback [9]. Accordingly, they should be able to perform, assess and select tasks that fulfill their personal needs [4]. Nevertheless, providing an online learning environment with a well-considered instructional design does not ensure its effectiveness [6]. The effectiveness of the online learning environment is strongly related to students' capacity to properly use the different components [8]. An important indicator of students' appropriate use is prior knowledge [4]. In addition, the effects of students' motivational aspects on their willingness to use the components should not be ignored [7]. In the next section the influence of prior knowledge and motivation on use will be discussed based on prior research findings.

2.2 Students' Cognitive and Motivational Characteristics

A 4C/ID-based online learning environment is claimed to stimulate self-directed and deep learning by providing different components at the student's disposal, containing learner support on the one hand and by offering a lot of learner control on the other [4]. Moreover, by giving students control of the use of the different components, adaptive learning based on their learning needs, should be possible. Despite this claim, we barely know if students actual benefit from these learning opportunities. Providing learning opportunities within an online learning environment is not sufficient to achieve better learning outcomes. A possible learner characteristic that could influence differences in use of the different components is students' prior knowledge [4]. Based on cognitive load theory, 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 [4, 13]. This would imply that students who perceive the task as more difficult use the components more or differently. Nevertheless, selecting various support or making additional exercises can be very challenging for students with low prior knowledge as they are more likely to perceive high cognitive load [4, 13, 14]. As a low level of prior knowledge increases cognitive load when faced with difficult learning tasks, those students might encounter problems to self-direct their learning. Accordingly, based on cognitive load theory, students with higher prior knowledge are more capable to self-direct their learning compared to students with lower prior knowledge [4, 15]. This would imply that students' prior knowledge can influence differences in use of the four components. However, there is no solid empirical basis for this theoretical claim [14]. Several studies investigated the influence of students' prior knowledge on differences in use. Van Seters, Ossevoort, Tramper and Goedhaert (2011) used online learning materials to demonstrate how university students work differently based on their prior knowledge. They investigated the learning path students followed when working with adaptive online 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 prior knowledge did not have an effect on students' learning path [16]. Furthermore, Taub, Azevedo, Bouchet and Khosravifar (2014) studied specific use of an online learning environment. Participants were 112 undergraduate students. Results revealed that all students visited a similar number of relevant pages regardless of their level of prior knowledge [17]. Additionally, Jiang, Elen and Clarebout (2009) conducted a study in which they measured variety in non-embedded tool use in an online 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. They found no influence of prior knowledge on the quantitative aspects of tool use [6]. Notwithstanding, research has shown that prior knowledge plays a primary role in learning achievement. Song, Kalett and Plass (2016) studied the direct and indirect effects of university students' prior knowledge on learning performance in online learning environments. SEM revealed that university students' prior knowledge directly positively affected their learning outcomes [18]. These aforementioned studies seem to confirm that students do not grasp learning opportunities based on their level of prior knowledge, but they do indicate the important role of students' prior domain knowledge on students' learning gain.

Additionally, motivational characteristics can have an important influence on students' learning behavior in online learning settings [7, 19]. According to expectancy-value theory, self-efficacy and task value are two key components for understanding students' specific use and academic outcomes [20]. Self-efficacy is defined as a learners' ability to execute the required behavior necessary for success [5]. 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 [21]. 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 [22]. Martens, Gulikers and Bastiaens (2004) investigated the impact of task value on the use of online 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. Explorative pages were defined as pages that students were not explicitly directed to by the external source [23]. 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 performance (i.e., students' mid-term scores) in an online learning context. Participants were 168 undergraduate university students. Results showed strong links of self-efficacy with performance, whereas task value was linked to course enrollment intentions [24]. Similarly, Joo, Lim and Kim (2013) investigated 897 learners in an online university course to unravel relationships between self-efficacy, task value and performance. Using SEM they found significant positive relationships between both task value and self-efficacy on course performance (i.e., the final grade on the course: midterm exam, attendance and final exam) [22]. However, Song et al. (2016) conducted a SEM-analysis to examine the direct effects of task value and self-efficacy on students' learning outcome, measured by a knowledge post-test. Participants were 368 university students. Results revealed no direct influence of self-efficacy and task value on students' learning outcome. Major difference with the study of Joo et al. (2013) is that important additional predictors of students' learning outcome were included in the research model such as prior knowledge and self-regulation [18]. In sum, based on these aforementioned theoretical and empirical claims, we hypothesize that prior knowledge, self-efficacy and task value influence differences in use of the four components and that students' cognitive and motivational characteristics can influence students' learning gain. Therefore, we formulate following first research question (RQ):

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

Differences in use of online learning components can influence students' performance. Lust, Juarez Collazo, Elen and Clarebout (2012) conducted a literature study which provided empirical evidence for the beneficial influence of differences in tool use (e.g., information, processing and scaffold tools), on students' performance [25]. Therefore in this study activity data of the four different components is studied separately in order to gain more insight in how students' differences in use of the four components contributes to performance, controlling for students' cognitive and motivational characteristics. Subsequently the following second research question is formulated:

RQ2: *Does differences in use of the four components of a 4C/ID-based online learning environment influence students' learning gain, taken into account students' cognitive and motivational characteristics?*

Based on these research questions a theoretical research model is proposed as shown in Fig. 1 containing all variables in order to elucidate the relationships among these variables.

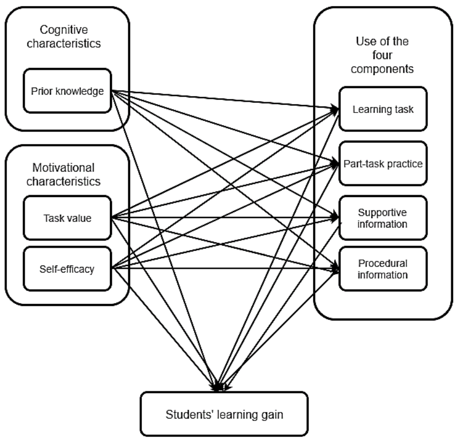

Figure 1: Research model

3 METHODOLOGY

3.1 Study Design

3.1.1 The intervention. The online learning environment in the present study focuses on French as a foreign language. In Flemish education students generally start learning French at the age of 10 in Grade 5. French is always the first second language that is introduced into the curriculum and remains a compulsory component throughout primary and secondary education. Accordingly, 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. The main topic is 'travelling in France'. The learning environment covers four task classes. Each task class focuses on a theme (e.g., ordering your food in a restaurant). The online learning environment takes about 1 hour and 15 minutes to complete. The learning environment contained multiple media: videos, recorded audio and articles from different websites and is designed within the Moodle open-source learning platform. The instructional design of the online learning environment was developed along the principles of the 4C/ID model. The learning tasks were based on authentic situations and sequenced in an simple-to-complex order. Each learning task started with an introduction where a worked example was given combined with clearly defined course objectives. Students received automatic generated feedback based on their scores (i.e., information about their achievements and guidelines). When students had an insufficient score they were advised to consult additional support and/or consult additional tasks in order to pass the learning task. When students finished their learning tasks, they had to hand in an assignment (e.g., writing down a conversation). The assignments were corrected by the instructor. Additional support and tasks were provided by the other three components of the 4C/ID-model, namely, supportive information (e.g., grammar explained by theory), procedural information (e.g., grammar explained by using keywords) and part-task practice (e.g., drill-and practice exercise of specific grammar). The supportive information, procedural information and part-task practice were non-embedded. More specifically, they were at the disposal of the students but the students had to decide whether or not to use them, and when they wanted to use them. Students had the opportunity to click on links to watch procedural or supportive information or to consult additional part-task practice (automatically rated by Moodle). In conclusion, consulting supportive and procedural information, making additional part-task practice or retrying a learning task was the students' responsibility. 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 since they were clustered and sequenced in a predefined order within a task class.

3.1.2 Participants. The study took place in the Flemish part of Belgium, at a Flemish university. The 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). Two students were perfectly bilingual (i.e. French and Dutch speakers). One student was German and had never learned French. Participation to research is part of the students training program, but French was not a part of their training program. Before answering the questions, informed consent was obtained from all individual participants included in the study.

3.1.3 Procedure. The design of the study consisted out of two administration sessions. The first administration session started with an introduction of the online learning environment and self-reported questionnaire on task value and self-efficacy. Task value and self-efficacy were measured after the introduction of the online learning environment to make sure students' had sufficient insight into the learning content. The students were asked to use the learning environment at home during two weeks. As the learning content was not a part of their training program, they received the instructions that consulting the four components was optional and that there was no strict trajectory on how to work in the online learning environment. Nevertheless, consulting the learning tasks was strongly recommended. This implies that a lot of learner control was given to the students.

3.2 Measurement Instruments

3.2.1 Prior knowledge and students' learning gain. To measure students' prior knowledge and students' learning gain of French a quantitative paper-and-pencil instrument constructed by Evens, Elen and Depaepe (2017) was used as pretest and posttest. 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 [26]. In this study students' learning gain are the results of the posttest, controlled for the pretest. The instruments' reliability was explored by calculating internal consistency, that is, Cronbach's α = .90 for the pretest and Cronbach's α = .89 for the posttest. Both results reveal a good internal consistency.

3.2.2 Self-efficacy and task value. Within this study the constructs self-efficacy and task value were retrieved from the motivated strategies for learning questionnaire (MSLQ) constructed by Pintrich and De Groot (1990). MSLQ consists of a motivation section and a learning section [27]. For this study we used the constructs self-efficacy (e.g., "I expect to do well in this course"), and task value e.g. ("It is important for me to learn the course content"), of the motivation section. The questionnaire was a 5-item scale with a 7-point Likert-type response format having 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 CFA model relates observed responses or 'indicators' to latent variables (i.e., measurement model). CFA indicated that the measurement model exhibited a good validity. The standardized factor loadings from the latent variable constructs were all significant with standardized values ranging from .73 to .93. and an average variance explained (AVE) of .76 for self-efficacy and .62 for task value. We can therefore suggest that the two measurement models for each construct were measured well in the current data. Internal consistency was investigated by measuring Cronbach's Alpha. The Cronbach's Alpha for self-efficacy was α = . 94 and for task value α = .84, which indicates high reliability [28].

3.2.3 Use of the different components. Information of students' use of the four components was collected by tracking students' activity. Students' activity includes any kind of interaction (e.g., views, attempts, submitting quizzes etc.) with the online learning environment during two weeks, tracked for each component of the 4C/ID-model separately. All data were anonymized through means of the use of random codes to safeguard the identities of the students. User activity was chosen instead of time spent because it gave more accurate information about the use of supportive and procedural information.

3.3 Analysis

Firstly, descriptive analyses such as mean, standard deviation and correlation analysis were conducted for the different variables (i.e., students characteristics and the four components of the 4C/ID model). Secondly, in order to find answers on the first research aim the effect of students' motivational and cognitive characteristics (i.e., latent variables), on the use of the four components (i.e., manifest) variables, was investigated by conducting SEM in R using the Lavaan package 3.4.0 [28]. Fig. 1 was specified as the statistical model using the latent variables as shown in Fig. 2 . SEM is a statistical approach to test hypotheses about the relationships among observed/manifest (i.e., rectangles) and latent variables (i.e., ovals). As shown in Fig. 2, self-efficacy and task value are the latent constructs. In the current study, in order to answer the first research question, students' cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics are the independent variables and the four components (i.e., learning task, part-task practice, supportive and procedural information) are the dependent variables. Additionally, to give answer to the second research question, the use of the four components, and students' cognitive and motivational characteristics are the independent variables, and students' learning gain the main dependent variable.

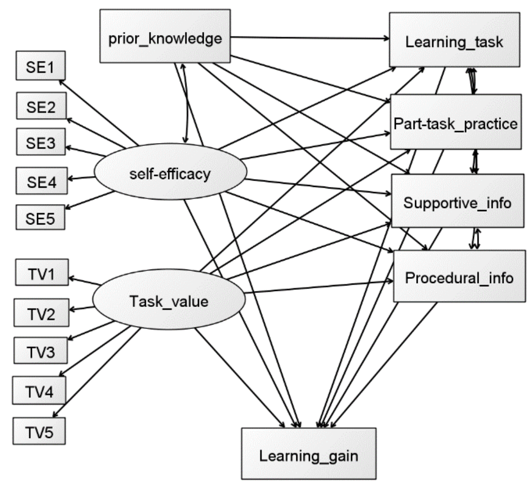

Figure 2: Statistical model

RESULTS

4.1 Preliminary Analysis

Results of the descriptive statistics of students' pretest and posttest can be found in Table 1. The average results on students' pretest was 52.32%. The average score on the posttest was 64.53%. This indicates that using the online learning environment improved their performance. Nearly all students consulted the learning tasks (*N* = 158). Not all students consulted supportive information (*N* = 125), procedural information (*N* = 140) and/or consulted part-task practice (*N* = 72). The average time spent on using the online learning is 66 minutes (*SD* = 27.34, *min.* = 10.44 minutes, *max.* = 151.43 minutes).

Table 1: Descriptive statistics of the manifest variables

Variable	N	Min	Max	Mean	SD
Pretest	151*	7.8	92.19	52.32	17
Posttest	152*	20.97	98.44	64.53	14.81
Learning task	158	15	180	80.60	25.90
Part-task Practice	161	0	85	10.50	19.85
Supportive info	161	0	64	9.04	10.94
Procedural info	161	0	36	9.30	8.52

Note. Not all students were present during the pretest/posttest. Results of the two bilingual students and the German student were removed as outliers.

4.2 Correlations Among the Variables

Table 2 gives an overview of the correlations among the variables. RQ1 investigates the influence of students' cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics on the use of the different components (i.e., use of the learning tasks, part-task practice, supportive and procedural information). There is a negative significant correlation between prior knowledge and part-task practice. Additionally, there is a negative significant correlation between prior knowledge and supportive information. There is a positive significant relationship between task value and learning tasks. Additionally there is a positive significant relationship between task value and supportive information. There are no significant relations between self-efficacy and use of the four components. RQ2 investigates the influence of the use of the different components on students' learning gain, taken into account students' cognitive and motivational characteristics. Results reveal that there is no significant relationship between the posttest and the components. Furthermore, results reveal a positive significant correlation between pretest, self-efficacy and posttest. Additionally, there is a positive significant correlation between self-efficacy and posttest.

Table 2: Correlations among the variables

	1	2	3	4	5	6	7	8
1.Pretest	1							
2.Self-E	.48**	1						
3.Task_V	.06	.28**	1					
4.Learn	-.12	.06	.22**	1				
5.Part_T	-.18**	-.00	.04	.31**	1			
6.Supp_I	-.18*	-.12	.18*	.38**	.58**	1		
7.Proc_I	-.08	-.07	.08	.22*	.09	.25**	1	
8.Posttest	.87**	.42**	.11	.02	-.14	-.10	.01	1

**correlation is significant at the .01 level; *correlation is significant at the .05 level

4.3 Structural Model

SEM was conducted in order to investigate the relationships between students ' cognitive and motivational characteristics, the four components of the 4C/ID-model and students' learning gain (i.e., RQ1 and RQ2). 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 [29]. Lavaan converged normally after 59 iterations. The hypothesized model, provided an adequate fit to the given data. 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, this is, χ^2-test divided by the degrees of freedom (*df*). Values smaller than 2.0 are considered to indicate acceptable fit [28]. 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. Table 3 summarizes the overall goodness-of fit measures of the model. SRMR is the difference between the observed variance and the predicted variance. A value less than .06 is considered a good fit. RMSEA is related to residuals in the model, by adjusting for the complexity of the model and the size of the sample. A marginal value for acceptance is < .08. CFI is the discrepancy function adjusted for the sample size. 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 for further analysis [28, 30, 31].

Table 3: Fit statistics for the measurement model

Fit measures	Values	Recommended value
Chi-square (χ^2)	155.56 (df = .99, p = .00)	non-significant
Normed Chi-square	1.6	X^2/df <.02
SRMR	.05	< .06
RMSA	.06	< .08
CFI	.97	> .95
TLI	.95	> .95

Using SEM analysis we firstly investigated the influence of students' characteristics on the four components of the 4C/ID model (i.e., RQ1). Fig. 3 gives an overview of the standardized path coefficients. The solid lines show the significant relationships. Significant relationships between students' cognitive and motivational characteristics and use of the four components were found. More specifically, a significant negative influence was found of students' prior knowledge on the use of part-task practice (β = -.21, p <.05). No significant relationships were found between students' self-efficacy and the use of the four components of the 4C/ID-model. Task value positively influences the use of learning task (β = .21, p <.05) and supportive information (β = .22, p <.05). The variance explained for the learning task is respectively (R^2 =.07), for part-task practice (R^2 =.03), for supportive information (R^2 =.08) and for procedural information (R^2 =.02).

RQ2 investigated the influence of the use of the four components on students' learning gain, taking into account students' characteristics. Significant relationships were found between the use of different components and students' learning gain. Respectively, a significant influence of the use of learning tasks (β = .12, p <.01) and procedural information (β = .08, p <.05) on students' learning gain was found. A positive significant relationships between students' prior knowledge on students' learning gain was found (β = .91, p <.001). No further relationships between students' motivational characteristics and their learning gain were found. The variance explained for students' learning gain was (R^2 = .79). In conclusion, students' use of the components of the 4C/ID model is negatively influenced by students' prior knowledge and positively by students' task value. Secondly, results indicate that when using a 4C/ID-based online learning environment, mainly using the learning tasks and procedural information contributes to students' learning gain. Additionally, students' learning gain is mainly influenced by their prior knowledge.

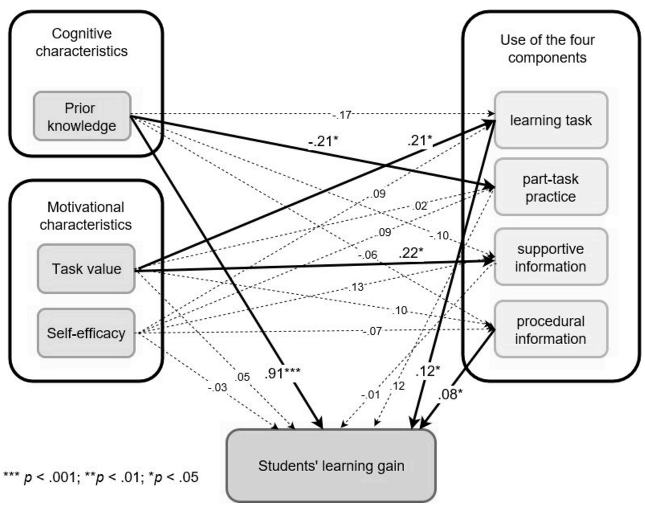

Figure 3: Structural model with standardized path coefficients

5 DISCUSSION

5.1 The Research Model

The current study strived to investigate (1) the influence of students' cognitive (i.e., prior knowledge), and motivational (i.e., task value and self-efficacy), characteristics on students' differences in use of the four components (i.e., RQ1) and (2) the influence of students' differences in use on students' learning gain, taken into account students' cognitive and motivational characteristics (i.e., RQ2). All variables were incorporated in a structural research model. Our results are based on data from a pretest (i.e., prior knowledge), self-reported questionnaires (i.e., task value and self-efficacy), platform log data from 161 students (i.e., activity of the four components of the 4C/ID-model) and a posttest, controlled for the pretest (i.e., students' learning gain). RQ1 investigates the influence of students' cognitive and motivational characteristics on differences in use of the four components. Results indicate that students' prior knowledge has a negative significant influence on the use of part-task practice. More specifically, results reveal that the lower students' prior knowledge was, the more students consulted additional part-task practice. Part-task practices contain additional exercises with more recurrent content in a drill and practice- format in order to prepare students to solve the learning tasks which contain both recurrent and non-recurrent content. Therefore, the current findings indicate that in general students seem to be aware that they are lacking routine knowledge to solve the learning tasks, and subsequently they self-direct their learning in order to achieve better results. Taking into account cognitive load theory, these results could imply that students did not experience high intrinsic cognitive load, as they were still able to self-direct their learning [13]. The current findings are in contrast to the study of Taub et al. (2014) which indicated that regardless of the sub-goals students were working on, there were no significant differences in students' use of the online learning environment (i.e., defined by the number of relevant pages visited) between lower and higher prior knowledge groups. Current findings are also different from the study of Jiang et al. (2009) who measured differences of use based on prior knowledge by looking at the frequency of tool use and proportional time spent on tools, but found no differences [6, 18]. A possible explanation for the different findings could be found in the respective procedure of the studies. Concretely, in both studies students worked with the online learning environment under supervision or in a controlled setting. By controlling the setting students might feel the pressure to complete different tasks in a given time which could result in following a more traditional linear path. Moreover, important self-regulation skills that are typical for online learning are not taken into account when the setting is controlled, such as time management (i.e., the ability to effectively manage learning) and environment structuring (i.e., being able to structure your own learning environment) [32,33]. These self-regulation skills could have an influence on differences in use between different prior knowledge groups. Furthermore, looking at the study of Taub et al. (2014) defining differences in use based on relevant pages visited might have been too narrow. In the study of Taub et al. (2014), multichannel data was collected including log-files, but also think-aloud protocols, electrodermal activity (EDA), facial expressions and eye-tracking to measure metacognitive and cognitive self-regulation. Based on multichannel data results did reveal that metacognitive self-regulation processes differed between lower and higher prior knowledge groups which indicates that prior knowledge groups do differ in how they use the online learning environment and/or self-direct their learning, but that the differences were not visible based on the relevant pages visited. Not only prior knowledge but also motivational characteristics seem to influence differences in students' use of the different components. Results indicate differences in activity based on students' task value. Prior research on expectancy-value theory has indeed shown that after controlling for prior knowledge, task value can predict differences in academic decisions [5]. Students' task value seems to have a positive influence on the activity of the learning tasks and supportive information. As supportive information provided broader background information this could imply that students with higher task value put more effort in solving the learning tasks qualitatively and/or are more eager to learn. The findings correspond with the study of Martens et al. (2004) which also analyzed log files and found that students with high intrinsic motivation showed more explorative study behavior. Explorative study behavior in their study was calculated by dividing the number of explorative pages a student had visited by the total number of visited pages [22]. Studying the influence of self-efficacy on the activity of the four components, no link between self-efficacy and the use of the four components was found. As correlations indicated that self-efficacy and prior knowledge were highly correlated. This indicates that in general students from this study could properly assess themselves. Moreover, this indicates that they did not feel the need to self-direct their learning in order to reach a certain quality standard [5].

RQ2 investigated the impact of differences in use of the four components on students' learning gain, taken into account students' characteristics. Results revealed a significant influence of students' use of the online learning environment on students' learning gain. Results indicate that activity of the learning tasks, and procedural information contributed to students' learning gain. These results indicate that the more learning tasks and procedural information were consulted, the higher students' learning gain. Procedural support and guidance can prevent learners from paying attention to irrelevant task aspects, and is therefore argued to reduce extraneous cognitive load, which on its turn can improve students' task performance [4,11,13]. This could be the reason why procedural information contributes to performance within this study. Activity of the supportive information and part-task practice did not contribute to course performance. This could be due to the fact that the learning tasks were not complex enough. Consulting procedural information must have been sufficient for students to solve the learning tasks. Accordingly, students did not feel the need to consults these components. When investigating the influence of differences in use on students' learning gain, it is important to take students' characteristics into account. Results revealed a major significant influence of students' prior knowledge on students' learning gain. Correlations already indicated that pretest and posttest were highly correlated. This indicates that students' learning outcomes were mainly influenced by students' prior knowledge. This is in line with previous research. The study of Song et al. (2016) already revealed a direct effect of prior knowledge on performance [17]. There was no effect of students' motivational characteristics on students' learning gain. More specifically, no significant effect of students' self-efficacy on students' learning gain was found. These findings are in contrast with the study of Joo et al. (2013) but are in line with those of the study of Song et al., (2016). Song et al. (2016) did not find a significant relationship between self-efficacy and students' learning outcome. A possible explanation for these different findings is that the online learning environment used in their study was highly complex [18,21]. Former studies have indicated that efficacious students can be less confident when they are challenged with challenging learning environments [34]. Different outcomes can also be influenced by the design of the research model. In contrast to the current study and the study of Song et al. (2016), Joo et al. (2013) did not incorporate prior knowledge into the research model as a predictor of students' learning outcome. Furthermore, students' task value has no influence on students' learning gain. However, this finding is in contrast with the study of Joo et al. (2013). They have conducted SEM analysis with self-efficacy and task value as predictors of performance and found a direct influence of task value on students' learning outcome [21]. It should be noted that the students in the study of Joo et al. (2013) were enrolled in an online university, which possible had an influence on the level of students' motivation. Therefore, possible clarification for the different findings is that students' task value in the current study was generally too low to have an effect on performance, since the online course was not a part of the students' study program.

5.2 Limitation and Future Research

A first important limitation of this study is that students' cognitive (i.e., prior knowledge) and motivational characteristics (i.e., task value and self-efficacy) explain little variance of the use of the different components. This implies that more predictors should be incorporated into the model to predict differences in use. In the current study a possible predictor of differences in use and students' learning gain is students' self-regulation skills. The influence of students' self-regulation skills is very important since online learning offers a lot of learner control and therefore gives the students a great degree of autonomy [18, 35]. Incorporating self-regulation skills in the research model could give more insight in why students use specific components during their learning process. A second important limitation is that little is known about the way in which the different components are used. By analyzing log-data more in detail, such as, looking at the sequences of use of the four components, more insight could be given on effective use. A possible example of effective use could be that when a student has an insufficient score, the student decides to consult supportive information. Subsequently, this detailed information could give more insight into their self-directed learning. A third limitation is that one component can contain a lot of different learning activities (e.g., quiz, reading and/or listening activity). More detailed studies are needed to measure the influence of the various learning activities. This could provide more insight in how to design tailor-made online learning environments [2]. Fourthly, the current study was conducted in an experimental setting.

Accordingly, students mainly used the online learning environment to accomplish the learning tasks, but not to study the specific content. More research needs to be done in contexts in which courses are actually part of the training program in order to have more knowledge about how students actually study in a 4C/ID based online learning environment. A fifth limitation is the cross-sectional design of this study. It would be interesting to conduct longitudinal research instead. This would provide insight into how students study within an online learning environment and how this influences students' learning and educational outcomes in the long term. Finally, future work should replicate and extend the current findings with other 4C/ID-based online learning environments and other target groups, to test generalizability. Former research has shown that students' use of online resources and their performance varied between courses, and that this strongly depends on the instructional design [36].

6 CONCLUSION

This study firstly provides more information about the influence of students' motivational and cognitive characteristics on the use of the four components in a 4C/ID-based learning environment. In general, results indicate that students' characteristics do influence differences in use of the four components when students receive a lot of learner control. Moreover, the 4C/ID-model seems to be an instructional design model that is adequate for students with different characteristics. It allows students to self-direct their learning by providing four components that can be consulted freely in a non-linear trajectory. Furthermore, the use of learning tasks and procedural information controlled for students' prior knowledge, seems to influence students' learning gain directly. This indicates the importance of combined use of learning tasks and procedural information. More insight into how students differ in use, based on their characteristics is an important step from an instructional design perspective. This could provide important suggestions for designing online learning environments that improves students' learning gain by allowing them to self-directed their learning to fulfill their personal needs.

REFERENCES

[1] Van Laer, S. and Elen, J. 2017. In search of attributes that support self-regulation in blended learning environments. *Education and Information Technologies.* 22, 4 (2017), 1395–1454. DOI: https://doi.org/10.1007/s10639-016-9505-x.

[2] Rienties, B. and Toetenel, L. 2016. The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules. *Computers in Human Behavior.* 60, (2016), 333–341. DOI: https://doi.org/10.1016/j.chb.2016.02.074.

[3] Cook, D.A. and McDonald, F.S. 2008. E-learning: is there anything special about the "E"? *Perspect Biol Med.* 51, 1 (2008), 5–21. DOI: https://doi.org/10.1353/pbm.2008.0007.

[4] Van Merriënboer, J.J.G. and Sluijsmans, D.M.A. 2009. Toward a synthesis of cognitive load theory, four-component instructional design, and self-directed learning. *Educational Psychology Review.* 21, 1 (2009), 55–66. DOI: https://doi.org/10.1007/s10648-008-9092-5.

[5] Greene, J.A. and Azevedo, R. 2007. A Theoretical Review of Winne and Hadwin's Model of Self-Regulated Learning: New Perspectives and Directions. *Review of Educational Research.* 77, 3 (2007), 334–372. DOI: https://doi.org/10.3102/003465430303953.

[6] Jiang, L., Elen, J. and Clarebout, G. 2009. The relationships between learner variables, tool-usage behaviour and performance. *Computers in Human Behavior.* 25, 2 (2009), 501–509. DOI: https://doi.org/10.1016/j.chb.2008.11.006.

[7] Rienties, B., Tempelaar, D., Van den Bossche, P., Gijselaers, W. and Segers, M. 2009. The role of academic motivation in Computer-Supported Collaborative Learning. *Computers in Human Behavior.* 25, 6 (2009), 1195–1206. DOI: https://doi.org/10.1016/j.chb.2009.05.012.

[8] Lust, G., Elen, J. and Clarebout, G. 2013. Students' tool-use within a web enhanced course: Explanatory mechanisms of students' tool-use pattern. *Computers in Human Behavior.* 29, 5 (2013), 2013–2021. DOI: https://doi.org/10.1016/j.chb.2013.03.014.

[9] Elen, J. Technologie en onderwijs: onderwijskundige beschouwingen. In *Muziekpedagogiek in beweging: technologie als medium.* Nijs, L. and De Baets, T. (Eds). Euprint Editions, Heverlee, 15-26.

[10] van Merriënboer, J.J.G., Clark, R.E. and de Croock, M.B.M. 2002. Blueprints for complex learning: The 4C/ID-model. *Educational Technology Research and Development.* 50, 2 (2002), 39–61. DOI: https://doi.org/10.1007/BF02504993.

[11] van Merrienboer, J.J.G., Kirschner, P.A. and Kester, L. 2003. Taking the Load Off a Learner's Mind: Instructional Design for Complex Learning. *Educational Psychologist.* 38, 1 (2003), 5–13. DOI: https://doi.org/10.1207/S15326985EP3801_2.

[12] Merrill, M.D. 2002. First principles of instruction. *Educational Technology Research and Development.* 50, 3 (2002), 43–59. DOI: https://doi.org/10.1007/BF02505024.

[13] Van Merriënboer, J.J.G. and Sweller, J. 2005. Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review.* 17, 2 (2005). DOI: 10.1007/s10648-005-3951-0 Clarebout, G.,

[14] Horz, H., Schnotz, W. and Elen, J. 2010. The relation between self-regulation and the embedding of support in learning environments. *Educational Technology Research and Development.* 58, 5 (2010), 573–587. DOI: https://doi.org/10.1007/s11423-009-9147-4.

[15] Moos, D.C. and Azevedo, R. 2009. Self-efficacy and prior domain knowledge: To what extent does monitoring mediate their relationship with hypermedia learning? *Metacognition and Learning.* 4, 3 (2009), 197–216. DOI: https://doi.org/10.1007/s11409-009-9045-5.

[16] Van Seters, J.R., Ossevoort, M.A., Tramper, J. and Goedhart, M.J. 2012. The influence of student characteristics on the use of adaptive e-learning material. *Computers and Education.* 58, 3 (2012), 942–952. DOI: https://doi.org/10.1016/j.compedu.2011.11.002.

[17] Taub, M., Azevedo, R., Bouchet, F. and Khosravifar, B. 2014. Can the use of cognitive and metacognitive self-regulated learning strategies be predicted by learners' levels of prior knowledge in hypermedia-learning environments? *Computers in Human Behavior.* 39, (2014), 356–367. DOI: https://doi.org/10.1016/j.chb.2014.07.018.

[18] Song, H.S., Kalet, A.L. and Plass, J.L. 2016. Interplay of prior knowledge, self-regulation and motivation in complex multimedia learning environments. *Journal of Computer Assisted Learning.* 32, 1 (2016), 31–50. DOI: https://doi.org/10.1111/jcal.12117.

[19] Chen, K.C. and Jang, S.J. 2010. Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior.* 26, 4 (2010), 741–752. DOI: https://doi.org/10.1016/j.chb.2010.01.011.

[20] Liem, A.D., Lau, S. and Nie, Y. 2008. The role of self-efficacy, task value, and achievement goals in predicting learning strategies, task disengagement, peer relationship, and achievement outcome. *Contemporary Educational Psychology.* 33, 4 (2008), 486–512. DOI: https://doi.org/10.1016/j.cedpsych.2007.08.001.

[21] Zimmerman, B.J. 2000. Self-Efficacy: An Essential Motive to Learn. *Contemporary Educational Psychology.* 25, 1 (2000), 82–91. DOI: https://doi.org/10.1006/ceps.1999.1016.

[22] Joo, Y.J., Lim, K.Y. and Kim, J. 2013. Locus of control, self-efficacy, and task value as predictors of learning outcome in an online university context. *Computers and Education.* 62, (2013), 149–158. DOI: https://doi.org/10.1016/j.compedu.2012.10.027.

[23] Martens, R.L., Gulikers, J. and Bastiaens, T. 2004. The impact of intrinsic motivation on e-learning in authentic computer tasks. *Journal of Computer Assisted Learning.* 20, 5 (2004), 368–376. DOI: https://doi.org/10.1111/j.1365-2729.2004.00096.x.

[24] Bong, M. 2001. Role of Self-Efficacy and Task-Value in Predicting College Students' Course Performance and Future Enrollment Intentions. *Contemporary Educational Psychology.* 26, 4 (2001), 553–570. DOI: https://doi.org/10.1006/ceps.2000.1048.

[25] Lust, G., Juarez Collazo, N.A., Elen, J. and Clarebout, G. 2012. Content

Management Systems: Enriched learning opportunities for all? *Computers in Human Behavior.* 28, 3 (2012). 795-808. DOI: https://doi.org/10.1016/j.chb.2011.12.009

[26] Evens, M., Elen, J. and Depaepe, F. In Press. Effect of opportunities to learn in teacher education on the development of teachers' professional knowledge. *Journal of Advances in Education Research*

[27] Pintrich, P.R. and de Groot, E. V. 1990. Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology.* 82, 1 (1990), 33–40. DOI: https://doi.org/10.1037/0022-0663.82.1.33.

[28] Rosseel, Y. 2012. lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software.* 48, 2 (2012), 1–36. DOI: https://doi.org/10.18637/jss.v048.i02.

[29] Savalei, V. and Bentler, P.M. 2009. A Two-Stage Approach to Missing Data: Theory and Application to Auxiliary Variables. *Structural Equation Modeling: A Multidisciplinary Journal.* 16, 3 (2009), 477–497. DOI: https://doi.org/10.1080/10705510903008238.

[30] Kline, R.B. 2011. *Principles and Practice of Structural Equation Modeling* (4the. Ed.). The Guildford Press. New York

[31] Hu, L.T. and Bentler, P.M. 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling.* 6, 1 (1999), 1–55. DOI: https://doi.org/10.1080/10705519909540118.

[32] Barnard-Brak, L., Paton, V.O. and Lan, W.Y. 2010. Self-regulation across time of first-generation online learners. *ALT-J: Research in Learning Technology.* 18, 1 (2010), 61–70. DOI: https://doi.org/10.1080/09687761003657572.

[33] J. J. G. van Merriënboer, R.E. Clark and M.B. de Croock. 2002. Bleuprints for complex learning: the 4C/ID-model. *Educ Technol Res Dev* 50, 2 (Jun. 2002), 39-40. Retrieved from https://link.springer.com/article/10.1007/BF02504993

[34] Greene, J.A., Moos, D.C., Azevedo, R. and Winters, F.I. 2008. Exploring differences between gifted and grade-level students' use of self-regulatory learning processes with hypermedia. *Computers and Education.* 50, 3 (2008), 1069–1083. DOI: https://doi.org/10.1016/j.compedu.2006.10.004.

[35] Tsai, C.W. 2013. An effective online teaching method: The combination of collaborative learning with initiation and self-regulation learning with feedback. *Behaviour and Information Technology.* 32, 7 (2013), 712–723. DOI: https://doi.org/10.1080/0144929X.2012.667441.

[36] Jeong, H. and Hmelo-Silver, C.E. 2010. Productive use of learning resources in an online problem-based learning environment. *Computers in Human Behavior.* 26, 1 (2010), 84–99. DOI: https://doi.org/10.1016/j.chb.2009.08.001.