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Acquisition of workplace knowledge through individual and cooperative self-regulated learning

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Abstract

A recent analysis comparing individual self-regulated learning and cooperative self-regulated learning in the context of adult education[1] found that cooperative learning methods do not automatically lead to better outcomes in terms of fostering mechanical engineering competences. To more closely examine the validity of this previous study, particularly criterion validity, a comparable analysis of declarative knowledge in the field of CAD and FEM was conducted in the present study. Mean values and equivalences were observed with 175 students from technical colleges in Germany. The analysis revealed significant learning progress for both learning arrangements in knowledge acquisition in the context of CAD and FEM. Partial strict invariance was observed in the cross-sectional data. In the longitudinal data, only the CAD and FEM-application dimensions of knowledge could be considered equivalent. In the cooperative self-regulated learning arrangement, students performed better in practical knowledge about FEM when compared to the individual self-regulated learning treatment group. Acquisition of FEM declarative-practical knowledge was more effective through a cooperative self-regulated learning arrangement, in comparison to an individual self-regulated learning arrangement. However, no difference in CAD declarative knowledge was found between the learning arrangements. This observation is important for the design of digital learning environments, but further studies with larger sample sizes are required to confirm these conclusions.

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Introduction and literature review

A recent original analysis by Huester and Morris[1] of the Computer-Aided Design Competence Modeling and Promotion 2024+ (CADCoM2024+) study showed that cooperative learning methods in the context of adult education are not necessarily superior to individual learning arrangements. *Self-regulated learning* (SRL) involves learner(s) engaging successfully in *self-regulation*, an important element in ensuring successful *progress* in a learning process, which involves "learner(s) applying the skill and capacity to take independent control and direction, thus intentional oversight, of psychological and physiological responses and actions so that their behavioral manifestations in their learning process are planned and systematic" ([1] p. 2).

Huester and Morris,[1] following on from Morris,[2] identified that the nature and demands of SRL in adult and vocational educational settings can take many forms. Two examples of different forms of SRL, as identified by Huester and Morris,[1] are individual SRL (ISRL) and cooperative SRL (CSRL). ISRL might include several forms of intentional oversight of psychological, physiological, and action responses such as being able to sit still, maintaining task attention, resisting distractions etcetera (e.g.,[3,4]). Nonetheless, Huester and Morris[1] highlight the point that when learners are learning knowledge, skills, and competences as part of a team, such as in a cooperative task (e.g., CSRL), learners are likely to have different self-regulatory demands, such as: communicating appropriately with members of the group, attending to group members work and ideas, making decisions regarding what and how group member's contributions are used in the product of the group work; dealing with group conflict; acting appropriately if one or more group member(s) do not offer an appropriate individual contribution to the group task, etcetera. Importantly therefore, the self-regulatory demands of group tasks such as in cooperative learning do not necessarily match the self-regulatory demands within an individual task (cf.[1]).

These findings are particularly novel in the context of self-regulated learning and pedagogical design within vocational education settings. Previous research on the success of cooperative learning formats has primarily focused on the implementation and execution of the structure, such as the five basic elements: promotive interaction, social skills, personal responsibility, positive interdependence and group processing.[5] Nonetheless, to more closely examine the validity of the findings of Huester and Morris,[1] particularly criterion validity, a comparable analysis of declarative *knowledge* in the field of CAD and FEM is required. In particular, knowledge and prior knowledge should be emphasized in cognitive architecture, as they are stored in long-term memory.[6] Compared to other personality characteristics, such as general basic cognitive abilities (cf.[7]), knowledge can be acquired relatively quickly. Through easily acquired prior knowledge, the limited and comparatively slow working memory[8] can be utilized more efficiently.[9] This prevents overloading of working memory, as described by cognitive load theory (cf.[10]). Concomitantly, there is a body of research that highlights the importance of the need for professionals to think in a flexible way in order to adapt their domain-specific knowledge in order to solve or resolve domain specific problems within *new* contextual conditions.[11,12,13]

In this regard, Ward et al.[14] proposed a set of teaching principles for vocational students including: (a) setting domain-specific projects of inquiry that become increasingly challenging; (b) stimulating student reflection and critical thinking through appropriate feedback; (c) enabling challenge, including setting challenging deadlines; (d) staging opportunities for students to make cross-comparison between cases/projects, especially concerning and highlighting contextual differences and the fittingness of concepts; and (e), teaching that provides students with a rich theoretical and conceptual knowledge base. Such teaching principles are proposed because in vocational education and practice there is a need for professionals to construct knowledge that is tailored to the specific needs of the understanding or the specific vocational problem.[13]

In this respect, Spiro et al.[15,13] highlighted the point that a good portion of vocational problems, questions, tasks, and issues are ill-structured: which results in a scenario where in such contexts, in the "payoff" context of vocational application, adaptivity/transferability of knowledge is reduced; and rather professionals are necessitated often to find creative solutions in a proactive process of adult learning.[16] In this regard, Spiro et al.[15,13] concluded that vocational education and training should include: (1) full context of application appreciation; (2) facilitating a understanding of the interconnectedness between individual problems in a variety of context; (3) maintenance of the complexity inherit in problems (4); learner exposure to and understanding of multiple problems, including complex and ill-structured cases; and, (5) facilitating of the educational process by a subject and didactical expert. However, Ward et al.[14] concluded that there is still a lack of comprehensive studies that examine the effectiveness of didactical principles that foster professional knowledge and competences.

However, knowledge and prior knowledge do not necessarily have to be acquired laboriously and with great effort via working memory for every workplace competence; there is knowledge that is instead based on our natural disposition, such as recognizing faces or mastering one's native language. Such knowledge is predominantly learned outside formal educational environments. Geary[17] highlighted the point that such knowledge (biologically primary) is rooted in our natural predisposition and contributes to what makes us human. In contrast, he distinguishes knowledge that must be laboriously learned via working memory, referring to such knowledge as biologically secondary. The latter includes, for example, reading, writing, arithmetic, as well as all culturally domain-specific knowledge for which there is no evolutionary predisposition. This raises the question of whether knowledge is equally significant for the practical implementation of a 3D model in CAD or for strength calculations using FEM, or whether there are in fact significant differences here. Both CAD and FEM are specialized fields within mechanical engineering. However, for the creation of a pure 3D model in CAD, it can be assumed that these competences can be acquired more individually and intuitively. After all, the programs are designed with corresponding symbols and user interfaces to enable operation that is as simple as possible. This does not apply, for example, to the interpretation of strength calculations.

It is therefore conceivable that declarative knowledge, which is consciously accessible, is less significant for CAD and, in contrast to strength calculations using FEM, plays a central role. Initial evidence for this can be obtained through the present analysis by testing both learning arrangements (ISRL and CSRL) using inferential statistics (structural equation modeling, SEM) in a longitudinal experimental design. Invariance tests are conducted in both cross-sectional and longitudinal analyses. Learning progression is estimated via comparisons of means. The mean values are estimated iteratively at the latent level. If the groups are invariant across cross-sectional and longitudinal data, these values are comparable and can be interpreted between the pretest and posttest. The change can be observed by setting the latent variable to zero in the pretest—for example, in a longitudinal design—and then estimating it freely in the posttest. Furthermore, the present analysis improves statements regarding validity (with respect to the criterion of external variables) to close this existing research gap. This also makes the analysis by Huester and Morris[1] more meaningful, as it allows for a connection to the control variable "knowledge" and makes potential implications for education and educational stakeholders more precise.

For empirical analysis, operationalization is of central importance to clearly define exactly what is being measured. However, the categorization of knowledge proposed by Geary,[17] which is especially relevant for the implementation of learning processes in the education sector, is not practical. For this reason, the operationalization of knowledge in the present analysis follows the criteria of Heinz-Martin Süß.[18] Süß differentiates between declarative-factual knowledge and declarative-practical knowledge. Both forms can be verbalized and are, therefore, conscious. Factual knowledge is knowledge about facts, while practical knowledge represents action strategies. According to Süß, factual and practical knowledge can also be unconsciously present. Here, he speaks of procedural-factual and procedural-practical knowledge. These forms are, therefore, not verbalizable and are thus unconsciously anchored in memory ([18] pp. 62–70).

In this context, in the present study three different learning groups—ISRL, CSRL, and the control group—were tested. These treatment groups have already been evaluated for competence development (cf.[1]). In that study, like the present study the ISRL learning group learned individually, where students learned entirely without interacting with their peers or the teacher; the CSRL learning group learned cooperatively in groups of three using the "jigsaw method"; while the control group worked on tasks from other subjects.[19] In all learning groups in both studies the learning sessions were 90 min in total.

In the present study, knowledge is measured in the form of declarative knowledge, as unconscious knowledge is difficult to capture. A distinction is made between declarative-factual knowledge and declarative-practical knowledge in the fields of CAD and FEM. Using confirmatory factor analysis (CFA), a theoretically viable three-dimensional knowledge model was identified. The three knowledge categories comprise declarative knowledge of CAD ξ_1, declarative factual knowledge ξ_2, and declarative practical knowledge ξ_3 of FEM.[20] Accordingly, these three knowledge dimensions are examined when comparing the ISRL and CSRL learning arrangements for CAD and FEM.

Hypotheses

Equivalence should be ensured, at least partially, across cross-sectional and longitudinal data for the three treatment groups. Preferably, this should be done at the most restrictive of the three levels—strict invariance—for all three dimensions of knowledge. This is achieved by examining adequate model fit indices such as WRMR, CFI, TLI, and REMSEA (see Table 4) as well as through non-significant chi-square difference tests between the three levels. Furthermore, learning progress should be clearly discernible in both learning arrangements and significantly distinguishable from the control group. For this purpose, the means *($\varkappa$)* of the exogenous latent variables *(ξ)* are set to zero at the first measurement point and freely estimated at the second measurement point. The change in the mean provides information about learning progress based on the given invariance (cf.[1]). Table 1 shows the families of hypotheses along with the specific hypotheses.

Methods

The study consisted of 175 students from four vocational colleges in Rhineland-Palatinate, Germany. Balthasar-Neumann-Technikum Trier (BNT), David-Roentgen-Schule Neuwied (DRS), Carl-Benz-Schule Koblenz (CBS), and Harald-Fissler-Schule in Idar-Oberstein are the colleges that have participated to date in the program for which ethical clearance for this study was approved by the Service Directorate in Trier (ADD). When it comes to estimating structural equation models, there are differing views on how large the sample size should be. Generally, there is a consensus that the larger the sample size, the better the estimates. The sample in this analysis, consisting of 175 students, is a small sample. A size of $n = 200$ is generally considered acceptable ([21] p. 993).

The participants were students currently studying mechanical engineering. The study, which was designed in a laboratory setting, was conducted under real-world conditions in a traditional vocational education setting. The present analysis is original but part of a larger study (CADCoM2024+); the present analysis used data derived from the same participants as a previous study on workplace competences.[1] The average age of the participants was 26.5 years. The three randomized treatment groups consisted of: ISRL *($n = 65$),* CSRL *($n = 62$),* and a control group *($n = 48$).* The groups were randomized by fortuitous selecting anonymized accounts on the learning platform. Consequently, for each school class, there were three groups of roughly equal size: the ISRL group, the CSRL group, and the control group. Knowledge in the areas of CAD and FEM was assessed based on the previous tests. For this purpose, students used a standardized single-choice procedure conducted via the Moodle learning platform (see Figure 1). The “Don’t know” option was included to reduce the probability of random guessing of correct answers and to increase test reliability. In total, the test comprised 15 dichotomous items. The test on declarative-practical knowledge of FEM application was an exception: This test contained 12 questions. Students had seven minutes to complete the tests. The three tests regarding knowledge (CAD and FEM) together generated a dichotomous data matrix for import into the Mplus software. The secondary quality criteria for test design were implemented through digital test standardization (cf.[22]).

Table 1. Hypotheses.

Main hypotheses	Sub hypotheses
H_1: Partial strict invariance can be confirmed across the three treatment groups (ISRL, CSRL, and the control group) for the three knowledge dimensions ξ_1, ξ_2, and ξ_3. This is tested in the pretest and posttest.	H_{1a}: $\xi_1 \rightarrow$ ISRL = CSRL= control group (pretest) H_{1b}: $\xi_2 \rightarrow$ ISRL = CSRL= control group (pretest) H_{1c}: $\xi_3 \rightarrow$ ISRL = CSRL= control group (pretest) H_{1d}: $\xi_1 \rightarrow$ ISRL = CSRL= control group (posttest) H_{1e}: $\xi_2 \rightarrow$ ISRL = CSRL= control group (posttest) H_{1f}: $\xi_3 \rightarrow$ ISRL = CSRL= control group (posttest)
H_2: Partial strict invariance can be observed longitudinally for the three treatment groups (ISRL, CSRL and the control group) and the three knowledge dimensions of domain-specific competence ξ_1, ξ_2, and ξ_3.	H_{2a}: ISRL $\rightarrow \xi_{11} = \xi_{12}$ H_{2b}: CSRL $\rightarrow \xi_{11} = \xi_{12}$ H_{2c}: Control Group $\rightarrow \xi_{11} = \xi_{12}$ H_{2d}: ISRL $\rightarrow \xi_{21} = \xi_{22}$ H_{2e}: CSRL $\rightarrow \xi_{21} = \xi_{22}$ H_{2f}: Control Group $\rightarrow \xi_{21} = \xi_{22}$ H_{2g}: ISRL $\rightarrow \xi_{31} = \xi_{32}$ H_{2h}: CSRL $\rightarrow \xi_{31} = \xi_{32}$ H_{2i}: Control Group $\rightarrow \xi_{31} = \xi_{32}$
H_3: The two learning arrangements (ISRL vs. CSRL) show significant increases in the latent mean values *($\varkappa$)* in both cross-sectional and longitudinal analyses as a result of learning progression. This is not observable for the control group. No significant learning progress can be observed in the control group. The test is carried out in the three knowledge dimensions ξ_1, ξ_2, and ξ_3. CSRL should show the highest learning progression in this regard (cf. [1]).	H_{3a}: ξ_1 *($\varkappa$)* $\rightarrow$ CSRL > ISRL > Control Group (cross-sectional) H_{3b}: ξ_2 *($\varkappa$)* $\rightarrow$ CSRL > ISRL > Control Group (cross-sectional) H_{3c}: ξ_3 *($\varkappa$)* $\rightarrow$ CSRL > ISRL > Control Group (cross-sectional) H_{3d}: ξ_1 *($\varkappa$)* $\rightarrow$ CSRL > ISRL > Control Group (longitudinal) H_{3e}: ξ_2 *($\varkappa$)* $\rightarrow$ CSRL > ISRL > Control Group (longitudinal) H_{3f}: ξ_3 *($\varkappa$)* $\rightarrow$ CSRL > ISRL > Control Group (longitudinal)

The 90-min learning session was the same as in the analysis of workplace competences in CAD and FEM.[1] Students in the CSRL group used the jigsaw method in groups of three (cf.[19]). Here, the study avoided competition as an incentive for cooperation (to prevent conflicts;[5] p. 67). Students in the ISRL group worked through the three vocational subject areas—declarative knowledge of CAD, declarative-factual knowledge of FEM and declarative-practical knowledge of FEM—on their own in 30-min intervals. The control group did not study between the pretest and posttest. The learning materials consisted of video vignettes and PDF documents and were the same for both learning groups ([1] pp. 8–14). During the period between the pretest and posttest, while the ISRL and CSRL groups were learning, the control group worked independently on

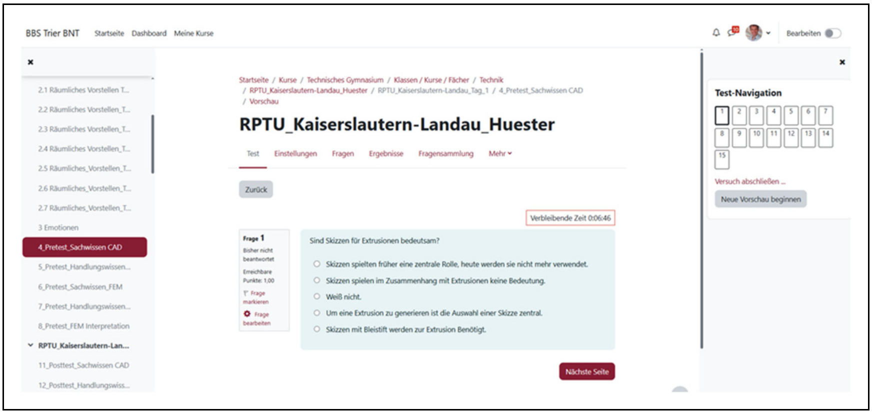

Figure 1. Single choice test design for assessing knowledge.

Table 2. ISRL learning arrangements versus CSRL (cf.[1] p. 14).

ISRL		
1	3D modeling CAD (task, drawing, and video vignette)	30 min.
2	FEM application (task and video vignette)	30 min.
3	FEM Interpretation (PDF Script)	30 min.
CSRL (Jigsaw)		
1	Expert groups on CAD (tasks, drawings, and video vignettes), FEM (tasks and video vignettes), and FEM interpretation (PDF Script)	30 min.
2	Core groups (learning groups) with a total of three experts in CAD, FEM, and FEM interpretation to help each other to tackle the learning tasks.	60 min.

assignments from other subjects. The difference from the previous analysis is that the pretest and posttest now measure knowledge rather than competences. The results also serve to provide a more precise interpretation of the first analysis, as it can be assumed that knowledge may represent a crucial control variable alongside other personality factors such as general cognitive abilities.[7] It is conceivable that, depending on the activity and the associated competency, explicit knowledge plays a more or less decisive role. Table 2 provides an overview of the organization and procedure of both learning arrangements, ISRL and CSRL, which are described in more detail by Huester and Morris.[1]

The measurement models for the pretest and posttest, designed to assess knowledge, had to omit a few manifest variables. The reason was that the slope of individual ability or item difficulty was too low. This means that some items were either too difficult or too easy for the students to answer. Since a sufficient number of items are available and the constructs can be represented in a content-valid manner, this does not appear to be a problem. In addition, invariance tests were conducted to enable a comparison of the

Table 3. Invariance testing of categorical dichotomous data ([25] p. 193;[23] p. 860).

Categorical variables	Loadings	Thresholds	Residuals	Means
Configural invariance	(*	*)	Fixed at 1	Fixed at 0
Strong invariance	(Fixed	Fixed)	Fixed at 1/*	Fixed at 0/*
Strict invariance	(Fixed	Fixed)	Fixed at 1	Fixed at 0/*

(* = free factor-loadings ***)** = free thresholds
Fixed at 1 = the residual variances are fixed at 1
Fixed at 0 = the latent means are fixed at 0
(Fixed = equal factor-loadings
Fixed) = equal thresholds
Fixed at 1/* = the reference group's residual variances are fixed at 1, and the variances for the other groups are estimated freely
Fixed at 0/* = the mean of the latent reference group is set to zero, and the means of the other groups are estimated freely.

pretest and posttest over time. This approach corresponds to the analysis of learning progression for the competences of both learning groups.[1]

The items were designed to cover essential knowledge areas related to CAD and FEM. These included the following technical aspects of CAD: sketches, extrusions, rotations, planes, fillets, chamfers, and material selection. The declarative factual knowledge of FEM included stresses, deformations, safety, loads, mesh size, and constraints. For the practical knowledge of FEM, the application of the areas just described to the factual knowledge of FEM were applicable. It is important that the items could be answered independently of one another and relate to the practical implementation of a FEM or a 3D model in CAD. The test items were not intended for selecting candidates for employment. They served purely scientific purposes and do not claim to be exhaustive. With 15 items, a seven-minute test cannot capture the entirety of knowledge regarding CAD, for example. Only very important characteristics were assessed. The subject areas mentioned above are significant for any 3D modeling in CAD or for any strength calculation using FEM. A 3D model without sketches, extrusion, or rotation is nearly impossible to create in CAD. Adequate technical knowledge of stresses, deformations, component safety, and their implementation in a FEM program is equally essential. The items were reviewed by experts with many years of professional experience in mechanical engineering. These included engineers, technicians, and teachers in this occupational context.

As in the previous analysis, the equivalence test was conducted in three stages following the procedure described by Schroeders and Wilhelm,[23] for both cross-sectional and longitudinal data. In general, the restrictions increase from configural to strong to strict invariance. A chi-square difference test is used to determine whether the models can still be retained or not. This is legitimate, as these are nested models ([24] pp. 163–166). If the chi-square test is not significant, this means that the more restrictive model is comparable to the less restrictive model. Since the more restrictive model is more parsimonious, it can be retained. However, if the chi-square difference test is significant, this indicates that the models are no longer equivalent and thus the more restrictive level cannot be reached. This test is intended for categorical data. In the first level of configural invariance, the

Table 4. Model fit indices ([27] pp. 109–115) / *WRMR modified ([38] pp. 453–466).

Fit	CFI	TLI	RMSEA	WRMR*
Bad	<.85	<.85	>.10	WRMR $\leq$ 1.0*
Secondary	.85-.90	.85-.90	.10-.08	
Acceptable	.90-.99	.90-.99	.08-.05	
Good	.95-.99	.95-.99	.05-.02	
Very good	>.99	>.99	<.01	

residual variances for the indicators are fixed at one and the means of the latent variables at zero. The thresholds and loadings of the manifest variables are estimated freely. The second level, strong invariance, involves equal loadings and thresholds for the indicators. For the latent reference group, the residual variances of the indicators are fixed at one and the means of the latent variable at zero. For the other latent variables, the means and residual variances of the indicators are estimated freely. In the third and final stage of the equivalence test, all restrictions from stage two are retained. An additional restriction consists of fixing all residual variances to one. This procedure is the same for cross-sectional and longitudinal data. The chi-square difference test is performed between the stages.[23,25]

For dichotomous data, the theta parameterization was used in the Mplus software.[26] Since the students' response patterns are similar but not completely identical, it may happen that not all parameter restrictions, such as residual variances, can be maintained for all items.[27] If a few restrictions on individual items are removed, this is referred to as partial invariance.[28] Partial invariance is to be expected from the experience of the analysis conducted previously.[1]

Table 3 illustrates the restrictions of the three invariance levels. The methodology is similar to the previous analysis of CAD and FEM competences and is described in more detail there.[1] The asterisk indicates a free estimate of the respective parameters. Fixed without explicit specification (1 or 0) denotes equality constraints (such as threshold t11) across the three groups.[23,25]

For the comparison of mean values, the restrictions from the strict invariance model were retained, the mean value *($\varkappa$)* at measurement time point one set to zero, and the mean value of the latent variable at measurement time point two was estimated freely ([29] pp. 434f.). The estimated models are evaluated based on the following model fit statistics for categorical data. In accordance (cf. Table 4), the *Tucker-Lewis Index* (TLI), the *Comparative Fit Index* (CFI), and the *Root Mean Square Error of Approximation* (RMSEA) were used for model estimation in the present work. Since this study also involves categorical data, the additional use of the *Weighted Root Mean Square Residual* (WRMR) is considered appropriate.[30]

Results

As explained in the previous chapter and in the analysis of domain-specific competence (cf.[1]), the strategy was first to determine invariance between the three treatment groups for the dimensions ξ_1, ξ_2, and ξ_3 in the cross-section. This was done in the pre- and post-tests. The communalities of the indicators, measured by McDonald's Omega, fall within an acceptable to good range *(ω = .736**-.818**)*. This speaks to the reliability of the indicators. The latent dimension declarative knowledge ξ_1 (declarative knowledge about CAD) actually shows strict invariance for the pretest and partial strict invariance for the posttest. The model fit values in the pretest are very good at the first level of configural invariance, with the exception of WRMR *(RMSEA = .038; CFI = .951; TLI = .943; WRMR = 1.398*). The reason for the high WRMR may be the relatively small sample size. The factor loadings of all fifteen manifest variables in the three groups are significant *(*p ≤ 0.05; **p ≤ 0.01)*. For the ISRL group (*n = 65)*, the fifteen loadings range from *λ = .261** to *λ = .773***. The CSRL group (*n = 62)* shows factor loadings ranging from *λ = .330** to *λ = .789***. The factor loadings of the control group (*n = 48) range from λ = .341* to λ = .758***. Compared to the more restrictive level of so-called strong invariance, the model fit values remain very good *(RMSEA = .031; CFI = .964; TLI = .962; WRMR = 1.473*). The chi-square difference test is also not significant *(p = 0.7135)*. The same applies to the chi-square difference test between the comparison of strong and strict invariance *(p = 0.3718)*. Accordingly, strict invariance exists between the three groups in the pretest, which means that hypothesis H_{1a} is correct. The mean values between the ISRL, CSRL and control groups vary *(ISRL ϰ =0.000; CSRL ϰ = −0.242; control group ϰ = −0.631)*. As a result, the groups have different mean values as their initial reference. For the post-test, the model fit values at the first level of configural invariance are also in a very good range *(RMSEA = .020; CFI = .980; TLI = .976; WRMR =1.285)*. The WRMR remains the exception. The factor loadings of all fifteen manifest variables in the three groups are predominantly highly significant *(*p ≤ 0.05; **p ≤ 0.01)*. For the ISRL group (*n = 65)*, the loadings range from *λ =- .042* to *λ = .741***. The CSRL group (*n = 62)* shows factor loadings ranging from *λ = .101* to *λ = .903***. The factor loadings for the control group (n = 48) range from *λ = .018 to λ = .722***. Compared to the more restrictive level of so-called strong invariance, the model fit values remain very good except for the WRMR *(RMSEA = .023; CFI = .971; TLI = .968; WRMR =1.420)* using the chi-square difference test. The chi-square difference test is also not significant *(p = 0.1147)*. Once again, some correlations between the indicators within the respective group are allowed. Consequently, only partial invariance can be maintained. The chi-square difference test is also not significant between the comparison of strong and strict invariance *(p = 0.2901)*. The model fit values remain in a very good range with the exception of WRMR. Accordingly, there is indeed partial strict invariance between the three groups in the post-test. Hypothesis H_{1d} can therefore be upheld. The mean values between the two learning groups (ISRL and CSRL) are not close to each other and differ by *Δ ϰ = 0.200*. However, the groups already had different starting points at the beginning, which means that the longitudinal test remains to be seen. However, with a mean value of *(ϰ = −1.172)*, the control group is so significantly below this that the learning progression of the two learning arrangements compared to the control group is apparent. This difference can already be interpreted as an initial indication of learning progression. Apparently, both learning groups have learned significantly and are thus at a higher level than the control group. This partially confirms hypothesis H_{3a}. Although learning progression compared to the control group is evident, the cooperative learning arrangement (CSRL) is not more effective than

Table 5. Hypotheses H_{1a}, H_{1d} and H_{3a} (cross-sectional invariance for ξ_1 in pretest and posttest).

	Pretest			Posttest		
Model Fit	*(RMSEA = .038; CFI = .951; TLI = .943; WRMR = 1.398)*			*(RMSEA = .020; CFI = .980; TLI = .976; WRMR =1.285)*		
Group	**ISRL**	**CSRL**	**Control**	**ISRL**	**CSRL**	**Control**
n	*65*	*62*	*48*	*65*	*62*	*48*
Δ ϰ	*fixed at 0*	*−0.242*	*−0.631*	*fixed at 0*	*0.200*	*−1.172*
λ	*.261* - .773***	*.330*-.789***	*.341* - .758***	*.042- .741***	*.101 - .903***	*.018 - .722***

individual (ISRL) in this subject-specific knowledge dimension ξ_1. The results are summarized again in Table 5.

The latent dimension of declarative-factual knowledge in dealing with FEM ξ_2 actually shows partial strict invariance for the pretest and posttest. The model fit values in the pretest are very good at the first level of configural invariance, with the exception of WRMR *(RMSEA = .000; CFI = 1.000; TLI = 1.005; WRMR = 1.104)*. As described above, the cause of the high WRMR could lie in the relatively small sample size. With one exception, the factor loadings of all nine manifest variables in the three groups are highly significant *($^*p \leq 0.05$; $^{**}p \leq 0.01$)*. For the individual group *(n = 65)*, the nine loadings range from *λ = .197 to λ = .860***. The cooperative group *(n = 62)* shows factor loadings ranging from *λ = .289 to λ = 1.000***. The factor loadings of the control group *(n = 48)* range from *λ = .153 to λ = .832***. Compared to the more restrictive level of so-called strong invariance, the model fit values remain very good *(RMSEA = .000; CFI = 1.000; TLI = 1.030; WRMR = 1.257)* with the exception of WRMR. The chi-square difference test is also not significant *(p = 0.6929)*. However, the restrictions cannot be fully implemented. For example, a few correlations within the respective groups of individual or cooperative must be allowed. This does not apply to the control group. Accordingly, only partial invariance can be said to exist in this second stage. The chi-square difference test is also not significant between the comparison of strong and strict invariance *(p = 0.1072)*. As a result, strict invariance is partially present between the three groups in the pretest, which does not refute hypothesis H_{1b}. The mean values between the groups are close to each other. The mean values of the latent variables do not differ significantly between the three groups ISRL, CSRL and the control group. The control group *(ϰ = −0.018)* is slightly below and the cooperative group slightly above *(ϰ = 0.042)* the reference group individual *(ϰ = 0.000)*. A CSRL result emerges for the post-test. The model fit values in the post-test are very good at the first level of configural invariance, with the exception of WRMR *(RMSEA = .035; CFI = .973; TLI = .961; WRMR = 1.192)*. As already known, the cause of the excessive WRMR could lie in the still relatively small sample size. The factor loadings of all nine manifest variables in the three groups are highly significant *($^*p \leq 0.05$; $^{**}p \leq 0.01$)* with one exception. For the individual group *(n = 65)*, the nine loadings range from *λ = .212 to λ = .720***. The CSRL group *(n = 62)* shows factor loadings ranging from *λ = .356 to λ = .794***. The factor loadings of the control group *(n = 48)* vary from *λ = -.084 to λ = .860***. Compared to the more restrictive level of so-called strong invariance, the model fit values remain very good *(RMSEA = .000; CFI = 1.000; TLI = 1.009; WRMR =*

Table 6. Hypotheses H_{1b}, H_{1e} and H_{3b} (cross-sectional invariance for ξ_2 in pretest and posttest).

	Pretest			Posttest		
Model Fit	*(RMSEA = .000; CFI = 1.000; TLI = 1.005; WRMR = 1.104)*			*(RMSEA = .035; CFI = .973; TLI = .961; WRMR = 1.192)*		
Group	**ISRL**	**CSRL**	**Control**	**ISRL**	**CSRL**	**Control**
n	*65*	*62*	*48*	*65*	*62*	*48*
Δ ϰ	*fixed at 0*	*0.042*	*−0.018*	*fixed at 0*	*0.073*	*−0.245*
λ	*.197 - .860****	*.289– 1.000****	*.153 - .832****	*.212 - .720****	*.356 - .794****	*.084 - .860****

1.304) with the exception of WRMR, as determined by the chi-square difference test. The chi-square difference test is also not significant $(p = 0.7743)$. However, the restrictions cannot be completely realized again. For example, a few correlations within the respective groups of ISRL, CSRL and the control group must be allowed. Consequently, the second level can only be described as partial invariance, comparable to the pretest. The chi-square difference test is also not significant between the comparison of strong and strict invariance $(p = 0.1931)$. Accordingly, strict invariance is also partially present between the three groups in the post-test, which means that hypothesis H_{1e} can be sustained. The mean values between the groups are no longer close together. The mean values of the latent variables differ significantly between the three groups ISRL, CSRL and the control group. The control group $(\varkappa = -0.245)$ is significantly below the two groups ISRL $(\varkappa = 0.000)$ and CSRL $(\varkappa = 0.073)$. This makes the learning progression of both learning arrangements compared to the control group visible in a way that is comparable to ξ_1 in the cross-section. Hypothesis H_{3b} can thus be partially confirmed. While the difference in the mean values of both learning groups compared to the control group is clearly recognizable, the higher mean value of cooperative learning compared to individual learning is relatively small. A higher learning progression from declarative factual knowledge to FEM interpretation would be consistent with a previous analysis of competences in this context.[1] The results are abridged in Table 6.

The latent dimension of declarative-practical knowledge for applying FEM ξ_3 also shows partial strict invariance for the pretest and posttest. The model fit values in the pretest are good to very good at the first level of configural invariance *(RMSEA = .000; CFI = 1.000; TLI = 1.088; WRMR = 1.013*). With one exception, the factor loadings of all eleven manifest variables in the three groups are highly significant $(^{*}p \leq 0.05;\ ^{**}p \leq 0.01)$. For the individual learning group ($n = 65$), the eleven loadings range from $\lambda = .325$ to $\lambda = .812^{**}$. The cooperative group ($n = 62$) shows factor loadings ranging from $\lambda = .250$ to $\lambda = .817^{**}$. The factor loadings for the control group ($n = 48$) vary from $\lambda = .608^{**}$ *to* $\lambda = .811^{**}$. Compared to the more restrictive level of so-called strong invariance, the model fit values remain within an acceptable, but mostly very good range *(RMSEA = .050; CFI = 1.000; TLI = 1.096; WRMR = 1.128*). The chi-square difference test is also not significant $(p = 0.7669)$. However, the restrictions cannot be completely realized. For example, an additional correlation between two manifest variables in the cooperative learning group must be allowed. Accordingly, only partial invariance can be said to exist in this second stage. The chi-square difference test is also not significant

Table 7. Hypotheses H_{1c}, H_{1f} and H_{3c} (cross-sectional invariance for ξ_3 in pretest and posttest).

	Pretest			Posttest		
Model Fit	*(RMSEA = .000; CFI = 1.000; TLI = 1.088; WRMR = 1.013)*			*(RMSEA = .000; CFI = 1.000; TLI = 1.002; WRMR = 1.055)*		
Group	**ISRL**	**CSRL**	**Control**	**ISRL**	**CSRL**	**Control**
n	*65*	*62*	*48*	*65*	*62*	*48*
Δ ϰ	*fixed at 0*	*0.000*	*0.169*	*fixed at 0*	*0.085*	*1.221*
λ	*.325 - .812***	*.250 - .817***	*.608** - .811***	*.378** - .929***	*.298- .875***	*. .397** - .996**.*

between the comparison of strong and strict invariance *(p = 0.0599).* Accordingly, strict invariance is partially present between the three groups in the pretest, which means that hypothesis H_{1c} is correct. The mean values between the groups are close to each other. The mean value of the latent variables does not differ between the two groups individual and cooperative. The control group is slightly above *(ϰ = 0.169*). For the post-test, the model fit values at the first stage of configural invariance are in a good to very good range *(RMSEA = .000; CFI = 1.000; TLI = 1.002; WRMR = 1.055*). The factor loadings of all eleven manifest variables in the three groups are predominantly highly significant *(*p ≤ 0.05; **p ≤ 0.01)*. For the individual group (*n = 65)*, the eleven loadings range from *λ = .378*** to *λ = .929***. The cooperative learning group (*n = 62)* shows factor loadings ranging from *λ = .298*** to *λ = .875***. The factor loadings for the control group (*n = 48) range from λ = .397** to λ = .996***. Compared to the more restrictive level of so-called strong invariance, the model fit values remain acceptable to very good *(RMSEA = .031; CFI = .991; TLI = .990; WRMR = 1.217*). The chi-square difference test is also not significant *(p = 0.0845).* The chi-square difference test is also not significant between the comparison of strong and strict invariance *(p = 0.0673).* The model fit values remain in an acceptable to very good range. Consequently, there is partial strict invariance between the three groups in the post-test. Hypothesis H_{1f} can therefore be sustained. The latent mean of the cooperative learning group does not differ from the reference group individual with *(Δ ϰ = 0.085)*. However, the difference between the two learning arrangements and the control group is striking *(Δ ϰ = −1.221).* This difference can already be interpreted as an initial indication of learning progression. Apparently, both learning groups were able to increase their knowledge dramatically. This partially confirms hypothesis H_{3c}. The results are drawn in Table 7.

In summary, a partial strict invariance can indeed be observed in the cross-section for the pre- and post-tests of the dimensions ξ_1, ξ_2, and ξ_3 declarative knowledge of CAD, declarative-factual and declarative-practical knowledge about FEM. The hypothesis family H_1 cannot be refuted and can therefore be retained. The mean values of the latent variables in the pretest between the three groups are approximately at the same level. This changes in the posttest. Here, significant differences to the control group become apparent, which allows initial indications of learning progression through the learning arrangements to be anticipated. Accordingly, hypotheses H_{3a}, H_{3b}, and H_{3c} can already be partially confirmed. The next step is to test the longitudinal

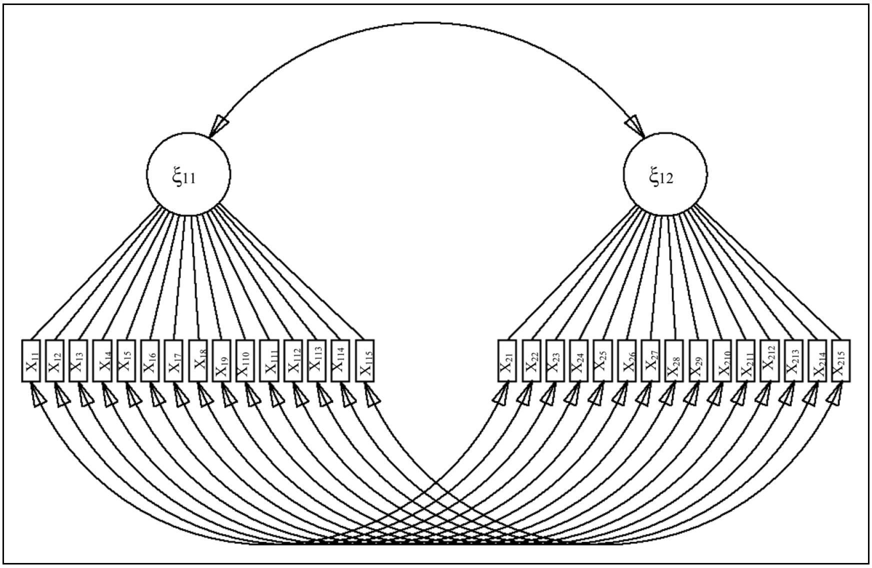

Figure 2. Longitudinal invariance test of the latent variable ξ1.
ξ_{11} = Latent Variable (CAD declarative knowledge at time of measurement 1) $X_{11–15}$ = Manifest Variables (CAD declarative knowledge at time of measurement 1) ξ_{12} = Latent Variable (CAD declarative knowledge at measurement time 2) $X_{21–25}$ = Manifest Variables (CAD declarative knowledge at time of measurement 2).

invariance of the latent variables across the two measurement points. This is only legitimate given the partial strict invariance in the cross-section for the pretest and posttest. Based on this, the hypothesis family H_2 is tested next, and then the changes in the mean values of the latent variables across the two measurement points are observed.

First, the dimension one of declarative knowledge ξ_1 (CAD) is checked for longitudinal invariance in the three treatment groups (cf. Figure 2). The configurational model of the individual group (*n = 65)* shows good to very good model fit values *(RMSEA = .028; CFI = .927; TLI = .918; WRMR = .875*). With one exception, the factor loadings of all manifest variables at both measurement points are highly significant *(*p ≤ 0.05; **p ≤ 0.01)*. For group ξ_{11} (pretest*)*, the loadings range from λ = *.184* to λ = *.778***. The group ξ_{12} (posttest) shows factor loadings ranging from λ = *.136* to λ = *.819***. Compared to the more restrictive level of so-called strong invariance, the model fit values remain good to very good *(RMSEA = .028; CFI = .929; TLI = .923; WRMR = .898*). The chi-square difference test is also not significant *(p = 0.1170)*. The restrictions can be fully realized. Accordingly, strong invariance can be assumed. The chi-square difference test is also not significant between the comparison of strong and strict invariance *(p = 0.0547)*. However, a correlation between two measurement points must be fixed for one indicator. Accordingly, only strict invariance is partially present between the two measurement points, which mean that hypothesis H_{2a} is correct. The mean change is *Δ*

Table 8. Hypotheses H_{2a}, H_{2b} and H_{3d} (longitudinal invariance for ξ_1 between pretest and posttest).

	Pretest- posttest		
Group	ISRL	CSRL	Control
Model Fit	*(RMSEA = .028; CFI = .927; TLI = .918; WRMR = .875)*	*(RMSEA = .040; CFI =.923; TLI = .913; WRMR = .910)*	-
n	*65*	*62*	-
$\Delta\varkappa$	*.504*	*.571*	-
λ	*.136 - .819***	*.244 - .851***	-

$\varkappa = .504$. As a result, strong progression through the learning arrangement (individual) is evident. Consequently, hypothesis H_{3d} is confirmed.

For the configural model of cooperative learning (*n = 62)*, good to very good model fit values were obtained *(RMSEA = .040; CFI =.923; TLI = .913; WRMR = .910*). With one exception, the factor loadings of all manifest variables at both measurement points are highly significant *(*p ≤ 0.05; **p ≤ 0.01)*. For group ξ_{11} (pretest*)*, the loadings range from $\lambda = .244$ to $\lambda = .851$**. Group ξ_{12} (posttest) shows factor loadings ranging from $\lambda = .320$* to $\lambda = .824$**. Compared to the more restrictive level of so-called strong invariance, the model fit values remain good to very good using the chi-square difference test *(RMSEA = .040; CFI = .918; TLI = .910; WRMR = .937*). Furthermore, the chi-square difference test is not significant *(p = 0.1198)*. However, the restrictions cannot be completely realized. Two additional correlations between two indicators at both measurement points must be allowed. Accordingly, only partial strong invariance can be said to exist. The chi-square difference test is also not significant between the comparison of strong and strict invariance *(p = 0.0940)*. Accordingly, strict invariance is partially present between the two measurement points, which means that hypothesis H_{2b} can be upheld. The mean change is $\Delta\ \varkappa = .571$, which shows strong learning progression through the cooperative learning arrangement. The summary is presented in Table 8.

For the control group, there are overlapping covariances during the estimation. This could be related to the fact that the groups are too similar at the two measurement points. For these reasons, the control group cannot be tested for longitudinal invariance and H_{2c} is not confirmed. In the cross-sectional analysis, however, invariance between the two learning groups for the pre- and post-tests had already been established. Comparing the mean changes in both learning groups, the learning progression in the cooperative group was insubstantially higher at $\Delta\ \varkappa = .571$ than in the individual learning group at $\Delta\ \varkappa = .504$. The learning arrangement through individual learning in the analysis of knowledge application in 3D modeling with CAD (cf.[1]) had already produced more effective results in favor of individual learning. Based on these findings, hypothesis H_{3d} can only be retained to a limited extent. No longitudinal invariance can be observed for ξ_2 (declarative-factual knowledge about FEM). Consequently, H_{2d}, H_{2e}, H_{2f}, and H_{3e} are rejected.

Next, the dimension ξ_3 declarative-practical knowledge (applying an FEM) is tested for longitudinal invariance across the three treatment groups (cf. Figure 3). The

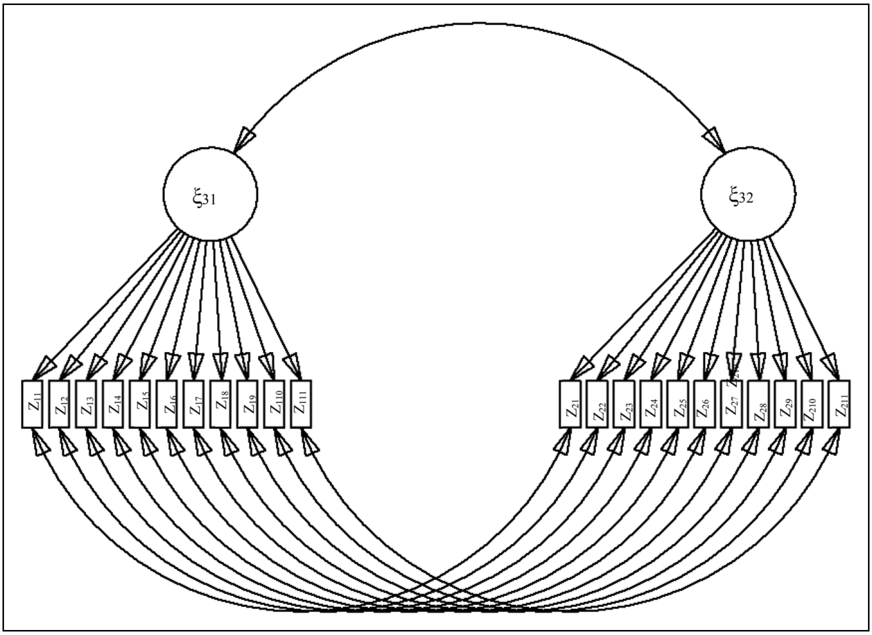

Figure 3. Longitudinal invariance test of the latent variable ξ_3.
ξ_{31} = Latent Variable (FEM declarative-practical knowledge at measurement time 1) Z_{11-110} = Manifest Variables (FEM declarative-practical knowledge at measurement time 1) ξ_{32} = Latent Variable (FEM declarative-practical knowledge at measurement time 2) Z_{21-210} = Manifest Variables (FEM declarative-practical knowledge at measurement time 2).

configurational model of the individual group *(n = 65)* shows very good model fit values *(RMSEA = .029; CFI = .973; TLI = .965; WRMR = .812).* With one exception, the factor loadings of all manifest variables at both measurement points are highly significant *(*p ≤ 0.05; **p ≤ 0.01).* For group ξ_{31} (pretest), the loadings range from $\lambda = .139$ to $\lambda = .785^{**}$. The group ξ_{32} (post-test) shows factor loadings within the range of $\lambda = .401^{**}$ to $\lambda = .835^{**}$. Compared to the more restrictive level of so-called strong invariance, the model fit values remain very good according to the chi-square difference test *(RMSEA = .020; CFI = .986; TLI = .983; WRMR = .827).* The chi-square difference test is also not significant *(p = 0.7855).* The restrictions can be implemented with the exception of one additional correlation between two indicators. Accordingly, partial strong invariance can be assumed. The chi-square difference test is also not significant between the comparison of strong and strict invariance *(p = 0.1923).* However, a correlation of one indicator between the two measurement points must be fixed. Accordingly, only strict invariance is partially present between the two measurement points, which mean that hypothesis H_{2g} is correct. The mean change is $\Delta\ \varkappa = 1.964$, which shows strong learning progression through the individual learning arrangement and confirms hypothesis H_{3f}.

Table 9. Hypotheses H_{2g}, H_{2h} and H_{3f} (longitudinal invariance for ξ_3 between pretest and posttest)

	Pretest- posttest		
Group	ISRL	CSRL	Control
Model Fit	*(RMSEA = .029; CFI = .973; TLI = .965; WRMR = .812)*	*(RMSEA = .026; CFI = .961; TLI = .951; WRMR = .807)*	-
N	*65*	*62*	-
Δ ϰ	*1.964*	*2.575*	-
Λ	*.139-.835***	*.112-.855***	-

The configurational model of cooperative learning for ξ_3 *($n = 62$)* again shows very good model fit values *(RMSEA = .026; CFI = .961; TLI = .951; WRMR = .807*). The factor loadings of the manifest variables at the two measurement points are largely highly significant *(*p ≤ 0.05; **p ≤ 0.01)*. For group ξ_{31} (pretest*)*, the eight loadings range from $\lambda = .287$ to $\lambda = .855^{**}$. The group ξ_{32} (post-test) shows factor loadings ranging from $\lambda = .112$ to $\lambda = .679^{**}$. The model fit values remain very good in comparison with the more restrictive level of so-called strong invariance using the chi-square difference test *(RMSEA = .000; CFI =1.000; TLI = 1.011; WRMR = .814*). The chi-square difference test is also not significant *($p = 0.9189$).* The restrictions can be completely realized. Accordingly, only strong invariance can be assumed. The chi-square difference test is also not significant between the comparison of strong and strict invariance *($p = 0.8324$)*. However, an additional correlation between two indicators must be allowed. Accordingly, strict invariance is partially present between the two measurement points, which means that hypothesis H_{2h} can be supported. The mean change is $\Delta\ \varkappa = 2.575$, which shows strong learning progression from the cooperative learning arrangement.

For the control group, overlapping covariances occur again during the estimation. As mentioned above, this could be related to the fact that the groups are too similar at the two measurement points. For these reasons, the control group cannot be tested for longitudinal invariance. H_{2i} is not retained. In the cross-sectional analysis, however, invariance between the two learning groups for the pre- and post-tests was already established. Comparing the mean changes in both learning groups, the learning progression in the cooperative group is significantly higher at $\varkappa = 2.575$ than in the ISRL group at $\varkappa = 1.964$. The learning arrangement through cooperative learning for applying the FEM is apparently most favorable, as theoretically assumed. Hypothesis H_{3f} is confirmed. In addition, the results are consistent with a previous analysis of domain-specific competence (cf.[1]). The overview is presented in Table 9.

It can be concluded that the entire family of hypotheses H_1 can be confirmed. This strongly suggests partial strict invariance across the three treatment groups in the pre- and post-tests. Longitudinal invariance is partially tested for both learning arrangements in dimensions ξ_1 and ξ_3. This means that H_{2a}, H_{2b}, H_{2g}, and H_{2h} are not refuted and can be retained. Problems with longitudinal testing only arose in dimension ξ_2.

The control groups of all dimensions are apparently too similar between the pretest and posttest, which is why the invariance test must be longitudinal for the control group, even though invariance to the other groups partially prevails in the cross-section. These results are also consistent with the analysis by Huester and Morris[1] in the context of competence. The observations of the mean changes in hypothesis family H_3 confirm the learning progression through the learning arrangements compared to the control group. For dimension ξ_3, cooperative learning has indeed proven to be the more effective learning environment. This is consistent with the analysis of domain-specific competence by Huester and Morris.[1] For the dimension ξ_1, there were no noteworthy differences between individual and cooperative learning. Consequently, the hypothesis family H_3 can be largely confirmed, albeit with some reservations.

Discussion and conclusion

Similar to the initial analysis of learning progression in the competences related to CAD and FEM (cf.[1]), the question that arose regarding knowledge acquisition between the two treatment groups in both cross-sectional and longitudinal terms. Cross-sectional findings affirm partial strict invariance across the three treatment-groups for the pretest and posttest in the dimensions ξ_1 (declarative knowledge about CAD), ξ_2 (declarative-factual knowledge about FEM) and ξ_3 (declarative-practical knowledge about FEM). In the longitudinally design, strict invariance was only partially found for the two learning arrangements ISRL and CSRL. Furthermore, this could only be observed in two dimensions declarative knowledge about CAD (ξ_1) and declarative-practical knowledge about FEM (ξ_3). As early as the second dimension, problems with inflated estimates became apparent in the pretest, and in the control group, the difference between the two measurement points was too small, leading to overlapping covariances. Nevertheless, invariance between the pretest and posttest can largely be established, making comparisons between the two measurement points possible. Accordingly, hypothesis family two can be substantially confirmed.

Another goal of the analysis was to determine learning progress. This was achieved by locating the change in the mean of the latent variables between the two measurement points using hypothesis family three. As anticipated, significant learning progress was demonstrated in both learning arrangements, which differed significantly from that of the control group. Declarative-practical knowledge regarding FEM (ξ_3) shows significant benefits in favor of the CSRL arrangement. This confirms the results of an earlier analysis conducted by Huester and Morris[1] within the framework of workplace competence in CAD and FEM.

Expectations regarding learning development in the area of declarative knowledge about CAD (ξ_1) were only partially fulfilled. The ISRL group showed significant learning progress in workplace competence in using CAD compared to the CSRL group. In line with this, such a difference would also have been conceivable for declarative knowledge in this dimension. There are no significant differences in learning progress between ISRL and CSRL. However, CSRL did not show any clearly recognizable superior learning outcomes compared to ISRL. Surprisingly, despite minimal differences in knowledge compared to the CSRL group, the students in the ISRL group were significantly more successful in implementing 3D modeling (cf.[1]). This could be because declarative knowledge is not of central importance when working with CAD and the knowledge required for 3D modeling is learned more intuitively and procedurally.

As expected, the analyses show that declarative knowledge cannot fully explain the competences. While the results for FEM, competence and knowledge gain are more favorable for the CSRL learning arrangement, such a harmonious picture does not hold true for CAD applications. Here, knowledge and competence gain vary differently across the learning arrangements. Correspondingly, 3D modeling would rather belong to the "biologically primary" category, while strength analysis would rather belong to the "biologically secondary" category.[17] In this respect, both categories can be identified and distinguished using the knowledge categorization proposed by Süß.[18] This is not a contradiction, as knowledge and competence are distinct constructs that are, however, closely correlated. Individual learning did not yield greater learning progress in declarative knowledge of CAD than cooperative learning. Nevertheless, the students who learned individually were better able to construct the 3D models (cf.[1]). It is possible that this competence is not as strongly dependent on consciously accessible knowledge as it appears to be in the case of FEM. This confirms the assumption from the first analysis regarding the promotion of competences in CAD and FEM that the success of the respective learning arrangement also depends on the chosen field of activity.[1] It can therefore be assumed that there are fields of occupation that are more suited to individual learning, and conversely, there are fields of practice that are well-suited to cooperative learning arrangements. Since both learning arrangements were very successful in the present analysis of knowledge acquisition, both can be recommended for use in teaching.

However, cooperative learning does not automatically lead to greater learning success, even if it is implemented appropriately, for example, according to the five cooperative basic-elements (cf. [31,32]). This was confirmed by the present analysis too. Of course, it is up to the teacher's pedagogical ambition to use cooperative learning arrangements even when individual learning would lead to higher occupational competence gains. The learning arrangement can also be defended on the grounds that it helps students learn cooperative behavior.

In the context of strength calculations, both original analyses from Huester and Morris demonstrate a favorable learning progression in favor of the cooperative learning arrangement (CSRL). Apparently, a strength calculation on a component using FEM corresponds more to the category of biologically secondary.[17] This means the learning process requires tremendous effort via the limited and slow working memory.[8] Cooperative behavior can make a valuable contribution here, as students support one another to overcome the existing barrier between the initial and final states (cf.[33]). In this way, an efficient use of working memory is achieved through an improved balance of cognitive load.[10] Strength calculations are evidently less in line with our natural inclinations than the creation of 3D objects using tailored, intuitively operable software. In this respect, 3D modeling for digital learning environments that students can explore individually would be preferable to strength calculations using FEM. But all this is only possible if the autopoietic system of students (cf.[34]) is able to practice information from the teacher's environment for its own commitments. In demand to find constructive solutions collectively, competitions within the group should be prevented (cf.[5]). In this regard, aligning the two regulatory models between students and the learning environment is crucial. Ultimately, it is up to the individual to decide whether or not to participate (cf.[35]).

Consequently, learning processes—which consist of a large, reciprocally interacting network of variables—can be effectively supported through appropriate design of the learning environment, but they cannot be controlled or calculated. This represents a striking contrast to the established and highly successful approaches in the engineering sciences for example. Learning processes can only be facilitated to a greater or lesser enablement for the individual through adequate design of the learning environment (cf.36,37).

Individual and cooperative self-regulated learning demonstrated significant learning progress, both in the analysis of competency development (cf.[1]) and in the present analysis of knowledge acquisition in the context of CAD and FEM in mechanical engineering. Both learning arrangements are recommended for the design of learning processes. Cooperative learning does not automatically lead to better results, even when implemented appropriately. 3D modeling with CAD appears to be better suited to individual learning than strength calculations and interpretation via FEM. These findings are important to inform policy and practice of vocational education and training, including for the design of digital learning environments.

From these observations and findings, the following recommendation for lesson design can be derived. If a lesson is to be self-directed and digitized, the subject area of 3D modeling in CAD appears to be particularly well-suited for this purpose. In this context, individual self-regulated learning has yielded better results than cooperative self-regulated learning. The learning environment was implemented using video vignettes. Verbal explanations are not even necessary for 3D modeling. This allows a class to be conducted even without a headphone system. Another option is to upload the video vignettes to a learning platform such as Moodle. This way, the assignments can be completed from home. This is particularly important for distance learning. However, this learning arrangement does not promote cooperative behavior. Digital isolation should also not be underrated. Of course, CAD instruction can also be implemented in a digital cooperative format. Experience has shown that conferencing software such as Alpha View is very well suited for this. Learning platforms such as Moodle are, of course, also suitable. In order to interpret a FEM with the corresponding declarative factual knowledge regarding stresses, the value of cooperative learning through discussion should not be overlooked. This can be done, for example, using the Jigsaw method where one person from each group joins others to form an expert group. These individuals first acquire knowledge and competences in a specific field on their own. The expert group then shares its knowledge to support the home group in their learning in the final step.[19] Certainly, this learning arrangement can also be implemented using digital learning platforms such as Moodle or OpenOLAT.

In the present study, both individual and cooperative self-regulated learning treatment groups demonstrated significant learning progress in knowledge acquisition in the context of CAD and FEM in mechanical engineering. Acquisition of FEM declarative-practical *knowledge* was more effective through a cooperative self-regulated learning arrangement, in comparison to an individual self-regulated learning arrangement. This original finding complements a previous study from Huester and Morris[1] who found that acquisition in FEM *competency* was better through cooperative self-regulated learning, in comparison to an individual self-regulated learning arrangement. Nonetheless, this finding contrasts with preferential learning arrangements for CAD; where in a previous study[1] students achieved greater learning success in CAD competence through individual self-regulated learning, in comparison to a cooperative self-regulated learning arrangement. However, in the present study, since no difference in CAD declarative knowledge was found between the learning arrangements, it is conceivable that competences in 3D modeling (CAD) are learned more procedurally and intuitively. This observation is relevant for the design of digital learning environments and to guide vocational education and training policy and practice.

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Data availability statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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