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Mine, ours, and yours: Whose engagement and prior knowledge affects individual achievement from online collaborative learning?

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Abstract

In computer-supported collaborative learning research, studies examining the combined effects of individual level, group level and within-group differences level measures on individual achievement are scarce. The current study addressed this by examining whether individual, group and within-group differences regarding engagement and prior knowledge predict individual achievement. Engagement was operationalised as group members' exhibited activities in the task space (i.e., discussing domain-content) and social space (i.e., regulating ideas, actions and socioemotional processes). Prior knowledge and achievement were operationalised as group members' performance on a domain-related pre-test and post-test, respectively. Data was collected for 95 triads of secondary education students collaborating on a complex business-economics problem. Subsequently, three different multilevel models were tested to examine the combined effect. First a model with the individual level measures (model 1) was tested and in subsequent models the group level measures (model 2) and within-group levels measures (model 3) were added. Findings indicate model 2 showed the best fit; group members' individual engagement in the social space activities as well as the groups' average prior knowledge positively predicts individual achievement. No effects were found for either group members' or groups' engagement in the task space and for the within-group differences.

KEYWORDS

collaborative learning, student engagement, student individual achievement, secondary education

1 | INTRODUCTION

Computer-supported collaborative learning (CSCL) is an instructional strategy in which collaborative learning is combined with the use of information and communication technology. By providing CSCL-environments, instructional designers hope to foster both group and individual achievement (Jeong & Hmelo-Silver, 2016; Stahl, Cress, Ludvigsen, & Law, 2014). Meta-analyses have revealed that when students learn collaboratively—online as well as face-to-face (F2F)—they exhibit better achievement, such as higher scores on knowledge tests and better problem-solutions, than working individually (Chen, Wang, Kirschner, & Tsai, 2018; Raes, Kyndt, Decuyper, van den Bossche, & Dochy, 2015). Important here is that the effectiveness of the collaborative endeavour, depend heavily on whether groups are able to adequately cope with factors that have been found to impede collaboration (de Dreu & Weingart, 2003; Lee, Huh, & Reigeluth, 2015), such as:

- not developing a well-developed understanding the domain-content and/or applying that understanding to the task,
- group members hoarding (i.e., not sharing) information and being unaware of each other's activities, and
- inadequately dealing with personal conflict within the group.

Process-oriented studies indicate that more effective groups are better able to cope with the impediments since they engage in activities in the task space as well as the social space (Barron, 2003; Fransen, Weinberger, & Kirschner, 2013; Kirschner, Kreijns, Phielix, & Fransen, 2015; Sinha, Rogat, Adams-Wiggins, & Hmelo-Silver, 2015). For the *task space* this means that group members must gain a proper insight into the domain-content and apply this to successfully carry out a task. This usually involves engaging in activities such as critically discussing ideas about (a) the task's goal, (b) the domain-related concepts and principles required for carrying out the task and (c) the best strategy for carrying out the task (Slof, Erkens, Kirschner, Jaspers, & Janssen, 2010; van Blankenstein, Dolmans, van der Vleuten, & Schmidt, 2013). Properly discussing the domain-content with others may stimulate students to integrate new information with their prior knowledge and consequently foster individual achievement (Stegmann, Wecker, Weinberger, & Fischer, 2012; Zheng & Warschauer, 2015). For the *social space* this means that group members have to engage in activities to regulate their own and each other's ideas, actions and socioemotional processes (van den Bossche, Gijselaers, Segers, Woltjer, & Kirschner, 2011; Volet, Summers, & Thurman, 2009). To this end, group members should create a shared topic of discourse and restore their focus when divergence occurs (Beers, Boshuizen, Kirschner, & Gijselaers, 2007; Erkens, Jaspers, Prangsma, & Kanselaar, 2005). Since not all concepts that are mentioned during discussion may be relevant, group members should also check the coherence of their shared understanding by giving a confirmative response or a denial when group members ask questions (Clark & Brennan, 1991). Regulation also requires that group members make their viewpoint and associated argumentation explicit. Arguments may facilitate knowledge construction processes if group members properly explain, justify and account for their viewpoints, and when they come to an agreement that is acceptable to all (Asterhan & Schwarz, 2016; Noroozi, Weinberger, Biemans, Mulder, & Chizari, 2013). Arguments could also make personal conflicts explicit and offer opportunities for resolving them (Belland, Glazewski, & Richardson, 2008).

Research in the CSCL-field has primarily examined specific interventions on group member engagement and the effects of those interventions on achievement. Most common are interventions in which group composition (e.g., gender, prior knowledge, prior team experience) is varied or interventions that offer group members tools (e.g., script, representational, awareness) explicitly designed to support groups to overcome the impediments often associated with collaborative learning are provided (Chen et al., 2018; Jeong & Hmelo-Silver, 2016; Kirschner, Sweller, Kirschner, & Zambrano, 2018; Zambrano, Kirschner, Sweller, & Kirschner, 2019; Zheng, Huang, & Yu, 2014). Such studies mainly focus on gaining insight into the effect of the intervention by examining between-group differences, mostly analysed through overall group-related measures or conducting multilevel analysis (MLA) based on individual group members' measures (Cress, 2008; Janssen, Cress, Erkens, & Kirschner, 2013). In both cases, the analysis is usually solely based on one unit of analysis, either the achievement of the whole group (i.e., task performance, average knowledge test score) or of its individual members (i.e., individual knowledge test score). In other words, less is known about (a) whether an individual member, all members or the other group members should be engaged, and (b) the effect of such engagement on achievement (Grau & Whitebread, 2012; Volet, Vauras, Salo, & Khosa, 2017). Knowing whether and how between- and within-group differences in engagement may affect learning in teams is important as it could provide insight into the mechanisms that seem to help more engaged group members and groups benefit from the collaboration (i.e., higher scores on knowledge tests, better task performance). This in turn could inform the design of CSCL-environments such as deciding how to best allocate members to groups (Kozlov & Große, 2016; Kuhn, 2015) and how to either avoid the aforementioned impediments or provide more tailored support for individual members and groups for overcoming them (Jeong & Hmelo-Silver, 2016; Olsen et al., 2014).

To address this, the current study examines the effects of two types of engagement (i.e., task and social space) at the individual level, group level and within-group differences level and prior knowledge on individual achievement. By doing so, the effect of engagement and prior knowledge can be determined for each separate level, namely the (a) individual (i.e., mine), (b) group (i.e., ours) and (c) within-group differences (i.e., yours).

2 | GROUP MEMBERS' ENGAGEMENT AND PRIOR KNOWLEDGE: MINE, OURS AND YOURS?

Research on the social space has revealed that when all group members are actively engaged in regulatory activities, this predicts higher knowledge test scores and better task performance (van den Bossche et al., 2011; Volet et al., 2009). By contrast, there are also studies where no relation was found between-group members' engagement in regulatory activities and achievement (Schoor & Bannert, 2012). A recent review by Levine (2018) indicated that sharing ideas, actions and socioemotional processes does not always lead to consensus. Even when consensus is reached, this is not necessarily beneficial for achievement. Due to personal preferences, members may choose to

(a) only share common instead of unique task strategies, (b) share inaccurate mental models and/or (c) apply (self-)protective relational conflict regulation procedures, leading to superficial agreement which undermines achievement (Levine, 2018). Possible explanations for these contrasting findings might be that CSCL-groups suffer from low engagement and that its members differ in how they engage in the activities (Cress, Kimmerle, & Hesse, 2009; Wise, Speer, Marbouti, & Hsiao, 2013). Some process-oriented studies, therefore, also examined the effects of group members' engagement and prior knowledge at a finer grain size (i.e., within-group differences). Within-group differences regarding group members' engagement might be accounted for by the roles group members adopt during their collaborative endeavour (de Wever, van Keer, Schellens, & Valcke, 2009; Strijbos & Weinberger, 2010). Group members may adopt different roles to allow them to process all task related knowledge and available resources (Hinsz, Tindale, & Vollrath, 1997; Porter, Gogus, & Chien-Feng Yu, 2010). This especially applies to complex problems; the working memory capacity required for the shared processing (i.e., transactional costs) outweighs the costs of processing the knowledge and resources individually (Kirschner et al., 2018).

For example, Benne and Sheats (1948) classified two productive roles, namely, task roles and building and maintaining roles. Task roles are aimed at selecting and defining the task and finding a solution. Group members focus their engagement on ensuring that the group has accurate and relevant information about the task and the domain-content. Building and maintaining roles develop and maintain a shared mental model as well as a group centred identity. Group members focus their engagement on making others aware of conflicting ideas, activities and socioemotional processes and looking for compromises. It is advocated that the functional roles should be flexibly adopted by at least one group member, indicating that it is not necessary that every member actively and equally engages in all activities (Meslec & Curşeu, 2015; Shirouzu, Miyake, & Masukawa, 2002). By contrast, there are also studies showing that an asymmetrical distribution of activities might (e.g., in the case of social loafing) impede achievement for at least some of the group members (Peñarroja, Orengo, & Zornoza, 2017; Simms & Nichols, 2014). Furthermore, there are studies indicating that group members need to regulate their own activities at the individual level but should also ensure that the activities are properly regulated at the group level (Järvenoja, Järvelä, & Malmberg, 2017; Panadero & Järvelä, 2015).

Flexibility can also refer to within-group differences concerning the distribution of prior knowledge which could also affect group members' engagement (Kozlov & Große, 2016; Weinberger, Stegmann, & Fischer, 2010). Prior studies investigated this by pairing group members based on their performance on a prior knowledge test. These studies, however, have led to mixed findings. Webb (1991), for example, revealed that high ability (i.e., more knowledgeable) group members gain higher scores on knowledge tests when they work with low ability (i.e., less knowledgeable) group members, than when they work with other high ability group members. This—partly—aligns with findings of studies investigating the effects of pairing medium ability group members with either high or low ability members, namely that the more knowledgeable member (high and medium ability, respectively) gains the most from the collaborative endeavour (Denessen, Veenman, Dobbelsteen, & van Schilt, 2008). A plausible explanation for these results could be that high ability members benefit from explaining things to less knowledgeable group members, which is often referred to as the self-explanation effect (Hausmann & VanLehn, 2010; Rittle-Johnson & Loehr, 2017). By contrast, other studies found that high ability group members benefit most from a collaborative endeavour with other high ability group members. In this case, it is argued that an unequal distribution of prior knowledge might impede the quality of the domain-related discussion. That is, less knowledgeable group members might easily accept the viewpoint of more knowledgeable group members which often results in discussions with less cognitive conflicts. In turn there is less need for conflict-resolution (i.e., in-depth discussion about the viewpoints) which impedes achievement (Adodo & Agbayewa, 2011; Fuchs, Fuchs, Hamlett, & Karns, 1998). Finally, there are also studies indicating that low ability group members can also benefit from a collaborative endeavour with high ability group members at no additional costs to the high ability member (Hooper & Hannafin, 1988; Kozlov & Große, 2016).

2.1 | Study: Aims and research questions

To our knowledge, CSCL-studies examining the combined effects of individual level, group level and within-group differences level measures on individual achievement are scarce. As such, this study examines the effect of engagement and prior knowledge on multiple levels instead of solely one level (i.e., often the group). By doing so, it can broaden the field's theoretical understanding (i.e., interplay between individual, group and within-group differences levels). It is important to better understand how unproductive engagement in the task and social space can be alleviated and how to remedy prior knowledge deficiencies so as to reduce or even eliminate the impediments that groups and their individual members may encounter. To this end, three different multilevel models are tested to examine the separate and combined effects of the three different measures. First, a model with solely the individual level measures will be tested (model 1), thereafter the group level measures (model 2) and the within-group differences levels measures (model 3) are subsequently added. In this way, this study attempts to answer the following research questions:

1 Does group members' *individual* engagement in the task and social space and individual prior knowledge affect their individual achievement?
2 Does *group* engagement in the task and social space and average group prior knowledge affect group members' individual achievement?
3 Do *within-group differences* regarding engagement in the task and social space and the distribution of prior knowledge in the group affect group members' individual achievement?

3 | METHOD

3.1 | Sampling and participants

The first author arranged the (convenience) sampling by calling and emailing business-economics teachers from several schools. A total of 310 secondary education students at pre-university level from 12 classes at the same grade and educational track (pre-university) within four Dutch high schools participated in this study. The average age of the participants (170 boys and 140 girls) was 16.21 years (*SD* = 0.83, Min = 15, Max = 18). Within classes, participants were randomly assigned to groups and were instructed to solve a complex problem in a CSCL-environment. The problem-solving task, associated materials and knowledge tests were developed in close collaboration with the teachers, ensuring alignment with the business-economics curriculum and consequently the ecological validity of this study. The teacher explained to participants that collaborative problem-solving task performance and individual achievement score would not affect their grades. Participants agreed by giving their passive consent to use and combine the gathered data. Due to restrictions in class size and absence, participants were assigned to 96 triads, nine dyads and one quartet. Since the pressure to contribute is higher in smaller groups and there is less competition for attention in smaller groups, it is likely that group size affects group members' engagement (Laughlin, Carey, & Kerr, 2008). To minimize the effects of group size, only the data from the 96 triads were used for further analysis. For ethical purposes, the authors want to make clear that parts of the reported-on data (and associated methodology) have been used for other publications (Slof et al., 2010; Slof, Erkens, Kirschner, & Helms-Lorenz, 2013; Slof, Nijdam, & Janssen, 2016). The current study, however, has an entirely different scope compared with those publications and the entire dataset will solely be used to answer the current research questions.

3.2 | Collaborative problem-solving task

As part of their business-economics curriculum, the 96 groups were given the task to advise a fictitious company on changing its business strategy, with profit maximisation as the main goal. A sound advice required proper completion of three problem phases, namely (a) determining the main factors that affect the company's results and relate them to the problem (e.g., turnover and cost determine the company result), (b) proposing two interventions aimed at increasing the company's results (e.g., increasing sales by initiating a new advertisement campaign) and (c) comparing financial effect (e.g., does the increased turnover outweigh the additional campaign and production costs?) of both interventions and coming to a final advice. Groups received 180 minutes (i.e., four lessons of 45 minutes) to carry out the task. In the first lesson, participants received information about the assigned task, group composition and CSCL-environment. The teacher was available to answer domain-content related questions and the first author was present for technical support and to ensure treatment fidelity.

3.3 | CSCL environment

Each group member worked on a separate computer with the Virtual Collaborative Research Institute (VCRI)-environment (Jaspers, Broeken, & Erkens, 2004). As depicted in Figure 1, the VCRI used four shared tools. A *chat-tool* to facilitate group members to engage in the task and social space. A text-processer (*co-writer*) facilitated groups to submit their solution for the questions posed in all three problem phases. In the *representational tool*, a concept map of the domain-content (i.e., concepts and interrelationships) was intended to foster a group member's reasoning about the problem-task. The *status bar* displayed which tool a specific group member was using. In addition, an individual tool (*notes*) enabled group members to store information and structure their own knowledge and ideas before making them explicit to others.

3.4 | Measurement group member's engagement

Group members' chat utterances were logged to collect data regarding their engagement in the task and social space. The content of chat-protocols represents what group members know and consider important during their collaborative endeavour (Chi, 1997; Moos & Azevedo, 2008). The multiple episode protocol analysis (MEPA) program (Erkens, 2005) was used to transfer the chat-protocols (i.e., one protocol for each triad) from the log-files. Engagement was measured by counting the activities group members exhibited in the task space (i.e., domain-content) and the social space (i.e., regulation).

Measurement of group members' *engagement in the task space* provided insight into their discussion of the domain-related concepts, interventions and the ways of interrelating them. Problematic here is that within a chat utterance, several concepts can be mentioned requiring multiple codes (Strijbos, Martens, Prins, & Jochems, 2006). This was remedied by segmenting chat-utterances into smaller, still meaningful, subunits. A segmentation MEPA-filter with 300 'if-then' decision rules, based on punctuation marks (e.g., exclamation mark, comma) and connecting phrases (e.g., 'but if'), was used to segment the utterances (see Erkens & Janssen, 2008). After segmentation, the utterances where automatically coded with a domain-content MEPA-filter. Based on 900 'if-then' decision rules, utterances containing explicit references to a concept, solution or relationship (e.g., name, synonyms and so forth) were coded as representing that concept, solution or relationship (see Table 1). That is, each mentioned concept, solution and relationship was counted and an overall score for each category was computed. Through an iterative process of testing and adapting the MEPA-filter, acceptable Cohen's Kappa's were reached (concepts = 0.86, solutions = 0.82 and relations = 0.7) when automatic coding was compared with hand coding of four chat-protocols (a total of 4,198 lines).

Measurement of group members' *engagement in the social space* provided insight into whether group members were able to regulate their collaborative endeavour by (a) having the same focus (i.e., focusing), (b) creating and maintaining a shared understanding (i.e., checking) and (c) negotiating about different perspectives (i.e.,

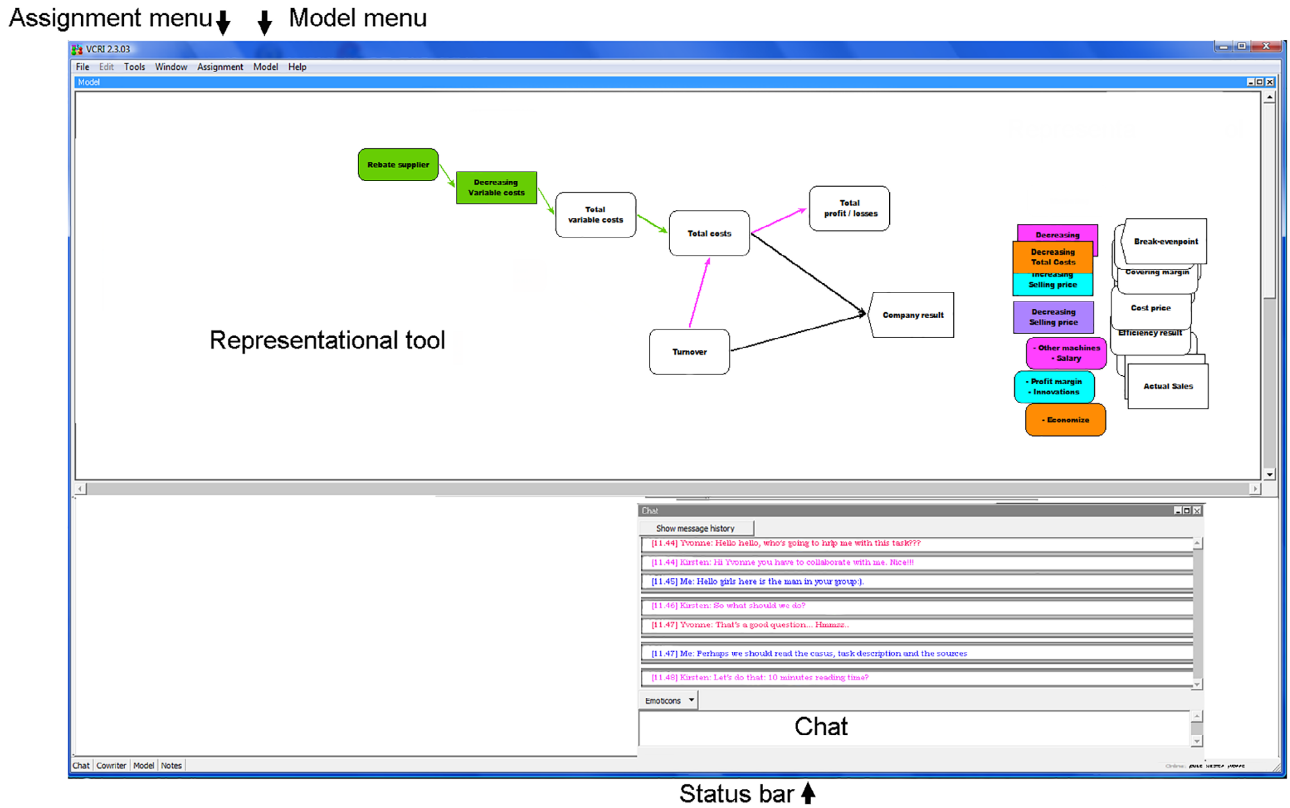

FIGURE 1 Screenshot of the VCRI-environment (based on Slof et al., 2010). VCRI, Virtual Collaborative Research Institute [Colour figure can be viewed at wileyonlinelibrary.com]

argumentation). The chat-protocols were automatically coded with a regulation MEPA-filter (see Erkens & Janssen, 2008) using 1,250 structured 'if-then' decision rules that use pattern matching to find characteristic words or phrases (i.e., discourse markers). The discourse markers, in turn, led to the automatic identification of the communicative function of an utterance (dialogue acts, see Erkens & Janssen, 2008; Mercer, Littleton, & Wegerif, 2004). Then, each specific dialogue act was counted and an overall score for (a) each subcategory (i.e., focusing, checking and argumentation) and (b) the social space (i.e., sum score three categories) was computed. An overview of the dialogue acts and the associated engagement in the social space can be found in Table 2. For the coding of all dialogue acts a Cohen's Kappa of 0.75 and an overall agreement of 79% was reached compared with hand coding, indicating that the automatic coding procedure was reliable (Erkens & Janssen, 2008).

3.5 | Measurement prior knowledge and individual achievement

Prior knowledge and individual achievement were measured with a domain-related knowledge test. A pre-test was administered before the problem-task to determine prior knowledge. Pre-test scores were not used to (re-)assign participants to the 96 groups. The post-test was administered a week after completion of the task to measure individual achievement. Both tests consisted of 27 unique multiple-choice questions constructed by the first author (a former business-economics teacher) in close collaboration with the participating teachers Participants were asked to answer questions such as 'Does an increase in selling price automatically lead to an increase in turnover?'. Due to negative item-rest correlations and low p-values (<.30) seven items for the pre-test and five for the post-test were excluded from further analysis. Pre-test and post-test scores were determined by computing the average score for the remaining items: 20 items (α = .478) for the pre-test and 22 items (α = .626) for the post-test.

3.6 | Analysis of individual, group and within-group differences

Since one group was unwilling to work seriously on the problem-task, data from 95 groups (285 participants) were used to answer the research questions. Sixteen participants were not present when the pre-test was administered. The analysis of individual achievement was thus based on 259 pre-tests scores and 285 post-test scores. Because participants were assigned to groups (i.e., triads) MLA was used to analyse the data. When collaboratively carrying out a task, group members' actions are not independent (a requirement for techniques such as t-tests and analyses of variance); the quality and quantity of their engagement depends—for a large part—on the engagement of

TABLE 1 Coding and category Kappa's (κ_c) MEPA-filter of students' engagement in the task space

Categories	Subcategories	Discussion of	κ_c
Concepts			0.86
	Sales	How many products are sold/have to produced	0.87
	Selling price	What it costs to produce and sell a product and what the customer has to pay for the product	0.50
	Costs	What the overall costs of the company are	0.83
	Turnover	What the total income of the company is	0.93
	Company result	Whether it is profitable to run the company	0.91
Solutions			0.82
	Changing costs	How the overall costs can be decreased	0.86
	Changing turnover	How the turnover can be increased	0.90
	Changing both	The combining of the other two solutions	0.80
Relations			0.70
	Conceptual	The definition/meaning of a concept/solution	0.73
	Causal	The causal relationship within/between concepts/ solutions	0.83
	Mathematical	The quantitative relationships within/between concepts	0.73

TABLE 2 Coding of students' engagement in the social space

Activities	Dialogue act	Description	Example discourse marker
Focusing	Elicitative proposal for action	Proposition for action	Let us start with the first part-task?
	Elicitative question open	Open question with a lot of alternatives	Shall we first look at the description of the assignment or at the description of the part-tasks?
	Imperative action	Command to perform an action	Finish the decision to the second part-task
	Imperative focus	Command for attention	Look at the representational tool!
	Elicitative question verify	Question that can only be answered with yes or no	Do you refer to the company result??
Checking	Elicitative question set	Question where the alternatives are already given (set)	Are you for or against increasing sales?
	Responsive confirm	Confirming answer	Yes, we indeed should start a promotion-campaign
	Responsive deny	Denying answer	No, that is, not a good solution
	Responsive accept	Accepting answer	Oh, Yes that OK
Argumentation	Argumentative reason	Reason	Because this solution does not affect our costs
	Argumentative against	Objection	But this would cost more money
	Argumentative conditional	Condition	If we increase the selling price…
	Argumentative then	Consequence	Then the cost price decreases
	Argumentative disjunctive	Disjunctive	We can increase the actual sales through a promotion-campaign or by decreasing the selling price or by ….
	Argumentative conclusion	Conclusion	Thus, we can conclude that the third solution leads to the best company result.

the other individuals in their group. This interdependence can very strongly affect group members' individual achievement during CSCL as it is at least partially affected by the engagement of the other members of the group as well as of the group as a whole (Garcia, Meagher, & Kenny, 2015). This is a threat to the reliability of more traditional analytical techniques (e.g., *t*-tests, MANOVA). MLA is suited to dealing with this as it can handle the non-independence of observations and missing data. It also has the advantage that the effects of multiple levels (individual, group and within-group differences) can be examined in one model (Cress, 2008; Janssen et al., 2013).

Data were analysed using a random intercept two-level model (students nested within groups). As indicated, three MLA models were computed to examine the combined effects of individual, group and within-group differences level measures. All MLA-models included the following predictor variables: (a) engagement in the task space, (b) engagement in the social space and (c) individual's prior knowledge test score. The first MLA-model consisted solely of the measurements at the individual level (i.e., group members' engagement and their pre-test score as an indication of prior knowledge). The second MLA-model also included measurements at the group level (i.e., group average engagement and group average prior knowledge score). In the final MLA-model, the within-group differences level measurements were added. At the within-group differences level, a Gini coefficient (for a review see Giorgi & Gigliarano, 2016) was used, to compute the (in)equality of the distribution of the measurement scores. A Gini coefficient varies between 0 and 1 whereby a coefficient of 0 represents perfect equality; values are the same for each group member. Perfect equality indicates that there are no within-group differences, and consequently there are no effects of adding this level to the second MLA model. For all measures (i.e., engagement in the task and social space and the pre-test scores) Gini coefficients were computed and included in the third MLA-model as within-group difference level predictor variables. The dependent variable in all three MLA-models was the individual's achievement score (i.e., post-test score). All MLA-models were run in SPSS using maximum likelihood estimation.

4 | RESULTS

4.1 | Descriptive statistics

Table 3 displays the descriptive statistics for all predictor variables and the dependent variable that were included in the MLA-models (see the following section). At the individual level, there were large differences between participants with respect to the number of chat utterances that were coded as engagement in the task and social space ranging, for example, from 0 to 286 activities for engagement in the task space. These differences were also observed at the group level: some groups engaged more extensively in task space (with a maximum observed number of activities of 634), while other groups did this relatively sporadically or not at all. The descriptive statistics with respect to within-group differences indicate that the large variations at the individual and group level are not replicated *within* groups. The average Gini coefficients for engagement and prior knowledge score measures were found to be 0.06, 0.16 and 0.16, and were thus relatively close to 0. In other words, though there are large differences between students and between groups with respect to their engagement, these differences are less pronounced when examining differences between-group members within groups (i.e., variance across groups is large, but is small within groups).

4.2 | Predicting student individual achievement from collaborative learning

We proceeded by conducting MLAs. The random effects part of the empty model (M0), in which no predictors are included, shows that a large part of the variation in the individual achievement scores (42%) is explained by the group level (see Table 4). In the subsequent multilevel models—M1, M2 and M3—predictor variables (i.e., engagement in the task and social space and prior knowledge scores) measured at the individual, group level, as well as within-group differences, were added. Examining the model fit by studying the two log-likelihood statistics in the last row of Table 4, reveals that M1 and M2 fit the data better than the empty model (with lower values indicating better model fit). Thus, adding predictor variables at the individual and the group levels significantly increased the explained variance. However, the model fit of M3 is not significantly better than M2; adding variables reflecting within-group differences, thus, did not lead to an increased explained variance. This finding is in line with the low Gini

TABLE 3 Descriptive statistics for predictor variables and individual achievement score

	N	Min	Max	M	SD	$R_{individual\ achievement\ score}$
Individual level						
Prior knowledge score	259	6	20	14.60	2.44	0.382**
Engagement task space	281	0	286	64.74	56.35	0.147*
Engagement social space	282	1	988	134.71	110.85	0.164**
Group level						
Prior knowledge score	95	10.33	18.00	14.57	1.75	0.497**
Engagement task space	95	0	634	191.51	140.67	0.153*
Engagement social space	95	30	1,688	399.86	281.22	0.131*
Within-group differences						
Prior knowledge score	91	0.00	0.50	0.06	0.07	−0.045
Engagement task space	94	0.00	0.78	0.16	0.15	−0.071
Engagement social space	95	0.01	0.42	0.16	0.09	−0.128*
Individual achievement score	263	5	22	16.16	3.00	

*p < .05; **p < .01.

TABLE 4 Multilevel analyses for the effect of individual level, group level and within-group difference predictors on individual achievement score

	M0	M1	M2	M3
Parameter	*B* (SE)	*B* (SE)	*B* (SE)	*B* (SE)
Fixed effects				
Intercept	16.204 (0.269)**	16.176 (0.235)**	16.123 (0.202)**	16.097 (0.198)**
Individual level				
Prior knowledge score		0.281 (0.070)**	0.032 (0.080)	0.036 (0.080)
Engagement task space		0.002 (0.004)	−0.001 (0.005)	−0.000 (0.005)
Engagement social space		0.004 (0.002)*	0.005 (0.003)*	0.005 (0.003)*
Group level				
Prior knowledge score			0.907 (0.144)**	0.925 (0.143)**
Engagement task space			−0.002 (0.003)	−0.000 (0.003)
Engagement social space			0.000 (0.001)	0.000 (0.001)
Within-group differences				
Prior knowledge score				0.755 (2.954)
Engagement task space				−1.725 (1.656)
Engagement social space				−3.124 (2.500)
Random effects				
σ^2_{u0} (group)	4.611 (0.993)**	3.080 (0.856)**	1.871 (0.581)**	1.731 (0.558)**
σ^2_e (individual)	4.556 (0.533)**	4.671 (0.572)**	4.420 (0.518)**	4.419 (0.517)**
−2 loglikelihood	1,142.132	1,122.372**	1,086.709**	1,083.116

*$p < .05$; **$p < .01$.

coefficients discussed in the Descriptive Statistics section. Since within-group differences were small, none of the predictors that reflect those within-group differences were associated with individual achievement score. This means that in the current sample, an (un) equal within-group distribution of prior knowledge or engagement in the task and social space neither beneficially nor negatively affected individual achievement.

We now zoom in on model M2 (*individual and group level*), given that this model had a significantly better fit than the empty model and M1. In M2, two predictor variables were found to significantly predict individual achievement. First, *individual* group members who engaged more in *the social space* in terms of regulating their own and each other's ideas, actions and socioemotional processes obtained higher scores on the post-test than group members who were less engaged in the social space. Further analyses concerning the specific subcategories (i.e., focusing, checking and argumentation) revealed that none of these activities significantly predicted individual achievement scores on their own. The other two predictors at the individual level, namely, prior knowledge and engagement in the task space, did not predict individual achievement. Thus, it is the *total* (the sum of all focusing, checking and argumentative interactions) of a student's engagement in the social space that predicts his or her individual achievement. Second, prior knowledge score measured at the *group level* significantly predicted individual achievement score. At the group level, neither engagement in the task space nor the social space predicted individual achievement score.

5 | DISCUSSION

In CSCL research, studies examining the combined effects of individual level measures, group level measures and within-group level differences on individual achievement are scarce. The current study, addressed this by examining whether individual, group and within-group differences regarding engagement and prior knowledge predict individual achievement. In the following the findings, limitations of this study and suggestions for future research and instructional design will be discussed.

5.1 | Interpretation of findings

This study answers the recent call to better understand the dynamics of collaborative endeavours (Järvenoja et al., 2017; Levine, 2018; Peñarroja et al., 2017; Volet et al., 2017). The findings indicated that the MLA model including multiple predictor variables at both the individual and group levels significantly explained more variance than the other models. By applying such a research methodology, this study advanced the CSCL-field by providing insight into how differences in engagement and prior knowledge affect a group members' individual achievement.

First, at the *individual level* engagement in the social space significantly predicted group members' individual achievement. Group members who engaged more in regulatory activities such as sharing of and argumentation about each other's ideas, actions and socioemotional processes performed better on the post-test. This is in line with previous studies stressing the importance of engaging in the social space during collaborative learning (Kreijns, Kirschner, & Vermeulen, 2013; van den Bossche et al., 2011). A contribution to earlier research is that it matters *who* engages in the activities in the social space. Whereas prior studies focused mainly on engagement at the group level, this study indicates that an individual group member's engagement in the social space positively predicts their individual learning gain. This aligns with recent findings that individual group members should actively be engaged in exhibiting regulatory activities (Järvenoja et al., 2017; Volet et al., 2017). Actively becoming aware and arguing about each other's ideas, actions and socioemotional processes foster one's own understanding of the domain-content which, in turn, might account for the higher individual achievement score (Sinha et al., 2015).

Second, at the *group level*, the group's average prior knowledge score significantly predicted a group member's individual achievement score. This means that when the average prior knowledge level within a group was higher, all group members achieved higher individual achievement scores compared with groups with a lower average prior knowledge score. A possible explanation might be that an (un)equal allocation of high-, medium- and low- ability group members affects individual achievement (Kozlov & Große, 2016; Weinberger et al., 2010). However, it seems more plausible that group members with higher prior knowledge test scores will score higher on the individual achievement regardless of group composition as no significant predictor effects (all levels) were found for the engagement in the task space (i.e., domain-related activities).

Findings also revealed that group members' average engagement in the social space did not significantly predict a group member's individual achievement score. This partly aligns with prior studies indicating that the average group engagement in regulatory activities does not account for between-group differences concerning their outcome measures (Schoor & Bannert, 2012). It, however, contradicts findings from other studies that found that between-group level engagement in regulatory activities might account for between-group differences in outcomes measures (Erkens et al., 2005; Järvenoja et al., 2017). Perhaps differences in the focus of the current study may explain the mixed findings. This study focused on individual achievement instead of collaborative group performance. If group members focus on their individual achievement, they may be willing to engage in activities aimed at verifying whether their own knowledge and ideas deviate from those of their group members. Based on this comparison, a group member might modify his or her understanding without making this explicit to the other group members or even share common are inaccurate mental models (Levine, 2018). When group members focus on collaboratively carrying out a complex task, they probably have more need to negotiate about their different viewpoints and co-regulate their collaborative endeavour (van den Bossche et al., 2011). Because group members were instructed that collaborative task achievement and individual achievement scores would not affect their grades, a different explanation seems more plausible.

Third, at the *within-group differences level* results indicate that, on average, groups had a more or less equal distribution of their members' prior knowledge scores and engagement in the task and social space. Consequently, the MLA-model revealed no significant effect of these measures on group members' individual achievement score. This contradicts earlier findings indicating that flexibly adopting different roles and associated responsibilities beneficially effects the collaborative endeavour and achievement resulting from it (Meslec & Curşeu, 2015; Shirouzu et al., 2002; Strijbos & Weinberger, 2010). Although the collaborative problem-solving task was developed in close cooperation with the teachers, it was probably not complex (i.e., cognitive demanding) enough to stimulate group members to subdivide tasks such as knowledge possessing and processing all available resources (Kirschner et al., 2018; Porter et al., 2010).

5.2 | Limitations and suggestions for future research

In this study, high school students in a pre-university track carried out a (complex) business-economics task in a tailored CSCL-environment. It remains to be seen whether the obtained findings can be replicated in other types of education, other domains or F2F settings. With respect to F2F-settings, online group members may—due to the lack of perceptual clues (e.g., eye contact)—be less aware of each other's ideas, actions and feelings. This lack of physical awareness may affect the need to cope with, for example, personal conflicts and group members engagement in the social space at the individual, group and within-group level (Janssen & Bodemer, 2013; Phielix, Prins, Kirschner, Erkens, & Jaspers, 2011). It would be interesting to examine whether engagement in the social space at the individual level also predicts individual achievement when collaborating in F2F-settings.

Furthermore, the descriptive statistics (see Table 3) revealed that groups were quite homogeneous regarding their members' engagement in the task and social space. When working in triads, there are only three possible interaction routes, which increases the pressure on group members to equally engage in the task and social space (Laughlin et al., 2008). This might also account for the lack of within-group differences and hindered a proper examination of a combined analysis of individual, group and within-group level differences measures on group members' individual achievement. Future research might want to address this by examining the individual, group and within-group differences and their effect on achievement in settings with either a larger group size or a more complex task. For example, when the group size increases some members may feel more inclined to exhibit social loafing—not participating in the discussions—behaviour (Simms & Nichols, 2014).

As indicated by others, the interplay between individual, group and within-group levels is an important topic for future research (Grau & Whitebread, 2012; Kozlov & Große, 2016; Volet et al., 2017). Future research could take an interest in deliberately creating more opportunities for obtaining within-group differences by allocating group members (a) to groups based on differences in prior knowledge and (b) different roles before or during the collaborative endeavour, instead of random allocation. Finally, no effects were obtained for engagement (individual and group level) in the task space. On the one hand, this might be accounted for by the relatively high average prior knowledge scores in combination with the rather symmetric distribution of the prior knowledge scores within groups. That is, if members already have a rather well-developed understanding of the domain-content and share this early in the discussion, they may feel less need to further elaborate on the domain-content during their collaborative endeavour. This aligns with results from previous studies in problem-based learning settings in which no (positive) correlations where obtained between the amount of elaboration and achievement (van Blankenstein et al., 2013; van Boxtel, van der Linden, & Kanselaar, 2000). In addition, providing a concept map—in which all concepts and their interrelationships were represented—might also hamper instead of foster group members' and group's engagement in the task space. They may feel less need to elaborate on the domain-content (Slof et al., 2013). On the other hand, it might also be accounted for by the manner in which engagement was operationalized. Solely coding and counting the concept, solutions and relationships does not lead to a complete understanding of the discussion of the domain-content (Suthers, 2006). To gain more insight into this matter, future research might want to examine how the knowledge construction and application process (e.g., defining, clarifying, agreeing, revising) develops over time (Cress, 2008; Popov, van Leeuwen, & Buis, 2017; Schellens & Valcke, 2005).

5.3 | Implications

The main finding indicates that students' individual engagement in the social space as well as the groups' average prior knowledge score positively predicted individual achievement. This means that factors at the individual as well as the group level should be taken into account when designing collaborative tasks and examining the effects of the collaborative endeavour. One factor could be the designer's/teacher's intended goal of the collaborative endeavour, namely to (a) develop a better understanding of the domain-content or (b) solve the problem and to learn how to do so. Depending on the goal it seems likely that different decisions regarding engagement and group composition will be made. That is, students might feel less need to engage in the social space at the group level (Levine, 2018) or might even be better off doing this by their selves (Kuhn, 2015) when the only goal is to develop a better understanding of the domain-content. Solving problems requires the application of the acquired knowledge and the acquisition of problem-solving skills (e.g., argumentation). With this goal in mind, an unequal distribution of group members prior knowledge scores (Hooper & Hannafin, 1988; Kozlov & Große, 2016) and providing instruction to reach a solution that is acceptable for all seems more appropriate.

Another factor might be the instructional support one wants to provide during the collaborative endeavour (Chen et al., 2018; Jeong & Hmelo-Silver, 2016). Since a group member's engagement predicts their individual achievement, it seems relevant to support individual group members to focus on the discussion topics, check whether they understood their group members correctly, and productively criticise each other's knowledge and ideas. This kind of support could be offered by prompts (Olsen et al., 2014), scripts (Noroozi et al., 2013) or assigning roles (de Wever et al., 2009). A different, more indirect, possibility is to augment the CSCL-environment with so-called awareness tools or widgets. Using such tools might support groups and group members in becoming more aware of their own and each other's ideas, actions and socio-emotional processes and in turn, foster the collaboration process and achievement (Beers et al., 2007; Janssen & Bodemer, 2013; Kreijns et al., 2013).

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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