Intelligent model-based feedback: helping students to monitor their individual learning progress

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Chapter 6
Intelligent Model-Based Feedback: Helping Learners to Monitor their Individual Learning Progress

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ABSTRACT
Automated knowledge assessment methodologies provide the technological background for producing instant feedback at all times during the learning process. It is expected that the availability of such individual, dynamic, and timely feedback supports the learner’s self-regulated learning. This chapter provides the theoretical background for an intelligent feedback approach and introduces two automated model-based feedback tools: TASA (Text-Guided Automated Self Assessment) and iGRAF (Instant Graphical Feedback). The chapter concludes with a discussion of the two feedback approaches and future research directions.

INTRODUCTION
The nature of feedback plays a critical role in learning and instruction, especially in computer-based and self-regulated learning environments (Simons & de Jong, 1992). Hence, feedback is considered a fundamental component for supporting and regulating learning processes. Depending on theoretical perspective, learning and instructional goals, objectives, research purposes, as well as methodological approaches, feedback can take many forms. Wagner and Wagner (1985) consider feedback to be any type of information provided to learners.
The importance of feedback for improving knowledge and skill acquisition has been discussed controversially in educational research (e.g., Azevedo & Bernard, 1995; Bangert-Drowns, Kulik, Kulik, & Morgan, 1991; Narciss, 2008; Narciss & Huth, 2004; Shute, 2008). Widely accepted forms of feedback include (a) knowledge of result, (b) knowledge of correct result, (c) knowledge of performance, (d) answer until correct, (e) knowledge of task constraints, (f) knowledge about concepts, (g) knowledge about mistakes, (h) knowledge about how to proceed, and (i) knowledge about metacognition (Narciss, 2008). Additionally, Schimmel (1983) found that feedback is most effective under conditions that encourage the learner’s conscious reception and engages the learner in reflecting on the response.

Automated knowledge assessment methodologies (e.g., Ifenthaler, 2010b; Pirnay-Dummer, Ifenthaler, & Spector, 2010) provide the technological background for producing instant feedback at all times during the learning process (Ifenthaler, 2009). It is expected that the availability of such individual, dynamic, and timely feedback supports the learner’s self-regulated learning (Zimmerman & Schunk, 2001).

Accordingly, this chapter will introduce the theoretical background for an intelligent feedback approach. Based on these theoretical assumptions, two intelligent and automated model-based feedback tools are described in the next section: (1) TASA (Text-Guided Automated Self Assessment), which generates automated feedback to learners based on natural language text input (Pirnay-Dummer & Ifenthaler, in press). (2) iGRAF (Instant Graphical Feedback), which automatically generates graphical representations based on the prior knowledge of the learner (Ifenthaler, 2009, 2010a). Finally, the chapter concludes with a discussion of the two feedback approaches and future research directions.

**THEORETICAL BACKGROUND**

The large body of theoretical and empirical studies on feedback provides very diverse insight into possible ways to support and regulate learning processes. Even meta-analyses (Azevedo & Bernard, 1995; Kluger & DeNisi, 1996; Schimmel, 1983) have provided contradictory results. However, feedback is considered to be an elementary component for facilitating learning outcomes. As feedback can take on many forms depending on the theoretical perspective, the role of feedback, and the methodological approach, it is important to consider which form of feedback is effective for a specific learning environment.

*Informative feedback* refers to all kinds of external post-response information used to inform the learner of his or her current state of learning or performance (Narciss, 2006, 2008). Furthermore, from an instructional point of view, feedback can be provided by internal (individual cognitive monitoring processes) or external (various types of correction variables) sources of information. Internal feedback may validate the externally provided feedback, or it may lead to resistance against it (Narciss, 2008). However, the empirical evidence regarding the effects of different types of feedback is rather inconsistent and somewhat contradictory (e.g., Bangert-Drowns, et al., 1991; Clariana, 1993; Kluger & DeNisi, 1996; Kulhavy, 1977; Mory, 2004).

Feedback on mental model construction, such as the use of *conceptual models* to help persons to build mental models of the system being studied, has also been investigated and discussed (see, for example, Mayer, 1989; Pirnay-Dummer & Ifenthaler, in press). Conceptual models highlight the most important objects and associated causal relations of the phenomenon in question. However, not only do new developments in computer technology enable us to dynamically generate simple conceptual models and expert representations, but they may also be used to generate direct responses to the learner’s interaction with the learning en-
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Numerous studies in the field of educational research have provided evidence that “mental models guide and regulate all human perceptions of the physical and social world” (Seel & Dinter, 1995, p. 5). Mental models are dynamic ad hoc constructions which provide subjectively plausible explanations on the basis of restricted domain-specific information (Johnson-Laird, 1989; Seel, 1991). Research studies have shown that it is very difficult but possible to influence such subjectively plausible mental models by providing specific information (see Anzai & Yokoyama, 1984; Ifenthaler, Masduki, & Seel, 2011; Mayer, 1989; Pirnay-Dummer & Ifenthaler, in press; Seel, 1995; Seel & Dinter, 1995). Ifenthaler and Seel (2005) argue that it is important to consider how such information is provided to the learner at specific times during the learning process and how it is structured. In accordance with the general definition of feedback introduced above (Wagner & Wagner, 1985), an important aspect of model-based feedback is providing dynamic feedback generated purposively and individually to student-constructed models (Ifenthaler, 2009).

INTELLIGENT MODEL-BASED FEEDBACK

Newly introduced automated knowledge assessment tools (e.g., Ifenthaler, 2010b; Pirnay-Dummer, et al., 2010) allow us to produce instant feedback on semantic and structural aspects of the student’s learning progression at all times during the learning process (Ifenthaler, 2009). Such dynamic and timely feedback can promote the learner’s self-regulated learning (Zimmerman & Schunk, 2001). Based on these new technologies, two intelligent and automated model-based feedback tools have been developed and implemented: (1) TASA (Text-Guided Automated Self Assessment), which generates automated feedback to learners based on natural language text input (Pirnay-Dummer & Ifenthaler, in press). (2) iGRAF (Instant Graphical Feedback), which automatically generates graphical representations based on the prior knowledge of the learner (Ifenthaler, 2009, 2010a). Both tools are described in detail in the following sections.

TASA (Text-Guided Automated Self-Assessment)

TASA is a web-based online tool for self-assessment while writing. It embeds the parts of HIMATT (Highly Integrated Model Assessment Technology and Tools; Pirnay-Dummer & Ifenthaler, 2010) which are necessary to generate intelligent feedback from the user’s text directly after the upload. With regard to the demand for instant feedback on the ongoing writing process, TASA has been developed, implemented, and empirically tested.

The omnipresence of writing plays an important role in institutionalized learning environments such as schools and universities. Eigler (2005) expects that writing leads to the reorganization and continual construction of knowledge. There exists a large and interdisciplinary body of literature on writing, focusing on the process of writing itself (e.g., Haswell, 2008; Lavelle & Zuercher, 2001; Rose, 1985) and into its technological issues issue (e.g., Cho & Schunn, 2007; Glaser & Brunstein, 2008; Kintsch, Steinhart, & Stahl, 2000). Moreover, a cognitive process theory of writing has been proposed by Flower and Hayes (1981) by dividing the process of writing into three main stages: Planning, translating, and reviewing. Monitoring these three steps in order to reflect or improve the necessary competencies is regarded as a crucial part of the self-regulated learning process.

Writing is often trained through face-to-face coaching. However, such coaching is not always possible (Boud, 1995). Be it due to limited resources, time or any other organizational constraints, e.g., teachers do not always have the time...
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to coach each student every week even if they want to. To this end, self-assessment appears on the list of options.

The idea of self-assessment is to give students tools, so that they can monitor their own process during their learning times without the need of a human supervisor (e.g., Fetterman, Kaftarian, & Wandersman, 1996). However, there are clear limits to the actual algorithms, especially when natural language is involved. Still, if the tools are well investigated and at the same time based on sound theoretical foundations, they may serve as a good complement to human training approaches. As long as we do not know too much about longitudinal effects, it would be best to start as closely to classical coaching as possible and implement the key features thereof. From our research on ongoing writing which already successfully implemented the automated visualization (e.g., Pirnay-Dummer & Ifenthaler, 2011, in press) we took the automation one small step further and transferred also large parts of the feedback to computer algorithms.

TASA is based on mental model theory (Seel, 2003) and psycholinguistics (Frazier, 1999). To represent the underlying models of the learner’s actual text, we used modules from the HIMATT toolset (Pirnay-Dummer & Ifenthaler, 2010). A text of more than 350 words can be graphically visualized by this toolset as an association net (see Pirnay-Dummer & Ifenthaler, 2010). It tracks the association of concepts from a text directly to a graph, using a heuristic to do so. The re-representation process is carried out automatically and uses multiple computer linguistic stages (see Pirnay-Dummer & Ifenthaler, in press). TASA’s feedback screen is shown in Figure 1.

From the second time the learner interacts with TASA, he or she will also get feedback on what has changed since the last upload of the written text. If two graphical representations are available – from the current and the previous version of the text – TASA gives feedback on the new associations, on the ones that are still in the model and on the links that are no longer dominant within the texts’ model (see Pirnay-Dummer & Ifenthaler, in press). It is also possible to tell whether a text gained more complexity or if it was simplified since the last time using available measures from graph theory (see Ifenthaler, 2010c; Tittmann,

Figure 1. TASA feedback screen including dynamic written and graphical feedback information
The measures are afterwards combined to features like complexity of the written text. Additionally, TASA tracks the time which the learners already spent using the system and generates general prompts from this information. E.g., at the beginning of the writing process, prompts on the outline and the process of structure will be given. Towards the end of the writing process the focus lies on the integration of concepts and the differentiation between key concepts and “phrase concepts” which may occur in weak phrase oriented writing (Frazier, 1999). In the latter case words like “role” may suddenly appear in the concepts of the learners’ model, referring back to the frequent use of phrases like “… played an important role at the end of the 20th century”. The general prompts were selected from the most frequently given advises during face-to-face coaching sessions (see Pirnay-Dummer & Ifenthaler, in press). The content-oriented and the general feedback are given to the users on the same screen (see Figure 1). Although the system is “blind” towards connections between both kinds of feedback, they will interact on the learners’ side and create sessions that resemble some of the important features of face-to-face training sessions.

Empirical Evidence

Pirnay-Dummer and Ifenthaler (in press) investigated the prototype of TASA in a design experiment, fully embedded in a learning environment at university level. The guiding research question was how students estimate the effectiveness of TASA as a tool to support self-guided writing processes. 37 undergraduate students (27 female and 10 male) participated in the study. Their average age was 22.4 years (SD = 1.3). The longitudinal research design was realized in the final five weeks of the semester. In each week, participants uploaded parts of the so far written research paper. The written research paper was the major assignment of the courses.

All participants received an automated feedback based on their previous and actual status of the paper after uploading parts of their written research paper. Subsequent to each coaching session, the participants filled in an abridged version of HILVE (Heidelberg Inventory of Course Evaluation; Rindermann & Amelang, 1994) in order to determine the effectiveness of teaching. HILVE is a standardized questionnaire for the evaluation of courses that is divided into 14 dimensions (Cronbach’s alpha r = .74 to r = .88). Each dimension consists of two to four items. The applied abridge version of HILVE included eight items which were combined as one factor: effectiveness of learning. In the weeks 1, 3 and 5 the graphical feedback (representation of the written text) is embedded into the feedback. In the remaining cases (2 and 4) only the feedback text is given.

A Friedman test was conducted to evaluate differences in effectiveness of learning for the five measurement points: MP1 (Median = 3.63), MP2 (Median = 3.25), MP3 (Median = 3.13), MP4 (Median = 2.86), and MP5 (Median = 2.75). The test was significant χ² (4, N = 37) = 35.47, p < .01, and the Kendall’s W = .243, indicated fairly strong differences among the five measurement points. Follow-up pairwise post-hoc comparisons were conducted using a Wilcoxon test and controlling for the Type I errors across theses comparisons at the .05 level using the LSD procedure. The median of MP1 was significantly greater than the median of MP2, p < .001. Also, we found that the median of MP3 was significantly greater than the median of MP4. However, the median between MP2 did not differ significantly from the median of MP3, p = .222, as well as the median of MP4 did not significantly differ from the median of MP5, p = .521.

The results of this initial study show that the written feedback which included the graphical representations at measurement points one and three were estimated more effective for learning than the written feedback without a graphical
representation (MP2 and MP4). However, our results also indicate that the TASA tools’ effectiveness lost power during the five weeks of our design experiment. This could have been caused through several reasons. One explanation could be that the participant’s motivation dropped during the five weeks.

It is a long way from face to face coaching to automated tools for self-assessment – and this is clearly no surprise. So far, we succeeded in implementing the crucial parts of the coaching into computer-based technology. Both static and dynamic feedbacks could be developed and implemented in future developments of TASA.

**iGRAF (Intant Graphical Feedback)**

An externalized representation of an internal mental model induces positive effects on internal information processing (Galbraith, 1999). Additionally, empirical findings on feedback (e.g., Schimmel, 1983) and mental models (e.g., Ifenthaler, Masduki, et al., 2011) suggest that effective model-based feedback is composed of externalized representations of internal mental models. Such an externalization of a mental model could be a concept map, a causal model, and written or spoken text (Ifenthaler, 2008). Further, model-based feedback should take into account the person’s prior understanding (initial mental model, pre-conception), because such preconceptions are in many cases resistant to change as they have a high subjective plausibility (Ifenthaler & Seel, 2005; Seel & Dinter, 1995). Past research studies lack this perspective in providing learners with conceptual models (i.e. explicit and consistent causal explanations of a given phenomenon) for improving a person’s understanding of a specific problem in a given context (e.g., Mayer, 1989; Norman, 1983; Seel & Dinter, 1995).

In order to fulfill the requirement and taking into account the learner’s prior understanding, iGRAF not only includes an expert’s solution of the given phenomenon. It processes the learner’s initial understanding of the phenomenon in question and produces automatically individualized feedback. Currently, two forms of model-based feedback are available: (1) cutaway model-based feedback and (2) discrepancy model-based feedback. These two forms of model-based feedback (see Figure 2) are considered as graphical re-representations constructed from a set of

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**Figure 2. Reference (a), subject (b), cutaway (c), and discrepancy (d) re-representations**
vertices whose relationships are represented by edges (Ifenthaler, 2010c).

The iGRAF feedback generation is realized within the HIMATT environment (Pirnay-Dummer, et al., 2010). It is implemented and runs on a Web server using Apache, MySQL, PERL, and additional packages. Conceptual graphs (e.g., concept maps) and written text can be analyzed quantitatively with the automated comparison functions (see Ifenthaler, 2010c). Additionally, Ifenthaler (2010b) introduced an automated feature to generate standardized graphical re-representations of subjects’ data with the help of the open source graph visualization software GraphViz (Ellson, Gansner, Koutsofios, North, & Woodhull, 2003). The algorithm generates domain-specific automated model-based feedback on the fly. In addition, iGRAF automatically generates standardized reference (e.g., expert), participant (e.g., learner), cutaway, and discrepancy re-representations.

A cutaway re-representation includes all propositions (vertex-edge-vertex) of the individual’s re-representation. Additionally, the semantically correct vertices (compared to a reference re-representation such as an expert solution) are graphically highlighted as circles (ellipses for dissimilar vertices).

The discrepancy re-representation of an individual only includes propositions (vertex-edge-vertex) which have no semantic similarity to a reference re-representation. Additionally, the semantically correct vertices (compared to a reference re-representation) are graphically highlighted as circles (ellipses for dissimilar vertices).

Figure 2 provides examples of simplified reference (a), participant (b), cutaway (c), and discrepancy (d) re-representations. These automated and standardized re-representations are generated on the fly while participants work within the HIMATT environment. They are then used for individual model-based feedback during work on a learning task.

The reference model (see a in Figure 2) represents a best practice solution by an expert or advanced learner for the task to be completed. The participant’s model (b) is a solution found after a specified time working on the task. With the reference (a) and participant (b) models at hand, HIMATT automatically generates the cutaway (c) and discrepancy (d) feedback models. The cutaway model allows the learner to see how many vertices are semantically correct (graphically highlighted circles compared to the expert solution). Additionally, the cutaway model provides information on the semantically incorrect vertices (ellipses). The discrepancy model only provides information on the semantically incorrect propositions as compared to the expert solution (vertex-edge-vertex). Additionally, semantically correct vertices are highlighted. We argue that either feedback model (c) or (d) will have different effects when presented during the learning process. As the cutaway feedback model (c) helps to confirm the correct understanding of the phenomenon in question (compared with an expert), the discrepancy feedback model (d) causes a cognitive conflict, because correct propositions (vertex-edge-vertex) of the person’s understanding are deleted from the re-representation (see Ifenthaler, 2010a).

Empirical Evidence

Ifenthaler (2009) conducted an experiment in which the effects of model-based feedback using iGRAF were investigated. The guiding research question addressed to which extent the model-based feedback (cutaway and discrepancy) facilitated the understanding of a specific phenomenon in question. Seventy-four university students (66 female and 8 male) participated in the study. Their average age was 21.9 years ($SD = 2.3$) and they were randomly assigned to the three experimental groups (1) cutaway feedback ($n = 26$), (2) discrepancy feedback ($n = 24$), and (3) expert feedback ($n = 24$). The learning content
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included an article on climate change, multiple choice-tests (pre- and post versions).

The results showed a significant effect between participants in the three experimental groups with regard to the richness of the learner’s responses, $F(2, 70) = 4.080, p = .021, \eta^2 = .10$, with participants of the expert feedback group increasing their number of vertices higher than the other experimental groups. One-way ANOVA also revealed a significant effect for the complexity of the learner’s responses, $F(2, 70) = 7.355, p = .001, \eta^2 = .17$. The increase of complexity of participants was higher in the expert feedback group than in the others. Between the experimental groups, the increase of complete structure of responses was also significant, $F(2, 70) = 3.140, p = .049, \eta^2 = .08$. Again, the participants in the expert feedback group outperformed the other experimental groups. For the semantic measure looking at the correctness of concepts we found a final significant effect, $F(2, 70) = 3.243, p = .045, \eta^2 = .08$. Here, learners in the cutaway feedback group gained more correct concepts than the participants in the other two groups.

The aim of this study conducted by Ifenthaler (2009) was to examine different forms of model-based feedback for improving expertise. Hence, two new forms of model-based feedback were introduced, which were defined as (1) cutaway model-based feedback and (2) discrepancy model-based feedback. As the model-based feedback was automatically generated and on the fly, the learners received the model-based feedback just after finishing their pre-test, which served to motivate them further. Additionally, the HIMATT analysis features mad an automated scoring of the learner’s solution possible within an instant. Not only do these automated process have very high objectivity, reliability, and validity (see Pirnay-Dummer, et al., 2010), they are also very economical, especially when large sets of data need to be analyzed within a short period of time (Ifenthaler, 2010b).

Learners who received the expert feedback added significantly more relations to their causal diagrams than did those in the other experimental groups. Accordingly, the expert feedback provided them a broad spectrum of concepts and relations, which were then integrated into their own understanding of the phenomenon in question. This also explains the significant differences between the measures for complexity and complete structure. As the number of relations of a causal diagram increases, there is a high probability that its complexity and complete structure will also increase.

However, an increase in these structural measures does not necessarily mean that the solutions of participants in the expert feedback group are better than those of the other participants. As a further analysis of the semantic measures revealed, participants in the cutaway feedback group outperformed the other participants with regard to their semantic understanding of the phenomenon in question. Accordingly, even if the structure increases, the semantic correctness of the learner’s understanding of the phenomenon in question will not automatically increase. Hence, learners may integrate a huge amount of concepts into their understanding of the phenomenon which do not necessarily help them to come to a better and more correct solution to the problem.

Further studies of iGRAF will focus on the learning trajectories while providing forms of model-based feedback. This will give us more detailed insight into the effects of model-based feedback generated with iGRAF and how it helps to support and improve problem-solving performance (see Ifenthaler, Kinshuk, Isaias, Sampson, & Spector, 2011).

FUTURE RESEARCH DIRECTIONS

Both, TASA and iGRAF are just being developed recently. Accordingly, further empirical research is needed to investigate the potential of both tools. However, initial findings show that intelligent
model-based feedback helps students to monitor their individual learning process accordingly. Both tools can be easily implemented in game-based learning environments (e.g., Eseryel, Ifenthaler, & Ge, in press) and other scenarios including intelligent feedback. This will, however, require further empirical investigations regarding the practicability and effectiveness of the tools.

As technology is emerging in such a rapid way, TASA and iGRAF need to be developed accordingly. However, the theoretical foundation of the model-based feedback approach will provide a solid basis for future developments, both from technological as well as from theoretical perspectives.

CONCLUSION

Since the beginnings of mental model research (e.g., Gentner & Stevens, 1983; Johnson-Laird, 1983; Seel, 1991) many research studies have provided evidence that human perception of the physical and social world is guided and regulated by mental models (Seel & Dinter, 1995). Various research studies have shown that it is very difficult but possible to influence such subjectively plausible mental models by providing specific information, e.g., through feedback (e.g., Anzai & Yokoyama, 1984; Ifenthaler, Masduki, et al., 2011; Ifenthaler & Seel, 2005; Mayer, 1989; Pirnay-Dummer & Ifenthaler, in press; Seel, 1995; Seel & Dinter, 1995). In the field of learning and instruction, feedback is considered an elementary component for supporting and regulating learning processes.

Intelligent model-based feedback helps students to monitor their individual learning process. Automated knowledge assessment tools provide the basis to produce instant feedback on semantic and structural aspects of a person’s learning progression at all times during the learning process (Ifenthaler, 2009). Such dynamic and timely feedback can promote the learner’s self-regulated learning (Zimmerman & Schunk, 2001). Based on these new technologies, two intelligent and automated model-based feedback tools have been developed and implemented: TASA (Text-Guided Automated Self Assessment), which generates automated feedback to learners based on natural language text input (Pirnay-Dummer & Ifenthaler, in press). iGRAF (Instant Graphical Feedback) automatically generates graphical representations based on the prior knowledge of the learner (Ifenthaler, 2009, 2010a).

The main limitations for TASA are on the volutional level. Hence, future studies will concentrate on this aspect and also consider several covariates on the learners’ side. With the additional data at hand, we should be able to make the tool more stimulating. TASA is applicable to any learning task which involves writing. It may be used for short writing assignments. However, its strength clearly unfolds in long-term writing assignments, in which the students may continuously monitor their own progress and make their own decisions when using the automated tool.

The graphical feedback produced with iGRAF proved to facilitate self-regulated learning. However, no systematic effect of the various forms of model-based feedback could be found yet. On the one hand, the expert feedback increased the structural features of the learner’s response to the phenomenon in question. On the other hand, the cutaway feedback increased the semantic correctness of the learner’s understanding of the phenomenon in question. Hence, learners provided with expert feedback may integrate a huge amount of concepts into their understanding of the phenomenon which do not necessarily help them to come to a better and more correct solution to the problem. Additionally, cutaway feedback may limit the learner’s overall structural skills while solving a problem. However, the overall effectiveness of feedback generated with iGRAF shows high potential.

Already available empirical evidence on the facilitation of self-regulated learning processes
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through intelligent model-based feedback (TASA and iGRAF) provides high hopes for future developments and practical implications. Therefore, model-based feedback will guide a promising voyage towards the world of learning within Web 3.0.

REFERENCES


**KEY TERMS AND DEFINITIONS**

**Assessment of Learning:** Activities of measuring learning achievement, performance, outcomes, and processes with the intent to provide feedback it improve or reinforce learning.

**HIMATT:** Highly Integrated Model Assessment Technology and Tools.

**iGRAF:** Instant Graphical Feedback.

**Informal Feedback:** Refers to all kinds of external post-response information used to inform the learner of his or her current state of learning or performance.

**Proposition:** Unit of a concept map containing node – link – node.

**Similarity Measure:** Quantity that reflects the strength of relationships between two concept maps or features of concept maps.

**TASA:** Text-guided Automated Self Assessment.