# A Psychological Perspective on Data Processing in Cognitive Group Awareness Tools

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**Abstract:** Cognitive Group Awareness Tools are a means to support collaboration processes by providing learners with knowledge-related information about learning partners or the group. Targeting cognitive rather than behavioral variables allows these tools to go beyond observable processes. Thus, tool designers have to make a number of relevant decisions on how to select, collect, transform and present the group awareness information. Because these decisions are so manifold, existing tools differ vastly and it is near to impossible to compare overall tool effects. Thus, in this paper, we conducted a literature search returning 25 papers describing 18 cognitive Group Awareness Tools. We then analyzed these tools with regard to data processing from a psychological perspective to identify key decisions that may affect the learners' collaborative learning processes. This allows us to systematically disentangle the effects of specific data processing decisions on tool functions to ultimately deduce guidelines for tool design.

**Keywords:** cognitive Group Awareness Tools, data processing, CSCL

## Introduction

There are different approaches on how to guide learners towards favorable collaborative learning and interaction processes. Group Awareness (GA) Tools support learners by providing them with relevant information about the social context to help select and execute relevant learning activities (Janssen & Bodemer, 2013). Cognitive Group Awareness Tools (cGA tools) focus on the socio-cognitive context and are designed to make learners aware of pre-selected socio-cognitive conditions by providing learners with information about content-relevant knowledge and/or opinions within the group (Bodemer, Janssen, & Schnaubert, 2018). By purposefully selecting and processing learner data, cGA tools foster and may even modify the learners' interpretation of the situation to facilitate appropriate action (Buder & Bodemer, 2008). Targeting cognitive rather than behavioral variables allows cGA tools go beyond observable processes and improve collaborative learning beyond face-to-face interaction (Buder, 2007). However, they also face specific challenges as tool designers not only need to select relevant cognitive concepts to be portrayed during collaboration, but also need to find an adequate way to purposefully collect, transform and present and thus process learner data. Thus, there are a great variety of tools assessing the content, extent, or quality of the learners' knowledge in different ways and it is hard to draw general conclusions about cGA tools and their generic functions (Schnaubert, Heimbuch, Erkens, & Bodemer, 2019). To tackle this issue, it is vital to take a systematic look at what concepts these tools portray and how they process learner data to identify key decisions tool designers have to make that may affect tool effectiveness. Thus, we conducted a literature search to identify GA tools targeting cognitive variables. For each identified tool and awareness information, we extracted detailed information on data selection and each data processing step (i.e., collection, transformation, presentation). We then analyzed differences and communalities considering research on learning processes to form psychologically meaningful categories of data selection and processing within cGA tools.

## Literature review

A Scopus search using the search string "TITLE-ABS-KEY (awareness AND (learn* OR know* OR cogniti*) AND (collaborat* OR cooperat* OR cscl) AND (computer* OR cscl OR techno* OR tool))" to cover psychological and technological papers returned a total of 3607 unique papers. We limited the search string to papers using the term "awareness" as we were interested in tools whose main aim was to support group awareness. Initial screening procedure excluded mostly papers in which awareness did not target cognitive group characteristics. Thorough analyses of the remaining 129 papers left us with 18 papers that matched the pre-defined parameters (awareness referred to group aspects of a collaborating group; these aspects were knowledge-related as they referred to the extent, content or quality of individual content-related knowledge or opinions or the state or distribution of said knowledge or opinions within a group; awareness was supported by a tool or technological device designed to do so; the context was peer learning; the description allowed thoroughly analyzing at least some of the steps). We further included 7 papers cited in the papers or previous reviews (i.e. Janssen & Bodemer, 2013; Lin, Mai, & Lai, 2015). Within the resulting 25 papers, 18 unique cGA tools (differing essentially from each other within at least one processing step) were described. Non-unique tools were all from the same primary researchers and were mostly close to identical. A number of tools provided more than one type of cognitive GA information at a time (e.g., Schnaubert & Bodemer, 2019). A list of the final 25 identified papers can be found here: https://osf.io/uvxtd/

## Selection of relevant awareness information

Before cGA tools process data, the educator or tool designer needs to select the awareness information that should be made available to learners. This decision should ideally include deliberating the types of cognitive activities learners are supposed to perform collaboratively considering the learning content, the situation and the educational goal. Within our sample, we identified cGA tools that targeted information on the extent of knowledge (e.g., Erkens, Bodemer, & Hoppe, 2016), quality of knowledge (e.g., Lin, Lai, Lai, & Chang, 2016) or specific content of knowledge (e.g., Bodemer, 2011). Thus, the data these tools present may be either qualitative or quantitative (although both may be combined when tools provide information on the frequency specific assumptions are held within a group, e.g., Leinonen & Järvelä, 2006). One further important distinction we found within the tools was whether the tool provided information on learners' knowledge or opinions. Although the distinction may be hard to draw conclusively within some studies (e.g., Buder & Bodemer, 2008), generally, opinions are non-verifiable beliefs and thus may not be evaluated in the same way as knowledge (although they may be used as indications for more general traits like pedagogical styles as in Jermann & Dillenbourg, 2003). Another relevant decision was if designers target cognitions of learners about the content matter in some form and/or metacognitions, i.e. cognitions about or evaluations of one's own cognitions (as in Dehler, Bodemer, Buder, & Hesse, 2011; Yang, Yuan, Wang, & Wang, 2018). While for some research traditions, asking learners to judge their knowledge may be a question of data collection rather than selection, Schnaubert and Bodemer (2019) argue that metacognitions may not be treated as cognitions that are merely collected via self-report, but need to be viewed as a distinct concept because of their specific role for self-regulatory processes (e.g., Winne & Hadwin, 1998). Thus, this decision is part of selection rather than data collection. Last but not least, we found that tools targeted distinct levels of information by providing information about the group as a whole (e.g., Ferradji & Zidani, 2016), learning partner(s) only (e.g., Sangin, Molinari, Nüssli, & Dillenbourg, 2011) and/or all learners including the learner receiving the information him-/herself (e.g., Erkens et al., 2016).

## Data collection

There is a great variety of ways to collect qualitative as well as quantitative aspects of knowledge in a learning environment. In terms of tool functions, one important distinction is the explicit involvement of the learner (Ghadirian, Ayub, Silong, Abu Bakar, & Hosseinzadeh, 2016) and thus, if the assessment process is potentially reactive (Buder, 2011). Explicitly asking learners to provide information highlights its importance and may focus learners' attention on the concept in question (e.g., specific content of knowledge). Additionally, providing information intentionally allows learners to adjust it in a way that seems appropriate and relevant to them making it valid or at least acceptable from a subjective point of view (Engelmann, Dehler, Bodemer, & Buder, 2009). On the other hand, using existing data is less obtrusive and may paint a more objectively valid picture as learners may not voluntarily or involuntarily distort the information (Romero & Ventura, 2010). However, within the analyzed studies, the settings rarely allowed to confidently make this distinction (Is data collection part of the experimental design or the pedagogic context?). A possible exception is the tool by Heimbuch and Bodemer (e.g., 2017) that codes the controversy of content within wiki discussion threads within an online community. However, since the authors not fully conceptualize the tool in terms of data processing, it was excluded from the analyses.

Another central distinction in terms of reactiveness is the type of activity a learner is asked to perform and the object of this activity. In the studies analyzed, some learners were asked to rate their knowledge to gain metacognitive information (e.g., Dehler et al., 2011). Such self-ratings require metacognitive self-evaluations and may thus trigger metacognitive monitoring processes (Schnaubert & Bodemer, 2019). Such monitoring processes are the central focus of theories on self-regulated learning (e.g., Winne & Hadwin, 1998). Empirically, metacognitive self-ratings have been found to affect learning on numerous occasions (e.g., Soderstrom, Clark, Halamish, & Bjork, 2015) and also within awareness tools (Schnaubert & Bodemer, 2017).

In other studies, learners were asked to perform various activities with regard to the learning content to gain cognitive information. Some tools required learners to rate content with regard to truth value or agreement (e.g., Gijlers & de Jong, 2009) and/or to select most favorable or correct answers (e.g., Sangin et al., 2011). Others required learners to relate concepts by, for example, actively constructing hypotheses or statements out of building blocks (e.g., Gijlers & de Jong, 2009) or by relating algebraic and visual information (e.g., Bodemer, 2011). Yet some tools asked learners to perform truly generative tasks such as making explanatory drawings (Bollen, Gijlers, & van Joolingen, 2012), writing text (e.g., Erkens et al., 2016) or constructing concept maps (e.g., Molinari, Sangin, Nüssli, & Dillenbourg, 2008). All these activities are directly related to the learning content and can be described on a generativity dimension in accordance with the activities required to perform the task. Choosing a correct answer or assigning a truth value is rather less generative than relating objects or building hypotheses out of building blocks which – in turn – is less generative than constructing sentences or making explanatory drawings. Generative tasks require learners to actively construct information and can have great impact on memory performance (known as the "generation effect", see for example Bertsch, Pesta, Wiscott, & McDaniel, 2007). The cognitive activities performed while handling content material may be crucial to assess their effects on learning as is studied within the research on testing effects (e.g., Roediger & Karpicke, 2006), but also on learning or practice tasks that may support self-regulatory processes and guide later learning attempts (see Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013). Learning tasks and testing material may be conceptually equivalent, with the distinction that the former precedes and the latter succeeds learning efforts. It can be argued that data collection within cGA tools is more similar to the former and may impact memory and succeeding (collaborative) learning (e.g., via self-regulatory mechanisms). While direct and indirect effects of learning or practice tasks on individual learning have been extensively researched, their impact on collaborative learning is largely unknown.

Apart from guiding self-regulatory processes, another function of cGA tools discussed within group awareness research is their impact through activating or organizing prior knowledge (Erkens & Bodemer, 2019) and constraining communication (Bodemer & Scholvien, 2014). Preceding tests can contribute to both functions when requiring learners to access and organize memory content while simultaneously providing information on the scope of the task, which may narrow the focus of later engagement with learning material (Hamaker, 1986) and thus help to focus on specific content using specific language during collaboration, potentially fostering grounding processes (see Clark & Brennan, 1991). While this needs empirical validation, it stands to reason that knowledge assessment in general and especially the generativity may impact collaborative learning independent of the actual provision of the information. However, testing effects may be circumvented by methods inferring cognitive information from rich existing learner data using computational methods like (educational) data mining.

In sum, data collection varied especially with regard to the generativity of the activity learners were asked to perform and if these were related to the learning content (requiring cognitive processes) or the learners' knowledge (requiring metacognitive processes). From a psychological perspective, this step may impact learning beyond mere group awareness functions as it may directly interfere with the learners and thus learning.

## Data transformation

After data collection, cGA tools may transform the data. While the term "transformation" in a broad sense may include any systematic changes to data content or form, we define it solely in terms of content, i.e. as changes that break up the bijective relation between the original and transformed data (changes to form are covered by the next processing step). Transforming awareness information means systematically pre-interpreting learner data by adding, subtracting, aggregating or otherwise relating information. Such interpretations generate feedback as they go beyond mirroring data (Soller, Martínez, Jermann, & Muehlenbrock, 2005) and add information which may include verification feedback on performance or even feedback on individual competence. While feedback may be a very powerful instructional method (see Hattie & Timperley, 2007), especially person-oriented (rather than strictly performance-related) feedback may be critical with regard to acceptance and even comprehension of the information. Thus, all transformation processes carry the risk of alienating learners when the information portrayed is incompatible with their self-conceptions. This is a critical issue for GA tools, because data subjects are equal to data clients and thus the information needs to target this audience (Greller & Drachsler, 2012). This becomes even more relevant considering the collaborative context, in which differences in competence between peers may be highlighted (see for example 'competence threat', e.g., Mugny, Butera, & Falomir, 2001).

Transformation processes may be necessary if the collected information is complex, unstructured or not aligned between learners. To allow learners to conduct cognitive operations like comparing, relating or integrating the information, data often needs to be simplified (Lee & Nelson, 2004). However, this very much relies on the data collected. Some tools may use minimal transformation and provide the information basically as assessed. This allows learners to fully understand how the information came about, potentially fostering acceptance (Anseel & Lievens, 2009). While acceptance may be a key part from a user perspective, transformation also serves an important input function for data presentation. Thus, this step not only interprets information, but pre-processes data to be usable for visualization techniques requiring a specific type of data.

However, we found a large number of tools not transforming the data at all. In terms of acceptance, learners may feel represented as the information provided in the next step exactly matches the information given, for example when using self-report (see Engelmann et al., 2009). Interestingly, data assessing metacognitive self-evaluations of knowledge was never transformed. This could be due to the fact that the self-report practice allows to outsource the transformation of the information to the learners themselves (Schnaubert & Bodemer, 2019).

While this may potentially impact the learners' own metacognitive processes (see Schnaubert & Bodemer, 2017), this step would be part of data collection rather than transformation from a tool perspective.

Apart from metacognitive self-evaluations requiring learners to rate their own knowledge, data collected requiring more generative activities was more likely to be untransformed than data requiring less generative activities, probably due to the nature of the data, which is per definition more complex, interrelated and often less structured. If data was transformed, there were different types of transformations that were used (see figure 1). For example, some tools aggregated the data by counting specific answers to specific questions within a group, thus aggregating information of different learners. This was most common with studies on opinions. If data was aggregated per person, this was never done without interpreting the data first. Interpreting the data means using further information to code or recode provided information, for example by using a fixed coding scheme (e.g., when coding for correctness of answers in a multiple-choice test, e.g., Sangin et al., 2011) or by semantically interpreting the data to identify similarities or differences between parts of learner- or group-related information. Thus, these approaches need external information or algorithms of high quality adjusted to the content domain (as pointed out by Schnaubert & Bodemer, 2019). For example, Erkens and colleagues (2016) used text mining methods to identify topic clusters within essays. These sample-based clusters were then used to categorize phrases within each learner's text. After applying such coding algorithms, data was aggregated per student and broader topic cluster. While coding in itself adds information in form of a coding scheme or domain model, aggregating the codes means losing the relation to specific, potentially richer data. If data is aggregated over learners, information on specific answers or opinions of individual learners is lost (although it may still be made available on request as in Tsovaltzi, Judele, Puhl, & Weinberger, 2015). Similarly, if data is aggregated within learners, the relations between the learner and specific contextualized activities indicating specific knowledge or assumptions are broken up (e.g., adding up correct answers in a multiple-choice test after coding them for correctness discards information on specific assumptions and thus the content of the learners' knowledge). Thus, aggregating information always includes a loss of information as the relation to the richer qualitative data is broken up.

After coding and aggregating data, we found some tools further changed the informative value of the information by categorizing learners or bits of content (e.g., Ferradji & Zidani, 2016). For example, Ayala and Yano (1998) used the information gained from the learners' task completion and help-seeking behavior to categorize a person in either competent enough to provide help or not, reducing the level of information further by aggregation and on the other hand adding a qualitative interpretation of the numerical value. Changing the informative value of the data is the nature of transformation, because – in our definition – it always entails meddling with the bijective relationship between information provided by the learners and information fed back by the tool. Thus, such processes may include adding information as well as subtracting information – often both.

In sum, tools differed in how they pre-interpreted data by adding and/or subtracting information. While transformations may be a way of extracting relevant information from complex data or adding relevant information about a domain, they always bear the risk of being incomprehensible (due to complexity or non-transparency) or not acceptable to learners (due to incompatibility with the learners' self-conceptions). Data collection and transformation determine the informative value of the data available for data presentation.

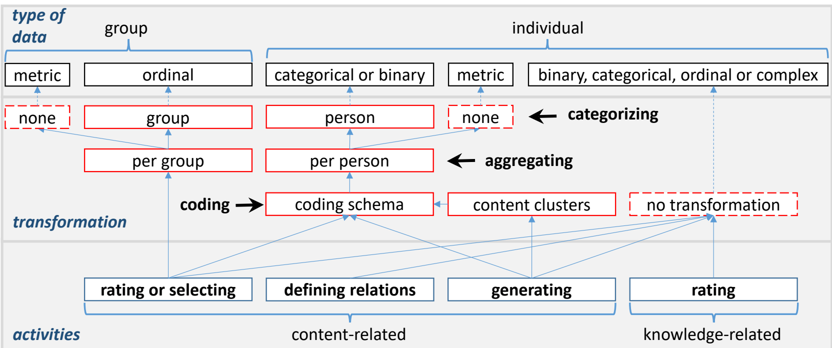


Figure 1. Activities, transformation processes (coding, aggregating, categorizing) and types of data.

## Data presentation

CGA tools commonly present the awareness information visually within the learning environment and usually foster the identification of discrepancies by easing comparison processes (Engelmann et al., 2009) drawing on the human inclination and capacity to compare closely adjunct visual features according to size, location, or color (e.g., Alhadad, 2018). While there are exceptions, especially if the information can be easily compared on an informational level (e.g., Bodemer, 2011), abstract graphical representations are thus a common feature in cGA tools as they may activate or support specific cognitive operations (Suthers & Hundhausen, 2003). Abstract social information is frequently linked to specific learning content by arrangement or visual connections (e.g., arrows) to support learners in relating social and content information (e.g., Bodemer & Scholvien, 2014). As creating representational affordances relies heavily on the data available, data presentation depends on all preceding steps.

For metric data containing information about individual learners, the default provision methods seem to be graphs (uni-dimensional) or grids (bi-dimensional). Using closeness and alignment, this supports comparisons between and possibly within learners. Thus, metric data seems to be used to provide information on the extent (Erkens et al., 2016) or quality (Sangin et al., 2011) of knowledge or its specific pattern within a two-dimensional space (Jermann & Dillenbourg, 2003), allowing learners to easily extract information about differences and similarities. Some tools provide numerical information in addition to a visual representation (e.g., Lin et al., 2016).

Ordinal data about learners (in this case mostly binary data with an underlying linear dimension) within our sample was color coded in 2 (out of 3) tools. Both color versions supported the ordinal character of the data (e.g., full green interpretable as more than hatched white green) and thus supported a quick interpretation of the data. Further, data was structured to support easy comparisons between (rows) and within (columns) learners (Dehler et al., 2011; Schnaubert & Bodemer, 2019). One tool using truly ordinal data (Gijlers & de Jong, 2009) used textual representations of the data (true – probably true – probably false – false) side by side to provide information on the learners' evaluations of propositions. To support comparison processes, the tool pre-interpreted and flagged differences in judgments drawing explicit attention to and thus highlighting discrepancies.

Truly categorical or binary data was the most diverse category within the sample. While one tool provided textual information per learner on separate learner profiles detached from the collaboration space (Ayala & Yano, 1998), another merely flagged answers learning partners had given in single choice tasks (Bodemer & Scholvien, 2014), while yet another provided information on unknown or known content within two separate lists but without sorting the information in any meaningful way (Yang et al., 2018). Thus, these tools may have provided the information in a way to easily detect (Bodemer & Scholvien, 2014) or interpret (Yang et al., 2018) the information, but provided no support for comparison. Contrarily, Bodemer and colleague (Bodemer, 2011; Bodemer & Scholvien, 2014) provided information on knowledge content by presenting algebraic terms in an easy to compare way (closeness), potentially triggering meaningful comparison processes. Similarly, Schnaubert and Bodemer (2019) spatially aligned true-false answers supporting comparison processes to detect conflicts.

By contrast, we found complex data (concept maps or drawings) to be presented to learners without particular support for comparison (e.g., Bollen et al., 2012; Molinari et al., 2008). While the information was presented side-by-side, its purpose seems to be helping to understand the learning partner in detail. In line with this reasoning, studies providing learners with such data generated individually (e.g., explanatory drawings) asked learners to conduct the same or a similar activity during collaboration (e.g., generate an explanatory drawing together; Bollen et al., 2012), requiring extensive processing of the awareness information.

Last but not least, we looked at data that provided information about the group as a whole with regard to certain content (mostly opinions). Here, metric data was provided either as graphs or distributions of answers per content unit (Leinonen & Järvelä, 2006) or as a numerical figure (Tsovaltzi et al., 2015). Both did not particularly support comparison processes as data was presented separately for each content unit. However, the tool using ordinal data to provide information on the group's agreement to hypotheses (Ferradji & Zidani, 2016) explicitly supported interpretation of the information by color coding (green, orange, red), thereby flagging rejected hypotheses (red). While this allowed for comparison processes, the color schema primarily supports detection and quick classification of categories (Ware, 2013). Thus, group-level information was mostly presented in a way that supported interpretation rather than comparison and may be designed to provide background information for collaboration rather than to support topic selection (with the possible exception of Ferradji & Zidani, 2016).

In sum, we found data presentation to vary according to type of data available after transformation, but we also identified several mechanisms that may impact cognitive processing. The representational form (abstract or concrete), intentional structuring of the information (e.g., closeness or alignment) or visual highlights may draw attention towards specific knowledge constellations and ease or trigger modes of processing the information, i.e. quick identification and interpretation or comparison. However, tools may also be designed to provide detailed background information about (the content of) the learning partners' knowledge requiring deeper elaboration of the information, especially if the information is integrated into the collaborative learning tasks.

## Conclusion and outlook: Linking data processing to tool functions

CGA tools vary extensively and thus, we conducted a structured review to look beyond specific tools and into more generic tool processing steps. By analyzing these from a psychological perspective, we were able to identify decisions that should be considered when designing for group awareness support, extending existing cGA research (e.g., Buder, 2011) by focusing on distinct decision steps during tool design. During the selection process, educators or tools designers have to decide upon the concept they want to portray. This includes decisions about the type of cognitive characteristic (opinion or knowledge or metacognition; content or extent or quality) but also the level of the characteristic in question (individual or group). These decisions have direct implications for data processing, especially for data collection (e.g., asking to rate statements with regard to agreement vs. truth value) and transformation (e.g., aggregating data of multiple individuals). Afterwards, the data needs to be collected, potentially transformed, and presented to the learners. Table 1 provides an overview over the basic processing decisions we extracted from the review and implications these decisions may have on collaborating learners.

Table 1: Design decisions and implications

| design decisions regarding data processing | potential impact on learners |
|---|---|
| *collection*<br>▪ requiring metacognitive vs. cognitive processes<br>▪ generativity (rate vs. select vs. relate vs. generate) | ▪ testing effects (e.g., activating prior knowledge, initiating monitoring, supporting self-regulation)<br>▪ generation effects (e.g., fostering elaboration)<br>▪ guidance (e.g., constraining learning and communication) |
| *transformation*<br>▪ simple vs. complex<br>▪ adding (enriching) or subtracting (simplifying) information<br>▪ transparency | ▪ feedback effects (e.g., verification of knowledge, correction of self-concept, competence threat)<br>▪ comprehension, acceptance, and usage of cGA information<br>▪ processing effort and informative value |
| *presentation*<br>▪ representational form (textual vs. color coding vs. bars, graphs and grids)<br>▪ structure (e.g., closeness, alignment)<br>▪ highlights (e.g., visual flagging, color) | ▪ cognitive processing (effortful elaboration vs. easy identification, interpretation or comparison)<br>▪ guidance (representational guidance, directing attention, suggesting modes of processing) |

As with all research, there are limitations to this work. Two of them concern the data base, i.e. the articles within our review: First, we found few computer science approaches, limiting our view on cGA tools to mostly psychologically driven research. This may have been due to the search terms used ("awareness" rather than "dashboards") and the overall data collection strategy (including merely reviews with a psychological focus; no forward snowballing to include other research fields). Second, the tool descriptions within the selected papers not always provided detailed information on how data was processed, especially concerning data collection and transformation, probably because most cGA-tool research rather focuses on tool implementation without looking into the composition of effects (as also mentioned by Bodemer et al., 2018). It begs the question if this was more transparent for the learners, which may be critical for tool acceptance. Last but not least, we were not able to look into all potentially relevant information or to cover all possible variations and interactions of data processing.

In conclusion, in this review, we identified important research areas relevant to dissect effects of cGA tools on collaborative learning and to draw concrete conclusions for tool design. While we tentatively connected data processing decisions to tool functions (some of them already discussed in the literature, e.g., Bodemer et al., 2018), it is now vital to systematically validate these proposed effects – theoretically and empirically. Such research should go beyond studying distinct processing steps by also look into possible interaction effects.

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