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# Weak versus strong knowledge interdependence: A comparison of two rationales for distributing information among learners in collaborative learning settings

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**Abstract:**

Traditional jigsaw-type scripts create strong knowledge interdependence by distributing information on core concepts between learners. However, previous research indicates that such knowledge interdependence may hinder interactive knowledge co-construction by reducing learners' common ground on core concepts. In an experiment with undergraduates (n= 78) in three-person-groups, we contrasted two rationales for distributing information: (1) establishing *strong knowledge interdependence* by distributing knowledge on core concepts as in a traditional jigsaw-type script, and (2) establishing *weak knowledge interdependence* by distributing only contextual information in a modified jigsaw-type script. Weak knowledge interdependence particularly benefitted low prior knowledge learners' transfer performance. Furthermore, it supported learners' interactive knowledge co-construction during collaboration, and this interactive co-construction mediated the effects of knowledge interdependence on individual learning. This study illustrates how collaborative and individual learning activities interrelate, and that a slightly modified jigsaw-type script makes a valuable addition to an instructor's toolbox.

**Keywords:**

- Collaborative learning
- Collaboration scripts
- Jigsaw method
- Interactive learning activities

## 1. Introduction

Collaborative learning is a powerful asset in an instructors' toolbox. Its overall effectiveness has been demonstrated in reviews and meta-analyses (Hattie, 2009; Johnson & Johnson, 2009; Slavin, Hurley, & Chamberlain, 2003). In effective collaborative learning, peers co-construct new knowledge that goes beyond what any of them knew before (Chi, 2009; Deiglmayr & Spada, 2010), for example by integrating diverging perspectives and ideas (Jucks & Paus, 2013; Schwartz, 1995), or resolving socio-cognitive conflicts (Buchs, Butera, & Mugny, 2004). Nevertheless, effective collaboration does not occur automatically. Instructors therefore scaffold collaboration by prescribing and sequencing learning activities, distributing roles and responsibilities, and providing coordination support in the form of collaboration scripts (Fischer, Kollar, Stegmann, & Wecker, 2013). However, when designing such scaffolding, instructors face difficult decisions.

One important decision concerns whether and how information on core concepts should be distributed between learners. We use the term *core concept* to refer to models, principles, or procedures needed for understanding and solving problems in a given domain (e.g., the principles needed to solve a specific mathematical problem; or the concepts needed to understand a class of medical diseases). On the one hand, distributing information on core concepts motivates collaboration by creating specialization, that is, by establishing strong *knowledge interdependence* among learners (Molinari, Sangin, Dillenbourg, & Nüssli, 2009). This strategy is, for example, employed in the widely-used jigsaw method (Aronson & Patnoe, 1997). On the other hand, providing information on core concepts to all learners from the start has the advantage that each learner can develop a first understanding of the to-be-learned concepts on which she can build during collaboration, and on which collaborators can ground their communication (Baker, Hansen, Joiner, & Traum, 1999).

What constitutes core concepts, and what contextual information, depends of course on the learning goals in a given learning situation. In mathematics, for example, students might learn from worked examples that embed mathematical principles (core concepts) in different story problems (context). In biology, students might learn the features distinguishing invertebrates from vertebrates (core concepts), exemplified by specific species (context). In educational psychology, students might study different sources of learning motivation (core concepts) by analyzing a set of authentic cases (context).

In the following, we argue that the strong knowledge interdependence that is created by traditional jigsaw-type collaboration scripts by distributing core concepts among learners might be suboptimal. We propose a modified jigsaw-type collaboration script in which weak, rather than strong, knowledge interdependence is created by distributing only contextual information. Our focal claim is that learners, in particular low prior knowledge learners, benefit more when only contextual information is distributed, while knowledge on core concepts is shared. As an important mediating mechanism, we assume that such weak knowledge interdependence will better prepare learners to participate in interactive knowledge construction during collaboration.

## 1.1 Interactive learning activities

In a recent review, Chi and Wiley (2014) argue that *interactive* learning activities are the most beneficial for increasing individual learning outcomes. Interactive learning activities are defined by their collaborative, co-constructive nature. Examples include the co-construction of solutions, arguments, or explanations in peer discussions. Interactive learning activities, which can only be enacted in collaboration with a learning partner, are hypothesized to be more effective for fostering individual learning than constructive learning activities, which are the most effective kinds of learning activities a learner can engage in the absence of a learning partner. Chi and Wylie define constructive learning activities as activities in which the learner goes beyond the information given, and engages deeply with core concepts of the learning domain (e.g., by self-explaining, elaborating, comparing, inferring, or integrating information). Interactive learning activities are supposed to be superior to constructive learning activities because the learner is constructive and, at the same time, takes up and builds upon contributions of collaborators. Thus, a learner benefits from learning partners because they provide additional knowledge resources, different perspectives, new ideas, or feedback (Chi & Wylie, 2014). Other researchers have likewise emphasized the crucial role of learners' participation in such co-constructive, or transactive discourse (e.g., Berkowitz & Gibbs, 1983; Deiglmayr & Spada, 2011; Fischer et al., 2013; van Boxtel, van der Linden, & Kanselaar, 2001).

The presumed benefit of interactive over constructive engagement is likely to depend on an individual's relevant prior knowledge. High prior knowledge learners benefit from a collaborative setting even if they take over the sole responsibility for the group`s task (e.g., by engaging with the task, generating self-directed explanations, and producing a solution), that is, by being constructive rather than interactive. For example, high prior knowledge learners often dominate the discussion, and also show the greatest learning gains (Salomon & Globerson, 1989). At the same time, high prior knowledge learners also benefit from being interactive, either by engaging in mutual knowledge co-construction with equally capable peers, or by tutoring less knowledgeable peers (Ploetzner, Dillenbourg, Praier, & Traum, 1999). Low prior knowledge learners, on the other hand, typically lack the necessary prerequisites to solve the task on their own in a constructive fashion, but profit from the explanations of more knowledgeable peers (Webb & Palincsar, 1996), or from the opportunity to mutually co-construct new insights (Chi & Wiley, 2014). Thus, interactive engagement in collaboration may be particularly beneficial for low prior knowledge learners. They depend more than high prior knowledge learners on the scaffolding, feedback, and additional insights that they may gain from interacting with others.

## 1.2 Knowledge interdependence and interactive learning activities

Knowledge interdependence means that learners collaborate on the basis of complementary expertise (Molinari et al., 2009). Learners have access to information on core concepts only via their learning partners, on whom they are thus dependent for their own learning (Buchs et al., 2004). Instructors can create strong knowledge interdependence either by having learners collaborate on the basis of pre-existing, complementary fields of expertise (Noroozi, Biemans, Weinberger, Mulder, & Chizari, 2013; Rummel & Spada, 2005), or by purposefully manipulating learners expertise by training each on a specific subset of core concepts prior to collaboration (Berger & Hänze, 2009).

The jigsaw method (Aronson & Patnoe, 1997) is a typical collaboration script following the latter approach. Several slightly different implementations of the jigsaw method exist. Nevertheless, all of these jigsaw-type collaboration scripts include at least two phases (Dillenbourg & Jermann, 2007): In an individual learning phase, learners study a specific concept and thus become an “expert” for this concept. Each learner becomes an expert for a different core concept, establishing strong knowledge interdependence. In a subsequent collaboration phase, learners explain the individually studied concepts to one another, and work on joint tasks requiring their complementary expertise.

### 1.2.1 Benefits of knowledge interdependence

The main benefit of establishing knowledge interdependence with regard to core concepts is motivational (Berger & Hänze, 2009). Knowledge interdependence creates a special form of positive social interdependence, which has well-documented, positive motivational effects

(Johnson & Johnson, 2009). When learners know that they can solve a joint task and reach their own learning goals only by pooling and integrating their complementary knowledge on core concepts, this interdependence renders collaboration meaningful and relevant, and thus increases individual motivation to participate (Buchs et al., 2004; Johnson & Johnson, 2009; Slavin et al., 2003). Additionally, some degree of knowledge interdependence is beneficial for fostering interactive knowledge co-construction, as differences in perspectives or opinions often lead to fruitful argumentation, elaboration, or mutual explanations (e.g., Jucks & Paus, 2013; Schwartz, 1995). Particularly positive motivational effects are reached when knowledge interdependence is combined with personal accountability, for example when learners expect to be tested regarding their individual knowledge about the whole range of core concepts (Johnson & Johnson, 2009).

### 1.2.2 Disadvantages of knowledge interdependence

When instructors establish strong knowledge interdependence within a group in order to motivate collaboration, this implies that each individual learner lacks knowledge on core concepts when entering collaboration. Under some circumstances this may be problematic, as existing knowledge is an important predictor of future learning (e.g., Schneider & Bullock, 2009). Thus, to constructively engage with learning materials, learners need basic knowledge on all to-be-learned core concepts, on which they can build, for example, by constructing principle-based self-explanations (Renkl, 2014), by devising well supported arguments (Noroozi, Weinberger, Biemans, Mulder, & Chizari, 2012), or by working out a comprehensive problem solution (Rummel & Spada, 2005). Such constructive, individual engagement is also the basis for effective interactive knowledge construction (Chi & Wylie, 2014).

If all learners study all core concepts prior to collaboration, this also ensures that learners have relevant shared knowledge, or common ground (Clark & Brennan, 1991). Common ground is important for efficient communication and coordination between collaborators. Thus, it plays an important role for successful collaborative learning arrangements (e.g., Baker et al., 1999; Beers, Boshuizen, Kirschner, & Gijselaers, 2005; Noroozi et al., 2013). Further, groups tend to focus their discussions on shared knowledge (Brodbeck, Kerschreiter, Mojzisch, & Schulz-Hardt, 2007), and have difficulties integrating the unique knowledge of individual group members (Deiglmayr & Spada, 2010, 2011). Thus, establishing core concepts as shared knowledge in a group, increases the likelihood that group members will discuss them. Under conditions of strong knowledge interdependence, however, core concepts do not constitute shared knowledge, and cannot serve as common ground.

Based on these considerations, we assume that strong knowledge interdependence, as realized by traditional jigsaw-type scripts, will not optimally prepare learners to profit from collaboration. Therefore, we propose a rationale for distributing information that creates a weaker form of knowledge interdependence to ensure that learners have sufficient knowledge on core concepts.

### 1.3 Two rationales for distributing information in jigsaw-type collaboration scripts

The traditional rationale for distributing learning content between students in a jigsaw-type collaboration script is to maximize knowledge interdependence in order to create a relevant and motivating task (Aronson & Patnoe, 1997; Dillenbourg & Jermann, 2007). For example, a mathematics teacher might distribute different mathematical core concepts among the learners during the individual learning phase, and later have them exchange and integrate their complementary expertise. We term this the *strong knowledge interdependence* rationale because core concepts are distributed between learners prior to collaboration.

Findings on the effectiveness of jigsaw-type scripts for fostering individual learning are, however, mixed (e.g., Slavin et al., 2003). These scripts have been shown to increase learners' motivation (Hänze & Berger, 2007; Johnson & Johnson, 2009), and to foster a cooperative climate (Aronson & Patnoe, 1997). At the same time, the decreased amount of shared knowledge, and thus, common ground, hampers knowledge exchange and integration in groups (Buchs et al., 2004; Deiglmayr & Spada, 2010, 2011). After collaboration, learners are typically still better informed about their own subset of core concepts than about those of their learning partners (Berger & Hänze, 2015; Hänze & Berger, 2007; Souvignier & Kronenberger, 2007). Furthermore, jigsaw-groups engage less often in knowledge co-construction than other collaborative groups (Moreno, 2009). In direct comparisons of jigsaw-type scripts to other collaborative learning methods establishing lower levels of knowledge interdependence (e.g., traditional small group learning), jigsaw learners have been found to gain less knowledge about core concepts than learners in the other collaborative condition (Berger & Hänze, 2009; Buchs et al., 2004; Moreno, 2009).

We therefore suggest a modified jigsaw-type script that establishes *weak knowledge interdependence*. Following this rationale for distributing information, information on core concepts is realized as shared knowledge between learners; that is, all learners study the same core concepts prior to collaboration. At the same time, collaboration is rendered meaningful and relevant by having each learner study the concepts in a different context. For example, all learners might study the same mathematical concepts, but for each learner, these would be embedded in a different context. Thus, this modified jigsaw-type script creates knowledge interdependence regarding contextual features only, but not regarding core concepts.

### 1.4 Hypotheses

We aimed to systematically assess whether weak knowledge interdependence is indeed more beneficial than strong knowledge interdependence for promoting individual participation in interactive knowledge co-construction, and individual learning outcomes. The learning domain was introductory probability theory, and the core concepts were three urn models (see Materials section for details). Worked examples illustrated the models' application in different contexts. In the *strong knowledge interdependence condition*, each learner became an expert for a different urn model by studying three worked examples that embedded the same model in three different contexts. In the *weak knowledge interdependence condition*, each learner became an expert for one context by studying three worked examples that embedded the three models in the same context.

We expected that the shared knowledge on core concepts would better prepare learners to participate in knowledge co-construction resulting in more interactive engagement during discussion, and in higher individual learning outcomes. As the opportunity to participate in interactive knowledge co-construction is particularly important for low-prior knowledge learners, we expected the highest gains for this group of learners. In all analyses, learners' pre-existing (i.e. not experimentally manipulated) prior knowledge on core concepts was included as a potential moderator. In this way, we could test whether *weak knowledge interdependence* was indeed particularly beneficial for increasing low-prior-knowledge learners` interactive engagement and individual learning outcomes.

> *Hypothesis 1:* Weak knowledge interdependence results in higher individual learning and transfer performance compared to strong knowledge interdependence, in particular for low prior knowledge learners.

Further, we expected that the common ground regarding core concepts in the weak knowledge interdependence condition would facilitate interactive knowledge co-construction during collaboration which, again, would be particularly beneficial for low prior knowledge learners.

> *Hypothesis 2:* Weak *knowledge* interdependence leads to a higher frequency of interactive knowledge co-construction activities during collaboration compared to strong knowledge interdependence, in particular for low prior knowledge learners.

Finally, we expected that learners' participation in interactive learning activities during collaboration mediated the effects of knowledge interdependence on individual learning and transfer performance.

> *Hypothesis 3:* The amount of interactive learning activities during collaboration mediates the effect of knowledge interdependence on individual learning and transfer.

We tested Hypotheses 2 and 3 based on data from extensive analyses of learners' discussions in the collaborative phase. To analyze the specific role of interactive learning activities, we identified both interactive and constructive turns, and ran all analyses for both kinds of learning activities. Thus, we could test whether it was indeed the frequency of interactive, rather than constructive, learning activities, which mediated the effect of knowledge interdependence on individual learning outcomes.

## 2. Method

### 2.1 Participants

In total, 87 Swiss undergraduate university students majoring in various subjects (but not mathematics or related subjects) participated for monetary compensation. All students were native speakers of German. Pre-studies had indicated that undergraduates generally had problems understanding and applying urn models without training (see also Berthold, Eysink, & Renkl, 2009).

Students were randomly assigned to a three-person-group (triad), and triads were randomly assigned to either the weak or the strong knowledge interdependence condition. Post-hoc, three triads were excluded from all analyses because at least one of their members did not pass the threshold in a basic prior knowledge test on adding and multiplying fractions (an essential prerequisite for understanding urn models), or because they did not follow instructions. This exclusion left a total of 78 participants (42 female, 36 male) in 26 triads. Their age ranged from 18 to 36 years ($M$=24.4, $SD$=4.0). Conditions differed neither in the proportions of men and women ($\chi^2_{(df=1)}$=.83; $p$=.36), nor in participants' age ($t_{(76)}$=.14; $p$=.89), or final high school grade in Mathematics ($t_{(68)}$=1.40; $p$=.17).

## 2.2 Materials

The to-be-learned core concepts were mathematical urn models. Urn models are used for determining the joint probability of a series of random events, like throwing a dice repeatedly, or drawing balls from an urn. We worked with four urn models (M1-M4). These models result from crossing two stochastic principles: relevance of order (relevant/irrelevant) and replacement (with/without). Model 1 (order relevant & drawing with replacement), Model 2 (order relevant & drawing without replacement), and Model 3 (order irrelevant & drawing with replacement) were trained. Model 4 (order irrelevant & drawing without replacement) can be derived from an integrated understanding of the other three models. Problems requiring the application of Model 4 were therefore used to assess transfer of learning.

The learning materials comprised a combination of instructional techniques that foster constructive engagement: worked examples (e.g., Renkl, 2014), self-explanation prompts (e.g., Chi, De Leeuw, Chiu, & Lavancher, 1994), and the possibility to compare and contrast the three examples (e.g., Alfieri, Nokes-Malach, & Schunn, 2013). The worked examples were adapted from a study by Berthold and Renkl (2009) and instantiated the three models

(M1, M2, and M3) within three different context stories (C1, C2, and C3). In the first context (C1), the urn models were applied to the random distribution of bike helmets among participants in a two-day mountain-bike course. In the second context (C2), the urn models were applied to the random distribution of ranks in a ski-jumping competition with two rounds of jumps, and in the third context (C3), to the random drawing of unlabeled bottles from two cabinets. We generated nine worked examples by combining the three models with the three context stories (see Appendix A for examples).

## 2.3 Procedure

Before starting the experiment, learners answered a demographic questionnaire. All instructions, learning materials, and tests for the experiment were delivered via a computer-supported collaborative learning (CSCL) environment, programmed in lessonLAMS (www.lessonlams.com). Participants sat at their individual PCs in separate cubicles and collaborated via a text-based chat. The computer-mediated communication setting allowed us to record participants` individual answers, along with the complete discussion that took place in the triad.

In the CSCL-environment, participants began with the pretest. For the subsequent learning phase, the environment was designed to establish knowledge interdependence, the defining feature of jigsaw-type collaborations (e.g. Dillenbourg & Jermann, 2007), and differed slightly from typical whole-classroom implementations of the method. Specifically, we did not include a phase in which learners discuss their individual learning materials with others who studied the same topic, and did not separate phases of information exchange and collaborative problem solving. In our scripts, each triad member first studied a different set of three worked examples during an individual learning phase (Figure 1). We prompted learners to compare and contrast their set of worked examples, and to type a written explanation of the similarities and the differences into a text box. Learners could proceed to the collaborative learning phase only after spending at least ten minutes on their individual materials, and completing the self-explanation task.

We realized two levels of knowledge interdependence during the individual learning phase. In the *strong knowledge interdependence condition*, each individual learner in a triad became an expert for a different model. Their materials comprised three worked examples for their model (M1, M2, or M3), each embedded in a different context (i.e., a single model was exemplified in three different contexts). In the *weak knowledge interdependence condition*, in contrast, each learner of a triad studied all three models, but these models were embedded in a single context. The context differed between learners (C1, C2, or C3). Thus, in a sense, each learner in this condition became an expert for a specific context. Note that in both conditions, each learner studied exactly three worked examples in the individual learning phase.

A collaborative learning phase followed the individual learning phase. Instructions and tasks in this phase were identical in both conditions (Figure 1). We designed this phase in order to give all learners the opportunity to process the entire set of core concepts (i.e. all nine model-context combinations), and to prompt information exchange between learners. Triads collaborated via chat to agree upon a joint answer to three self-explanation tasks, one for each of the three models. The discussion prompts were:

- Task 1, referring to Model 1: “Discuss and explain: Why are the fractions always multiplied, rather than added up in these examples?”
- Task 2, referring to Model 2: “Discuss and explain: Why is the fractions’ denominator decreasing?”
- Task 3, referring to Model 3: “Discuss and explain: Why does the solution to Model 3 require both addition and multiplication?”

Finally, after finishing the collaboration phase, learners individually completed a post-test. In total, the experiment lasted about 2.5 hours.

## 2.4 Measures

### 2.4.1 Questionnaire

In the demographic questionnaire participants stated their age, gender, native language, subject of study, and final high school grade in Mathematics.

### 2.4.2 Pretest

In addition to six basic knowledge questions on adding and multiplying fractions used for screening participants, the pretest contained four story problems assessing learners' prior knowledge about Models 1 through 4 (M1-M4). For example, the word problem for Model 3 was (translated from German):

> You are turning, twice, a fortune wheel that has five equally large sections, each showing a different symbol: shamrock, heart, tomato, frog, and mushroom. You win if your two turns show the shamrock and the heart (no matter in which order). What is your likelihood of winning? Please state both the equation and the final solution.

We coded learners' answers as correct if they produced any of the possible mathematically equivalents of the correct equation (for the example above, 1/5*1/5+1/5*1/5, which is mathematically equivalent, for example, to 2/5*1/5, or 2*1/5^2). The number of correctly solved word problems constituted learners` pretest score (*M*=2.19; *SD*=.99). The internal consistency of this measure was acceptable ($\omega_{total}$=.69).

### 2.4.3 Posttest

The posttest included application and transfer tasks. The application tasks comprised six word problems assessing learners' ability to apply the three trained models (M1-M3). Three application problems were identical to the M1-M3 problems from the pretest, three used novel cover stories. The transfer tasks comprised three word problems. These word problems required learners to infer the solution procedure for the untrained Model 4. The transfer problem used the context stories that learners were familiar with from the training phase (see Appendix B for an example). We informed learners that these tasks constituted a new type of urn model, but that they would be able to solve them by combining what they had learned before.

For each problem of the posttest, an answer was scored as correct only if a learner produced a mathematical equivalent of the correct equation (e.g., 1/5*1/4+1/5*1/4 for the example in Appendix B). We computed two separate post-test scores: the number of correct solutions to the six problems assessing Models 1 through 3 (application score; $M$=4.52; $SD$=1.27), and the number of correct solutions to the three problems assessing Model 4 (transfer score; $M$=1.63; $SD$=1.21). The internal consistencies of these two measures were acceptable (application score: $\omega_{total}$=.76; transfer score: $\omega_{total}$=.83).

## 2.5 Coding Procedure

We gathered two types of process data in this experiment: (1) students' answers to the self-explanation prompts in the individual learning phase, and (2) the chat communication during the collaboration phase. We aimed to identify learning activities, such as explanations, arguments, questions, or solution attempts, in which learners referred to relevant principles. Such principle-based elaborations are a particularly important learning activity in example-based learning scenarios (cf. Renkl, 2014) like the one we employed in this study.

Based on previous studies using similar materials (e.g., Berthold & Renkl, 2009), we identified three basic stochastic principles to be relevant for the worked examples. Two principles identify the specific urn model: (1) relevance of order (relevant/irrelevant) and (2) replacement (with/without). The third, more general principle, concerns the need to (3) multiply the probabilities of individual events in order to compute their joint probability. It is important to note that the three principles are relevant for explaining each of the worked examples, independent of the model it exemplifies, or of the context in which it is embedded. That is, in each worked example, the drawing is either with or without replacement, the order of events is either relevant or irrelevant, and the problem solution always requires multiplication of probabilities.

We did not expect learners to provide specific labels for the three stochastic principles. Instead, we coded whether they gave correct explanations for specific features of the solution equation that corresponded with the principles. For example, a learner might have noted that the solution of a worked example contained two fractions with identical (or: different) denominators. If she explained this fact as resulting from the number of objects remaining constant (or: decreasing) from one draw to the next in the example, she received credit for a principle-based self-explanation (in this case, referring to the principle of drawing with/without replacement).

### 2.5.1 Individual self-explanations

For the self-explanations produced in the individual learning phase, participants received one point for each of the three stochastic principles that could be identified. Two coders independently rated all 78 individual self-explanations. Inter-rater agreement was satisfactory ($ICC_{absolute}$=.84 [*95%-CI:* .77; .89]). Disagreements were resolved by discussion.

### 2.5.2 Chat analyses

In analyzing the chat protocols (*n*=1873 turns), we identified principle-based elaborations that were either individual contributions that did not build upon previous contributions by others (constructive), or that were part of an interactive process of co-constructing an explanation (interactive). We used a two-step coding procedure.

In a first step, we narrowed down the coding sample by identifying turns in which a learner engaged with the learning materials in at least a constructive mode. We termed these *knowledge-building* turns. Examples include learners suggesting a solution, attempting an explanation, rephrasing the problem, raising a question, critiquing or elaborating on another learner's contribution, or proving justification. Turns in which learners coordinated their collaboration, engaged in social talk, or discussed technical issues were not coded as knowledge building turns. To determine inter-rater agreement, a second coder rated ten randomly selected chat protocols ($n$=30 learners). Inter-rater agreement for the number of knowledge-building turns per learner was high ($ICC_{absolute}$=.97 [*95%-CI*: .92; .99]). Disagreements were resolved by discussion. This first coding step yielded a total of $n$=499 *knowledge building turns* in the whole sample.

In the second step, we assigned each knowledge building turn two codes. First, we coded each knowledge building turn as either principle-based, or not principle-based. To be *principle-based*, a turn had to be relevant with regard to one of the three stochastic principles described above. Second, we coded all knowledge building turns as either constructive or interactive. Recall that, by our definition, all knowledge building turns were at least constructive. We coded a knowledge building turn to be *interactive* if it built on a previous knowledge building turn by a learning partner, for example by referencing, elaborating, or rephrasing that contribution, or by providing an answer or a critique (cf. Chi & Wylie, 2014). If learners raised a new topic, ignored their partners' contributions, or elaborated on one of their own previous turns, we coded the turn as *constructive*. Combining both sets of codes, two scores resulted for each learner: the number of *constructive principle-based turns*, and the number of *interactive principle-based turns*.

To determine inter-rater agreement, a second coder rated another set of ten randomly selected chat protocols ($n$=30 learners). Agreement was high for both, *constructive principle-based contributions* ($ICC_{absolute}$=.95 *95%-CI* [.89; .98]) and *interactive principle-based contributions* ($ICC_{absolute}$=.91 *95%-CI* [.81; .96]). Disagreements were resolved by discussion. The analysis yielded $n$=144 *constructive principle-based turns* and $n$=166 *interactive principle-based turns* in the whole sample.

## 3. Results

### 3.1 Pretest

There were no relevant differences between experimental conditions in participants' prior knowledge as assessed in the pretest ($t_{(76)}$=.11; $p$=.91; see Table 1).

### 3.2 Individual self-explanations

There was substantial variance in learners' self-explanation scores (see Table 1), but it could not be explained by systematic differences between conditions ($B$=.68; $SE$=.78; $Exp(B)$=1.98; 95%-CI [.43; 9.07]; $p$=.38), learners' prior knowledge ($B$=.37; $SE$=.23; $Exp(B)$=1.44; 95%-CI [.92; 2.27]; $p$=.11), or the interaction between experimental condition and prior knowledge ($B$=-.07; $SE$=.30; $Exp(B)$=.93; 95%-CI [.51; 1.68]; $p$=.81) in a generalized logistic regression analysis. This result is important, because it shows that differences in learning and transfer between conditions cannot be fully explained by students' activities in the individual learning phase.

### 3.3 Learning outcomes

Table 1 provides an overview of the proportion of correct responses on the pretest, the application test, and the transfer test in both conditions. The intra-class correlations were $ICC_{consistency}$=- .07 (*95%-CI* [-.24; .19]; *p*=.70) for the application score, and $ICC_{consistency}$=-.21 (*95%-CI* [-.33; 0]; *p*=.98) for the transfer score, indicating a non-hierarchical data structure. Therefore, we conducted the following analyses on the level of individual learners.

Since the posttest data originally consisted of a series of binary (incorrect or correct) responses, we calculated generalized logistic regression models (using SPSS's GENLIN procedure, with a logit link function) rather than ANOVAs as our primary method of analysis (Jaeger, 2008). We included prior knowledge (number of pretest problems solved correctly), and the interaction term of prior knowledge and condition as predictors in all regression models. Condition was dummy coded, with parameter estimates referring to the effect of being in the weak knowledge interdependence condition. For performance on the application tasks, prior knowledge was the only statistically significant predictor (*B*=.99; *SE*=.21; *Exp(B)*=2.71; 95%-CI [1.78; 4.13]; *p*<.001). The two experimental conditions did not differ significantly with regard to the application score (*B*=.70; *SE*=.56; *Exp(B)*=2.02; 95%-CI [.68; 6.01]; *p*=.21), and there also was no statistically significant interaction of condition and prior knowledge (*B*=-.36; *SE*=.28; *Exp(B)*=.70; 95%-CI [.40; 1.22]; *p*=.21). Thus, for students' ability to apply the three trained models, Hypothesis 1 received no support: Independent of learners` prior knowledge, both conditions were equally effective.

For performance on the transfer tasks, experimental condition, prior knowledge, and their interaction were statistically significant predictors. All parameter estimates from the generalized logistic regression can be found in Table 2 (Regression Model 1). To further probe the interaction effect, and confirm it with a different technique, we performed a median split for prior knowledge (*Median*=0.5), and compared learners with low and high levels of prior knowledge in both conditions (Figure 2). Learners with high prior knowledge obtained high transfer scores regardless of condition ($t_{(23)}$=.81; *p*=.43). However, learners with low prior knowledge benefitted more from the weak compared to the strong knowledge interdependence condition ($t_{(51)}$=2.89; $p$=.01). The findings regarding transfer performance are thus in line with Hypothesis 1.

### 3.4 Chat analyses: Principle-based turns

Table 3 gives an overview of the mean numbers of constructive and interactive principle-based turns that individual learners produced in both conditions. The number of constructive turns produced by one triad member was not influenced by the number of constructive turns produced by the other triad members ($ICC_{consistency}$=-.19; 95%-CI [-.32; .02]; $p$=.96). This independence was expected given the definition of constructive turns as non-interactive (Chi & Wiley, 2014). For the number of interactive turns, on the other hand, our analysis points towards a positive dynamic, in that two members of the same triad show significantly higher similarity regarding their interactive engagement than any two randomly chosen learners ($ICC_{consistency}$=.31; 95%-CI [.07; .57]; $p$=.01).

As the numbers of constructive and interactive principle-based turns in the chat constitute count data, we calculated generalized linear regression models assuming a Poisson distribution and a logistic link function, again using SPSS's GENLIN procedure. To assess whether the number of learners' constructive and interactive principle-based contributions to the chat mediated the effects of experimental condition, we followed the approach suggested by Baron and Kenny (1986). This approach can handle input from different kinds of generalized linear regression models, such as the combination of logistic and Poisson regression used in the present analysis. In our analysis, the numbers of constructive/interactive principle-based turns served as the potential mediators, and prior knowledge was included as a potential moderator.

3.4.1 Constructive principle-based turns

Figure 3a shows the mean number of *constructive* principle based turns produced by learners with low versus high levels of prior knowledge in both conditions (note that prior knowledge served as a continuous predictor in the regression analyses). The Poisson regression yielded non-significant effects for experimental condition ($B$=.25; $SE$=.43; $Exp(B)$=1.29; 95%-CI [.55; 2.99]; $p$=.56), and for the interaction between experimental condition and learners' prior knowledge ($B$=-.14; $SE$=.16; $Exp(B)$=.87; 95%-CI [.64; 1.20]; $p$=.40). The only statistically significant predictor was prior knowledge ($B$=.32; $SE$=.12; $Exp(B)$=1.38; 95%-CI [1.10; 1.73]; $p$=.01).

Because it could not be regressed on experimental condition, the number of constructive principle-based turns did not qualify as a potential mediator to explain the effect of experimental condition on individual transfer performance. Also, even though the number of constructive principle-based turns showed a moderate correlation with learners' application score from the post-test ($r$=.36; $p$=.01), it did not correlate with students' transfer score ($r$=.17; $p$=.15).

3.4.2 Interactive principle-based turns

Figure 3b shows the mean number of *interactive* principle-based turns produced by learners with low and high levels of prior knowledge in both conditions. Visual inspection suggests an interaction, with low prior knowledge learners being more interactive in the weak knowledge interdependence condition, and high prior knowledge learners being more interactive in the strong knowledge interdependence condition. In fact, the Poisson regression yielded significant effects for experimental condition, prior knowledge, and their interaction (see Table 2, Regression Model 2). To further probe the interaction effect, we again compared learners below and above the median prior knowledge score in both conditions. Learners with high prior knowledge did not produce more interactive principle-based turns under weak, compared to strong knowledge interdependence ($t_{(23)}$= -1.81 $p$=.08). Low prior knowledge learners, however, produced more interactive principle-based turns under weak, compared to strong knowledge interdependence ($t_{(37.98)}$=2.34; $p$=.03). The results are thus in line with Hypothesis 2.

In the next analytic step, we included the number of interactive principle-based turns as an additional predictor in Regression Model 3. The number of interactive principle-based turns significantly predicted the transfer score, even when controlling for experimental condition, prior knowledge, and their interaction (Table 2, Regression Model 3). Further, including interactive principle-based turns reduced the explanatory power of the other three predictors; that is, their *Exp(B)*s (*Odds Ratios*) were closer to 1 in Regression Model 3 compared to Regression Model 1. However, the effect of experimental condition was still statistically significant, yielding support only for partial mediation, and thus, partial support for Hypothesis 3.

## 4. Discussion

In the present study, we contrasted two rationales for distributing information between learners. The first rationale, implemented in traditional jigsaw-type collaboration scripts (e.g., Aronson & Patnoe, 1997), is to design for strong knowledge interdependence. Accordingly, information on core concepts is distributed between learners prior to collaboration. The second rationale is to design for weak knowledge interdependence, as in the modified jigsaw-type script developed for the present research. Accordingly, a common ground regarding core concepts is established among learners, and only contextual features are distributed between learners prior to collaboration.

In line with Hypothesis 1, we found that low prior knowledge learners, in particular, learned better under conditions of weak, rather than strong knowledge interdependence, whereas high prior knowledge learners profited equally in both condition. This effect was, however, only found for the transfer test. This test assessed learners' ability to derive the application of a fourth, untrained stochastic model from their knowledge about the three trained models, and thus, required a deep understanding of the trained models. Low prior knowledge learners engaged more actively in collaborative knowledge construction under conditions of weak, compared to strong knowledge interdependence, as indicated by a higher number of interactive principle-based turns (supporting Hypothesis 2). In line with Hypothesis 3, higher interactive engagement partially mediated the beneficial effects of weak knowledge interdependence on transfer performance.

The crucial experimental manipulation in our study concerned the ways in which information was distributed between learners, and thus the kinds of materials that learners studied prior to collaboration. In the strong knowledge interdependence condition, learners compared three worked examples illustrating a single mathematical concept embedded in three different contexts. In the weak knowledge interdependence condition, in contrast, learners studied three worked examples illustrating three different mathematical concepts within the same context. In our study, the number of worked examples and the time for studying was held constant across conditions to ensure comparability beyond this crucial difference.

An alternative attempt to explain our findings might posit that the differential effects of weak versus strong knowledge interdependence arose solely from learners' engagement with the different types of learning materials during the individual learning phase. This explanation, however, is insufficient to account for the full range of findings. First, the analyses showed no substantial differences regarding the number of principle-based explanations that learners' produced during the individual learning phase. Thus, learners in both conditions engaged in principle-based, constructive learning activities to a comparable extent during the individual learning phase. Second, the chat analyses confirmed that both kinds of knowledge interdependence had differential effects on learners' engagement with core concepts during collaboration. Thus, the individual learning materials in the weak knowledge interdependence condition did make a difference, but they did so by better preparing low prior knowledge learners for participating in, and learning from interactive engagement in collaboration.

### 4.1 The role of interactive learning activities

Important parts of our argumentation are in line with the recent review by Chi and Wylie (2014). They argue that interactive learning activities, such as the co-construction of explanations, are superior to constructive learning activities, such as individual generation of self-explanations. However, all evidence presented by Chi and Wylie (2014) comes from studies that compared the effectiveness of collaborative versus individual learning settings, thus equating collaborative learning settings with interactive learning activities, and specific forms of individual learning settings with constructive learning activities. Nevertheless, while collaborative learning is certainly unique in affording interactive learning activities, a collaborative learning setting alone does not guarantee that learners will, in fact, engage in interactive learning activities. Consequentially, studies employing detailed analyses of the actually occurring learning activities, using process data, are needed. With the present study, we have provided such an analysis. Complementing Chi and Wylie's (2014) reasoning, we found that interactive, but not constructive learning activities (partially) mediated between the degree of knowledge interdependence and individual learning outcomes in a collaborative learning setting.

## 4.2 Limitations

Our findings indicate that low prior knowledge learners benefit more from weak knowledge interdependence than high prior knowledge learners. It would be highly interesting to conduct more fine-grained analyses of how group composition with regard to prior knowledge influences the occurrence and effectiveness of interactive learning activities. Unfortunately, such analyses were beyond the scope of the present study. However, future studies comparing intentionally created homogeneously and heterogeneously composed groups may contribute to a better understanding. In addition, as our study showed that members of the same triad tended to be more similar in their level of interactive engagement, it would be highly interesting to further study the links between the general level of interactive engagement within a group, an individuals` active participation in interactive knowledge construction, and individual learning outcomes. Such analyses would, however, require much larger samples sizes allowing for hierarchical data modelling.

Further, while we could demonstrate a relevant benefit of weak over strong knowledge interdependence for individual learning outcomes, it would also be interesting to study alternatives outcomes such as learners` motivation, interpersonal relations, or social skills. Further research is needed to investigate whether different degrees of knowledge interdependence influence these kinds of outcomes.

Finally, limitations of the present study`s ecological validity arise from the laboratory setting and the computer-mediated communication. Thus, a valuable next step would be to implement the two rationales on distributing information in more natural learning settings, to check the robustness and practical relevance of the present findings.

## 4.3 Conclusion

Strong knowledge interdependence is easy to implement, because instructors only have to distribute core content among learners that would anyways be studied, for example, by distributing chapters in a textbook that describe different core concepts. Designing for weak knowledge interdependence requires more work: The instructor has to develop a variety of different contexts for embedding or applying the core concepts. Existing learning resources, such as textbooks, are typically not structured in this way. However, our results show that this extra work might be worth the effort.

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**Figure 1: Overview of the two learning phases in both experimental conditions.**

Note: In the individual learning phase, each learner processed distinct sets of three worked examples and, thus, became expert for a specific stochastic model in the strong knowledge interdependence condition, or expert for a specific context in the weak knowledge interdependence condition. Worked examples are represented as greyscale rectangles with M1-M3 representing the three statistical models, and the greyscales representing the three different contexts. In the subsequent collaborative learning phase (identical for both conditions), the triads of learners solved three consecutive tasks.

Two rationales for distributing information

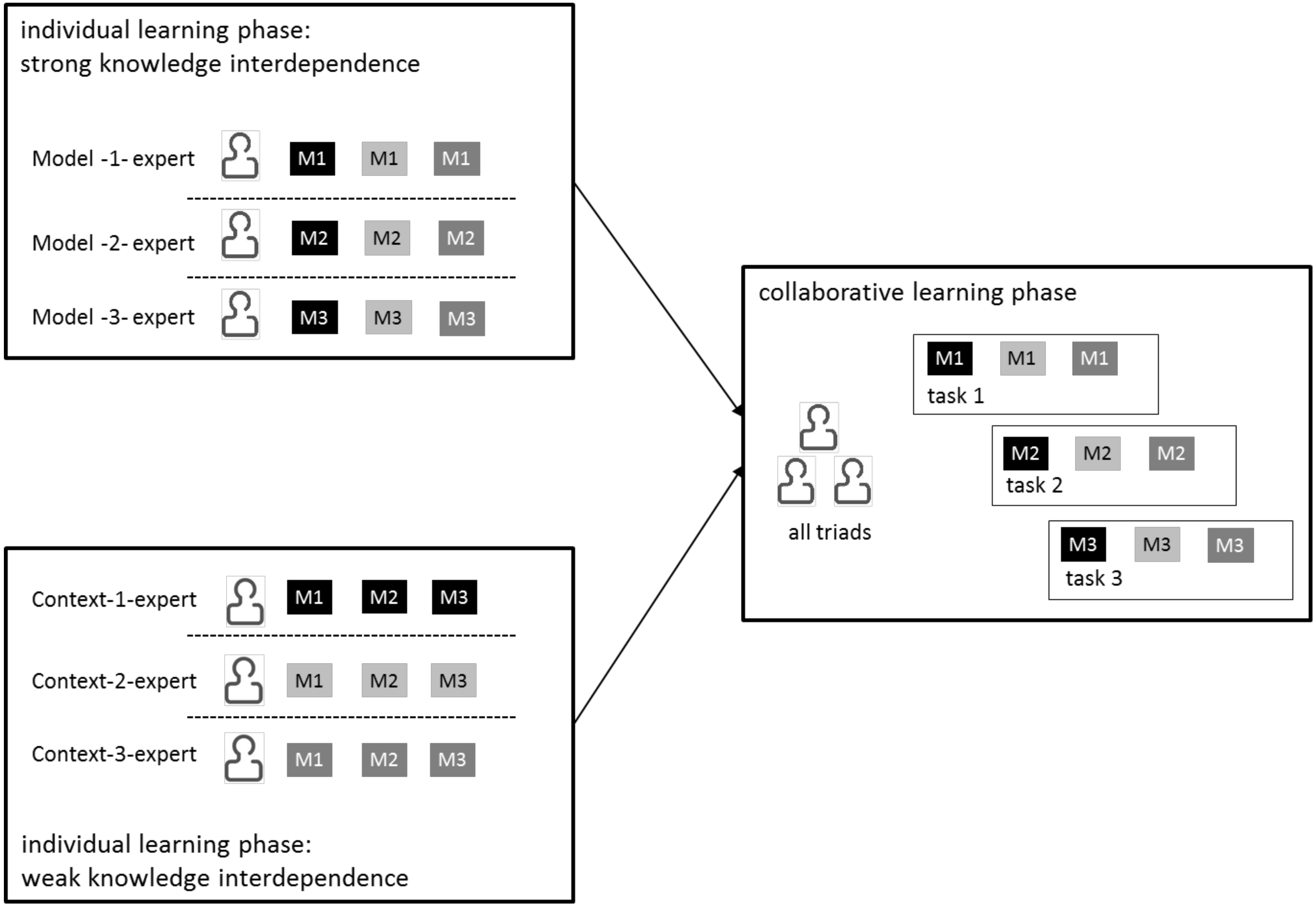

**Figure 2: Transfer scores (*M*s and *SE*s) of low and high prior knowledge learners in both experimental conditions (KI= knowledge interdependence).**

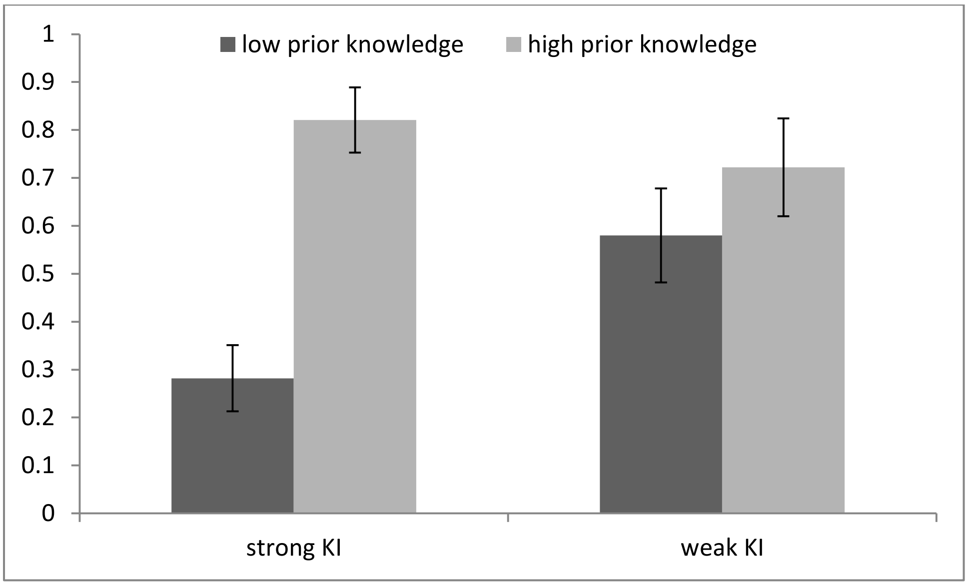

**Figure 3: Constructive and interactive principle-based turns (*M*s and *SE*s) contributed by low and high prior knowledge learners in both experimental conditions (KI= knowledge interdependence).**

*Figure 3a*: Constructive principle-based turns

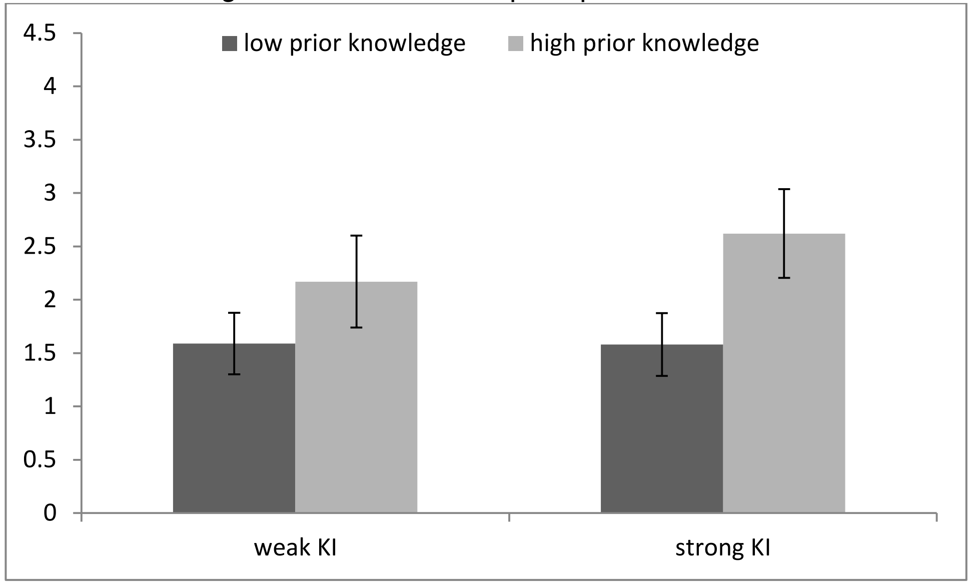


*Figure 3b*: Interactive principle-based turns

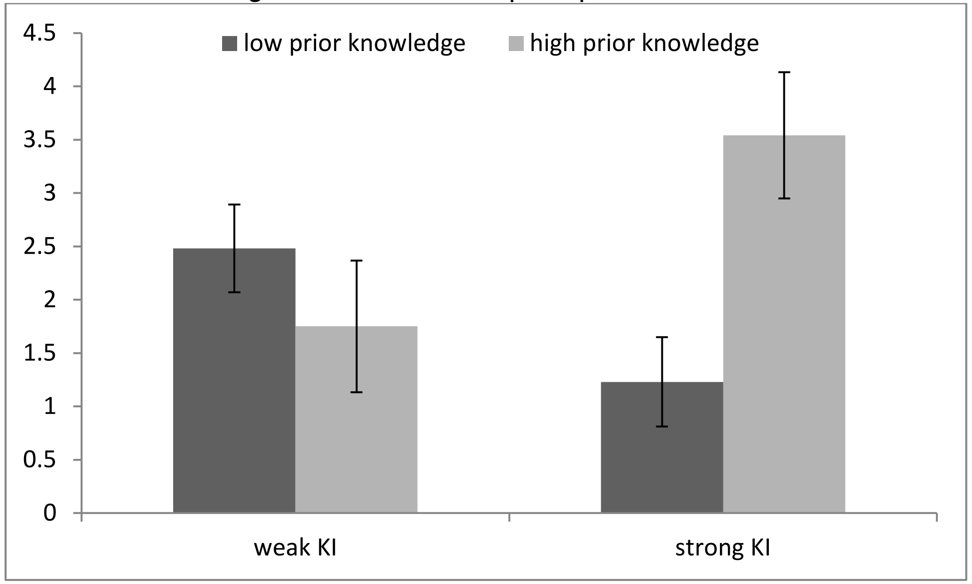

***Table 1*: Mean proportions correct (standard deviations) of pre- and post-test scores in both experimental conditions.**

| | strong knowledge interdependence *(n=39)* | weak knowledge interdependence *(n=39)* |
|---|---|---|
| Pretest | *.55 (.24)* | *.54 (.26)* |
| Self-explanation | *.21 (.19)* | *.31 (.29)* |
| Posttest: | | |
| application | *.75 (.23)* | *.76 (.19)* |
| transfer | *.46 (.44)* | *.62 (.35)* |

***Table 2:*** **Overview of the three regression models for testing the mediating effect of interactive principle-based turns.**

| | *Regression Model 1* | | | *Regression Model 2* | | | *Regression Model 3* | | |
|---|---|---|---|---|---|---|---|---|---|
| outcome | transfer score | | | interactive principle-based turns | | | transfer score | | |
| generalized linear regression model | binomial distribution (events-in-trials data); logit link | | | Poisson distribution (count data); log link | | | binomial distribution (events-in-trials data); logit link | | |
| predictors: | *B (logit)* | *SE* | *Exp(B)* *[95%-CI]* | *B (log)* | *SE* | *Exp(B)* *[95%-CI]* | *B (logit)* | *SE* | *Exp(B)* *[95%-CI]* |
| experimental condition | 2.44*** | .76 | 11.52*** [2.59; 51.24] | 1.78*** | .42 | 5.90*** [2.59; 13.48] | 1.92* | .79 | 6.83* [1.43; 32.62] |
| prior knowledge | 1.21*** | .26 | 3.34*** [2.01; 5.55] | .61*** | .11 | 1.83*** [1.47; 2.28] | 1.02*** | .27 | 2.77*** [1.62; 4.73] |
| prior knowledge x experimental condition (moderation) | -.79* | .33 | .45* [.24; .87] | -.67*** | .16 | .51*** [.38; .69] | -.57 | .35 | .56 [.28; 1.11] |
| interactive principle-based turns (mediator) | | | | | | | .17* | .08 | 1.19* [1.02; 1.38] |

Note: For experimental condition, regression parameters refer to the effect of being in the weak knowledge interdependence condition.

*$p$<.05; **$p$<.01; ***$p$<.001

***Table 3:*** **Mean number (standard deviations) of constructive and interactive principle-based turns per learner in both conditions.**

| | strong knowledge interdependence *(n=39)* | weak knowledge interdependence *(n=39)* |
|---|---|---|
| *constructive* | *1.92 (1.71)* | *1.77 (1.33)* |
| *interactive* | *2.00 (1.97)* | *2.26 (2.51)* |

**Appendix A**

Example learning materials from the individual learning phase (translated from German; M denotes the stochastic model, C denotes the context in which a model is embedded)

Appendix A.1

**The three worked examples compared and contrasted by the Model-2-expert (strong knowledge interdependence condition)**

| M2-C1 | M2-C2 | M2-C3 |
|---|---|---|
| You and a friend are in a two-day mountain bike course. Each morning your instructor hands out five bicycle helmets (orange, green, black, red, and yellow) in random order. You are always the first to receive a helmet and your friend the second.<br><br>What is the probability that you will receive the red and your friend will receive the yellow helmet on the first day of the course?<br><br>Approach: $\frac{1}{5} * \frac{1}{4}$ Solution: $= \frac{1}{20}$ | The four ski jumpers Adam, Beat, Christoph, and Daniel have often competed on the old Engelberg ski-jumping hill. They are all equally good. Thus, who jumps the furthest depends only on random factors (e.g., wind). Today, they test a new ski-jumping hill for the first time.<br><br>What is the probability that Adam will land on the first place, and Beat on the second place after the first round of jumps?<br><br>Approach: $\frac{1}{4} * \frac{1}{3}$ Solution: $= \frac{1}{12}$ | A chemist keeps noble gases in two cabinets. There are three bottles in each cabinet, one containing Argon, one containing Krypton, and one containing Xenon. Unfortunately, the chemist forgot to label the bottles properly and now has to pick them at random. For her experiment she needs two different gases.<br><br>The chemist consecutively takes two bottles out of the first cabinet. What is the probability that the first bottle contains Argon and the second bottle contains Xenon?<br><br>Approach: $\frac{1}{3} * \frac{1}{2}$ Solution: $= \frac{1}{6}$ |

Appendix A.2

**The three worked examples compared and contrasted by the Context-1-expert (weak knowledge interdependence condition)**

| M1-C1 | M2-C2 | M3-C1 |
|---|---|---|
| You and a friend are in a two-day mountain bike course. Each morning your instructor hands out five bicycle helmets (orange, green, black, red, and yellow) in random order. You are always the first to receive a helmet and your friend the second.<br><br>What is the probability that you will receive the red helmet on the first day and the yellow helmet on the second day? | You and a friend are in a two-day mountain bike course. Each morning your instructor hands out five bicycle helmets (orange, green, black, red, and yellow) in random order. You are always the first to receive a helmet and your friend the second.<br><br>What is the probability that you will receive the red helmet and your friend will receive the yellow helmet on the first day of the course? | You and a friend are in a two-day mountain bike course. Each morning your instructor hands out five bicycle helmets (orange, green, black, red, and yellow) in random order. You are always the first to receive a helmet and your friend the second.<br><br>What is the probability that you will receive both a red and a yellow helmet over the two-day course?<br><br>Hint: There are two possible orders:<br>1) first day red, second day yellow<br>2) first day yellow, second day red |
| Approach: $\frac{1}{5} * \frac{1}{5}$ Solution: $= \frac{1}{25}$ | Approach: $\frac{1}{5} * \frac{1}{4}$ Solution: $= \frac{1}{20}$ | Approach: $\frac{1}{5} * \frac{1}{5} + \frac{1}{5} * \frac{1}{5}$ Solution: $= \frac{2}{25}$ |

## Appendix B

Example transfer task (translated from German)

You and a friend are in a two-day mountain bike course. Each morning your instructor hands out five bicycle helmets (orange, green, black, red, and yellow) in random order. You are always the first to receive a helmet, and your friend the second.
What is the probability that, today, you and your friend will receive the red and the yellow helmet (it doesn`t matter who receives which)? Please state both the equation and the final solution.