# Remembering the knowledge of experts and novices in computer-supported collaborative learning: A multinomial processing tree approach

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**Abstract**: Accurately assessing learning partners' knowledge profiles improves collaborative learning. Group awareness tools facilitate constructing such social context knowledge during learning and the formation of learning partner models retrievable afterwards. In this experimental study ($N$ = 70), we investigated potential schema effects in partner modeling: Participants were first provided with descriptions of two learning partners (expert vs. novice of an area) and with their knowledge profiles consisting of knowledge levels (high vs. low) regarding certain topics of this area. In a memory test, participants had to remember the specific knowledge levels of both partners. Partner modeling was analyzed with multinomial processing tree models, as these models disentangle memory and guessing, which are often confounded when schema effects on memory are examined. High and low knowledge levels were equally well remembered for both partners. However, participants showed metacognitive biases, expecting their memory to be better for high knowledge levels. Additionally, knowledge profile estimations revealed that while novices' knowledge was estimated accurately, experts' knowledge was overestimated. We discuss the results and potential benefits of using multinomial processing tree models in the learning sciences for and beyond analyzing schema effects in partner modeling.

**Keywords**: Computer-supported collaborative learning, Group awareness tools, Partner modeling, Schemas, Multinomial processing tree modeling

## 1. Introduction

Collaborative learning is an omnipresent component of education in nearly all formal and informal settings. However, effective social learning relies on learners being aware of their learning partners' knowledge profiles (i.e., what they know or do not know about a learning topic). If they are, targeted questions and explanations can be adapted to the learning partners and facilitate knowledge construction (Erkens & Bodemer, 2019; Webb, 1989). Such cognitive *group awareness,* i.e., the perception of competence or knowledge levels (Janssen & Bodemer, 2013), can be enhanced in computer-supported collaborative learning (CSCL) settings: *Group awareness tools* (GATs) collect, transform, and present relevant knowledge-related characteristics of learning partners (Bodemer et al., 2018) and learners can more effortlessly perceive and use relevant information about their partners' knowledge. However, especially in (long-term) repeated collaboration, it is crucial to memorize knowledge-related information about learning partners: Does the partner know a lot about a topic and thus can be asked questions, or does the partner have low knowledge and might need explanations? Indeed, these specific *partner modeling* (PM) processes, i.e., estimating others' knowledge (Dillenbourg et al., 2016), can have beneficial effects on learning (Sangin et al., 2011).

Heterogeneous groups (regarding expertise) sometimes outperform homogeneous groups because of useful interactions between learners, such as asking questions to an expert and providing explanations to a novice (Webb, 1989). In some cases, a learner might learn collaboratively with both: A high knowledge partner (expert) and a low knowledge partner (novice) regarding an area (e.g., animals). Social schemas (e.g., "animal experts") can help us navigate through the world, but they can also be dangerous as they can be inaccurate (Schnaubert & Bodemer, 2022). It is reasonable to assume that an expert has rather high knowledge in many different content-specific topics. However, it is also possible that the expert has low knowledge in some topics. Schemas carry the risk of overestimating partner competence and corresponding biases. In an experimental study, we explore potential schema effects and investigate whether PM processes differ for expert and novice partners. While, for example, Erkens and Bodemer (2019) found no differences in PM for high and low knowledge partners, we further disentangle PM processes and use analysis methods, i.e. *multinomial processing tree* (MPT) *models*, which are novel in CSCL research, but often used to analyze schema effects in source memory or person memory research.

### 1.1 Expected partner modeling advantage for schema-inconsistent information

Source memory and person memory research suggest an *inconsistency-effect*: Information which is inconsistent with a schema (here: partner expertise) is better remembered than schema-consistent information (e.g., Bell et al., 2015). For example, it is better remembered when trustworthy appearing persons cheat or untrustworthy appearing persons cooperate (Mieth et al., 2021). Here, we test whether such results can be transferred to PM processes when specific knowledge levels of experts and novices must be remembered. Biased modeling of learning partners' knowledge levels could hinder efficient knowledge exchange processes in collaborative learning, such as asking questions about the right topics or giving explanations adjusted to partners' low-level topics. Based on the inconsistency-effect, we expect that memory for low knowledge levels of an expert should be more accurate than memory for high knowledge levels (*H1a*) and memory for high knowledge levels of a novice should be more accurate than memory for low knowledge levels (*H1b*).

### 1.2 Expected metacognitive beliefs of higher schema-consistent modeling accuracy

Beyond actual memory processes, we explore participants' metacognitive beliefs regarding their PM accuracy, as these beliefs themselves can influence behavior (Schaper & Bayen, 2023). In contrast to the inconsistency-effect observed in actual memory performance, when people judge their own memory performances, schema-consistent effects can be found: People assume their memory to be better for schema-consistent information than for schema-inconsistent information. For example, Mieth et al. (2021) have shown that while cooperation by untrustworthy people and cheating by trustworthy people is better remembered, people assume their memory to be better for the opposite. As these *metacognitive illusions* can lead to poor regulation and control processes, we considered metacognitive assumptions in addition to actual memory performances. Based on metacognitive illusions in source memory and person memory, we anticipate schema-consistent assumptions of learners: Participants' metacognitive assumptions of their own PM accuracy for an expert should be higher for high knowledge than for low knowledge (*H2a*), and for a novice partner, assumptions of own PM accuracy should be higher for low knowledge than for high knowledge (*H2b*).

### 1.3 Exploratory analysis and study aim

We will also exploratively examine global PM accuracy: We tested the accuracy of perceived knowledge profiles regarding the amount of high and low knowledge topics of both partners. This study investigates potential schema effects in PM processes using MPT models, accurately assessing (schema driven) memory for different knowledge levels by disentangling memory and guessing processes (Bröder & Meiser, 2007). The novel use of MPT models in PM processes and combining paradigms used in different research fields can enrich CSCL research. This consequently enables a holistic view on long-term effects of tool usage in CSCL to better find instructions beneficial for learners and theory driven implications for tool design.

## 2. Methods

$N$ = 70 participants took part in the experimental study. Some descriptive data and dependent variables have some missing data, resulting in different degrees of freedom. The age range ($N$ = 67) was between 18 and 40 years ($M$ = 22.81, $SD$ = 4.40), and the sample was a student sample ($N$ = 69, 94.20% students, 49 female, 20 male). We used a 2 × 2 within-subject design with the factors *partner schema* induced by providing expertise labels and descriptions (expert vs. novice) and partner *knowledge level* for specific learning topics (high vs. low).

The procedure is illustrated in Figure 1. Participants were first informed that two persons would be presented with information about their knowledge of certain animals. Also, participants would (allegedly) have to read texts about certain animals, learn collaboratively with the presented persons, and finally take a knowledge test. Next, descriptions about the partners (expert vs. novice) followed. Both were described as a 24-year-old man: While the *expert* was described as a zoology student with a passion for animals and who is seen as an expert regarding animals, the *novice* was described as a history student without pets, who is seen a novice regarding animals. Both partners' presentation order was counterbalanced.

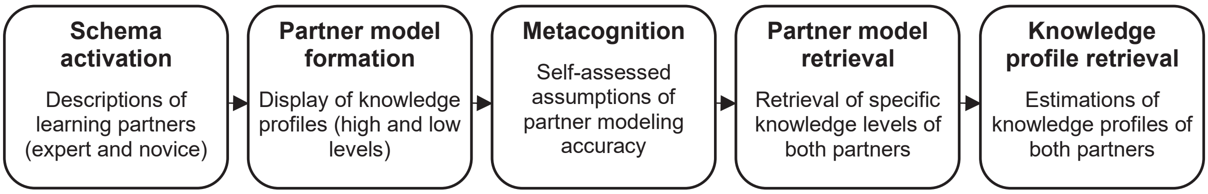


*Figure 1*. Schematic illustration of the key phases of the experiment.

In the partner model formation phase, participants were informed that both partners conducted a test and that their knowledge levels about specific animals would be presented (high vs. low). In a norming study, $N$ = 14 participants rated 160 animals regarding their knowledge about them. We chose 80 animals with moderate ratings. From this pool, 20 animals were ascribed to the expert and 20 to the novice under different randomization conditions. On separate pages for each partner, a GAT presented knowledge profiles with knowledge levels about 20 animals in a table. Animals were displayed on the right side with their according knowledge level on the left side, with high levels shown in green boxes and low levels in white boxes (Figure 2a). Participants had 3 to 5 minutes to view the knowledge profile of each partner. While the expert's knowledge profile consisted of 12 high and 8 low knowledge levels, the novice's pattern was reversed to ensure credible schemas.

| Knowledge level | Animal |
|---|---|
| ■ | Otter |
| □ | Buffalo |
| ■ | Hawk |

(a)

| | | | |
|---|---|---|---|
| **Sloth** | high | low | new |
| **Penguin** | high | low | new |
| **Buffalo** | high | low | new |

(b)

Figure 2. Schematic illustrations of the partner model formation (a) and partner model retrieval phases (b).

Participants next provided metacognitive assumptions of their perceived modeling accuracy. On scales from 0% to 100%, participants indicated for each of the 4 categories (expert high, expert low, novice high, novice low) for how many of the remembered topics the correct knowledge level (high, low) was memorized. After providing demographic information, the partner model retrieval phase started (Figure 2b). Here, for each partner the 20 animals of the partner model formation phase were presented intermixed with 20 new animals. On separate pages for each partner, participants had to remember the information of the GAT in the learning phase: Participants indicated whether each animal was associated with high knowledge, low knowledge, or was new. On the final page, participants provided knowledge profile estimations (global PM): For both partners, the proportion of high and low knowledge levels had to be indicated by sharing 100% between both categories ("Please indicate for what percentage of the animals the expert and novice had high and low knowledge levels").

## 3. Results

### 3.1 Multinomial processing tree models: Schema effects on partner modeling (H1)

When memory for context information of items (here, *high* vs. *low* knowledge for certain topics) is assessed, especially in contexts with schemas (*expert* vs. *novice* partners), analyses based on hit and false-alarm rates can lead to the conclusion that schema-consistent information can be memorized better due to guessing biases (Bröder & Meiser, 2007). *Multinomial processing tree* (MPT) *models* offer a solution: Based on observed category frequencies (e.g., number of "high" responses to high knowledge topics), these models disentangle different memory and guessing processes and enable probability estimations of these processes (for an overview of MPT models, see Erdfelder et al., 2009). Here, we adapted the two-high threshold MPT model of source monitoring (Bayen et al., 1996) for our study purposes (Figure 3) to assess (schema effects on) PM in collaborative learning. The model illustrates that combinations of different cognitive processes can lead to the same response in the partner model retrieval phase. For example, the response "high" to an actual high knowledge topic may be based on correct memory processes ($D_{High} \times d_{High}$) or guessing processes, e.g., $D_{High} \times (1 - d_{High}) \times a$.

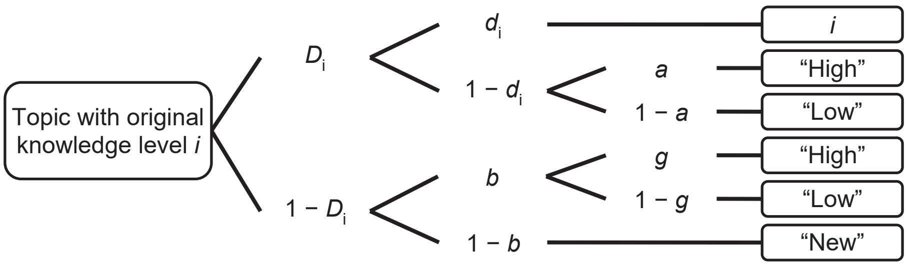


*Figure 3*. Multinomial processing tree model of source monitoring (Bayen et al., 1996), adapted for our study purposes with two sets (for the expert and novice). Rectangle on the left side represents the type of presented topic in the partner model retrieval phase. Index *i* denotes the associated knowledge level regarding that topic, $i \in$ {high, low}. Rectangles on the right side represent the possible answers of participants. Letters along the links represent probabilities of cognitive processes: *D* = Recognizing that a topic was old (i.e., presented before); *d* = Remembering the associated knowledge level of an old topic (specific partner modeling); *b* = Guessing that a topic was old; *a, g* = Guessing that a recognized (*a*) or unrecognized (*g*) topic was associated with a high level. The processing tree for new topics follows a similar principle (for an example, see Bayen et al., 1996).

To use our model, an identifiable base model with certain parameter restrictions must first be found. None of the identifiable base models (see Bayen et al., 1996, Figure 4) fit our data, models 5: $G^2(2) > 31.76$, $p < .001$, model 4: $G^2(4) = 277.18$, $p < .001$. We thus had to find a base model which fits the data with restrictions across both conditions. A model with the restrictions $D_{Low\_Expert} = D_{New\_Expert}$; $D_{Low\_Novice} = D_{New\_Novice}$; $d_{High\_Expert} = d_{Low\_Expert} = d_{High\_Novice} = d_{Low\_Novice}$ shows good fit, $G^2(1) = 1.19$, $p = .276$. The restriction of the PM-parameters ($d = .76$, $SE = 0.03$) inherently means that specific PM does not differ within and between both partners: High and low knowledge of experts and novices seem to be equally well modelled. Consequently, the hypotheses *H1a* and *H1b* cannot be supported by the data: Our findings do not provide evidence for an inconsistency effect in PM. Participants demonstrated relatively accurate PM abilities with a 76% probability of remembering the knowledge levels.

### 3.2 Schema effects on metacognitive assumptions of partner modeling accuracy (H2)

A 2 × 2 repeated-measures ANOVA (descriptive data in Figure 4a) revealed no significant main effect of partner schema on metacognitive assumptions, $F(1, 67) = 0.85$, $p = .360$, $\eta_p^2 = .01$. There was, however, a significant main effect of knowledge level, $F(1, 67) = 56.74$, $p < .001$, $\eta_p^2 = .46$. Although actual memory performances between high and low knowledge levels did not differ (see section 3.1), participants assumed that they remembered high knowledge better than low knowledge. The ANOVA further revealed a significant interaction effect, $F(1, 67) = 13.32$, $p < .001$, $\eta_p^2 = .17$ (all follow-up pairwise comparisons were significant, $t(67) > 2.78$, $p_{Holm} < .009$): Participants assumed better memory for high knowledge compared to low knowledge both for the expert (contradicting *H2a*) and the novice (supporting *H2b*), but the difference was greater for novice partners than for expert partners.

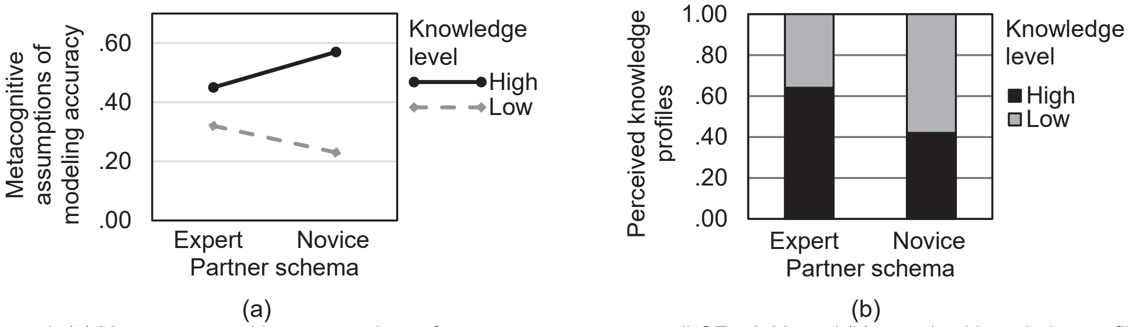


Figure 4. (a) Mean metacognitive assumptions of own memory accuracy, all *SE* = 0.03, and (b) perceived knowledge profiles as estimated percentages of high and low knowledge topics ($SE_{Expert}$ = 0.05, $SE_{Novice}$ = 0.01). Note that the expert's knowledge profile consisted of 60% high knowledge topics and the novice's knowledge profile consisted of 40% high knowledge topics.

### *3.3 Global partner modeling accuracy: Perceived knowledge profiles (explorative)*

We further tested global PM accuracy (Figure 4b). One sample *t*-tests revealed that the expert's knowledge was overestimated: Mean estimations of the number of topics with high knowledge were higher than 60%, $t(65) = 3.08$, $p = .003$, $d = 0.38$. However, the proportion of high and low knowledge topics of the novice was accurately estimated, $t(65) = 1.00$, $p = .319$, $d = 0.12$. The novice's knowledge was only descriptively overestimated.

## 4. Discussion

*Group awareness tools* (GATs) provide knowledge related information about learning partners to support effective CSCL processes. Sometimes, knowledge related information needs to be remembered in retrospect (*partner modeling*, PM), both in short- and long-term collaborations. We investigated whether learners model knowledge of experts and novices differently, predicting a memory advantage for unexpected information (e.g., knowledge gaps of experts). However, we could not observe such an *inconsistency-effect* in PM: High and low knowledge were equally well encoded for expert and novice partners (contradicting *H1*). For educational practice, this implies that in short-term collaboration—for example in heterogeneous groups with high and low knowledge students—such PM biases do not impair collaborative learning processes but allow for asking and answering questions properly adapted to the learning partners. However, other studies found the inconsistency effect. We can thus assume that there may be conditions and moderating variables affecting the results. For example, Ehrenberg and Klauer (2005) found the inconsistency-effect primarily in contexts with higher cognitive load during encoding and longer retention-intervals, which are given in many educational settings. Consequently, manipulations of collaboration duration could be employed to test whether the inconsistency effect is generally absent in PM, or whether our results are limited to short-term collaborative learning situations.

We further considered metacognitive assumptions, as wrong metacognitive assumptions can also influence control processes and study behavior (Schaper et al., 2023). Here, learners generally assumed memory for high knowledge to be better than for low knowledge (supporting *H2a*, but contradicting *H2b*). When students mistakenly assume that they would remember high partner knowledge better than low knowledge, they might ask only about their partners' knowledge gaps, even though asking for high knowledge topics would give them the opportunity to immediately access the best explanations. Metacognitive prompts can enhance students' metacognitive awareness when collaborating (Teng, 2022). Integrating prompts into GATs can assist students recognizing the metacognitive illusion of alleged better modeling of high levels, thereby countering the illusion and fostering better help-seeking.

Exploratively examining knowledge profile estimations (global PM) revealed that novices' knowledge was estimated accurately, which is desirable, as both, over- and underestimations of novices by more knowledgeable partners can impair novices' learning (Wittwer et al., 2008). Experts' knowledge, however, was overestimated, which might pose a danger: Students might over-trust experts and their explanations, without adequately verifying their produced learning contents. Again, metacognitive prompts or cues—delivered through guidance from educators or integrated into GATs—could potentially make learners aware of potential overestimations and aid them in critically questioning their assessments.

From a methodological perspective, MPT models can disentangle memory and guessing processes and thus offer diverse applications in the field of learning sciences. They have the potential to reveal cognitive biases beyond (potential) schema effects in PM: For example, learners might project their own knowledge onto peers when failing to remember their knowledge (Nickerson, 1999). MPT models could test this assumption by assessing whether the guessing parameters of the model differ based on students' prior knowledge. Accurately disentangling different PM processes and biases can help to derive sound implications for instructors and tool designers. While this study was a first attempt to use MPT models to test the impact of collaboration tools on PM processes, further drawing on methods, paradigms, and findings of research areas such as source memory holds the potential to enrich CSCL research, ultimately benefiting learners.

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