BABEŞ-BOLYAI UNIVERSITY, CLUJ-NAPOCA
FACULTY OF PSYCHOLOGY AND EDUCATIONAL SCIENCES
DEPARTMENT OF PSYCHOLOGY

MIHALCA LOREDANA

DESIGN AND EVALUATION OF INSTRUCTIONAL TECHNOLOGY . A COGNITIVE PERSPECTIVE

PhD thesis abstract

SCIENTIFIC SUPERVISOR:

Prof. Univ. Dr. MIRCEA MICLEA

CLUJ-NAPOCA
2011

TABLE OF CONTENTS:

Cuvinte cheie: cognitive load, adaptive instruction, learner-controlled instruction, learning efficiency, eye tracking, thinking aloud protocols, cued retrospective reporting

INTRODUCTION

With the development of personal computers (PCs) in the early '70s and with the advent of the Internet (in 1989), there has been an unprecedented technological explosion, with major implications for all areas of human activity.

The fast technological development has put pressure on education from the perspective of at least two essential requirements. First, it is necessary, more than ever, that the educational system equips students with the abilities and knowledge necessary to deal with the rapid changes that have taken (and still take) place in all areas of human activity. Second, information sources must be easy to access, create, change and be available *anytime* and *anywhere* the students desire, so that they may accomplish their goals and fulfill their personal learning needs.

In an attempt to respond to these requirements, instructional design research has put forward two approaches: (a) using real-life learning tasks, with a high complexity that will help students acquire transferable abilities (Corbalan, Kester, & Van Merriënboer, 2006), and (b) increasing the flexibility of instructional programs (especially the computer-based ones), so that they correspond to demands such as *just-in-time learning* and *education-on-demand*.

In a flexible educational program, not all learners benefit from the same instructional interventions (the same program for all); instead, each follows their own learning path, dynamically adapted to their personal needs, progress and preferences (education-on-demand). Additionally, learners must be offered the possibility to benefit from instruction precisely when and where they need it (just-in-time learning). This approach implies in fact the *personalization of instruction*, which can be accomplished either by the *computer program* (e.g., the e-learning application assesses subjects' progress and selects adequate learning tasks of adequate difficulty and amount of support), or by the *learners* (students monitor their own progress and select the appropriate learning tasks). In the latter case we are talking about *learner-controlled instruction*.

Both approaches can be found in this dissertation, as the learning tasks used in the computer program designed by us are characterized not only by realism – having a practical applicability – but also by complexity. Additionally, the sequence of learning tasks (in the adaptive program control) was conceived as a dynamic entity, in the sense that the tasks were permanently adapted to the learners' level of expertise.

The aim of the studies presented in this dissertation was to investigate the degree to which personalized instruction, accomplished either by a computer program, or by the learners, optimizes the learning process, increases test performance and stimulates subjects' motivation, taking as a reference point fixed instruction, controlled by the program (a non-adaptive program control).

The analysis we conducted has sought to mainly answer two questions: (1) *which type of instructional control (program control – adaptive vs. nonadaptive - or learner control) is more beneficial in terms of performance, time on task, learning efficiency (performance combined with invested mental effort and time on task) and motivation?* and *(2) to what extent does learners' prior knowledge mediate these effects or influence the task selection process?*

The theoretical perspective that has guided our approach was *cognitive load theory* (Sweller, 1988), subsumed to the general *cognitivist* paradigm. The necessity to adapt instruction to the constraints of the learners' cognitive system represents the main concern of this theory, Sweller (1988) suggesting that, since a defining aspect of the human cognitive architecture is represented by the limited capacity of working memory, all instructional designs must be analyzed from the perspective of cognitive load theory.

The first three chapters in this dissertation are dedicated to the theoretical framework, the next five chapters present the empirical studies conducted, while the last chapter presents the final conclusions of the dissertation.

In the first chapter, alongside the conceptual clarifications undertaken, we review the main learning paradigms that have had (and still have) an impact upon instructional technologies: *behaviorism, cognitivism* and *constructivism*. A relevant aspect in this sense is represented by the fact that in the field of instructional design there have been major changes both at the level of instructional technologies, as well as the level of learning paradigms that underlie them. Additionally, the first chapter also focuses on *cognitive load theory* (Sweller, 1988), emphasizing theoretical and practical contributions of this approach for instructional design, but also the limits it has.

Chapter 2 presents a theoretical framework of adaptive instructional technologies, with an emphasis on approaches and models of *adaptation at the macrolevel, the microlevel* and of *aptitude-treatment interactions*. From the point of view of the empirical approach developed in this dissertation, the most valid model of adaptation at the microlevel is the *two-level model of adaptive instruction* (Tennyson & Christensen, 1988), which allows for the moment-to-moment adjustment of instruction to the learners' (ever-changing) performance.

In chapter 3 we review operationalizations of learner-controlled instruction (internal control), the theoretical and research paradigms used in this field, and factors that influence (mediate) the effectiveness of this type of control. Extant research does not appear to support the hypothesis that learner-controlled instruction has a higher efficacy under all circumstances, compared to program-controlled instruction.

Chapter 4 introduces a hybrid model of adapting instruction (put forward by us), which integrates the assumptions of the two-level model of adaptive instruction and of the four-component instructional design model (4C/ID; Van Merriënboer, 1997), as well as of the assumptions of cognitive load theory (Sweller, 1988). This personalized model allows for the dynamic selection of the learning tasks based on the learner's performance scores and invested mental effort. A computer-assisted instructional program for the learning of genetics has been developed to put the model into practice. Additionally, in this chapter we present the results of formative evaluation, whose purpose was to test the functionality, usability, but also the efficiency of the developed computerized learning environment in reaching the learning objectives set.

Chapter 5 presents two closely related empirical studies investigating the effects that different types of instructional control have on the effectiveness and learning efficiency in learning genetics using students of different prior knowledge levels: students with low prior knowledge (i.e., high school students) vs. students with a higher prior knowledge (i.e., college students). More specifically, the first study compares – in terms of performance and learning efficiency– the following four types of instructional control: a non-adaptive program control, a full learner control, a limited learner control, and an adaptive program control. The second study represents a replication of the previous study with the purpose of verifying predictions regarding the influence of the type of instructional control on performance and learning efficiency in the context of increased level of learner expertise (inclusion of PhD students in the study).

In chapter 6, the focus was on the task selection process and the features processed by the learners in this case (relevant vs. irrelevant task information). More specifically, the study aimed to investigate the differences between learners with a high prior knowledge level and those with a low prior knowledge level in the field of genetics, with respect to the manner of processing relevant information (structural fetures) versus irrelevant task information (surface features) in the selection process. To this end, several process-tracing techniques were combined, such as eye tracking, thinking aloud protocol, and cued retrospective reporting.

Chapter 7 presents two closely related studies whose purpose was to examine the influence of the type of instructional control upon the motivation of learners with different levels of expertise, as well as the relationship between their motivation and performance, invested mental effort, and time on task, respectively.

In an attempt to capture mechanisms that explain the occurrence of significant individual differences in terms of performance obtained with the computer-based program developed, a quantitative analysis (semistructured interview) was conducted in chapter 8. The purpose of this analysis was to identify difficulties that learners have encountered in their interaction with the computer-based learning environment, and the manner in which these difficulties were reflected at the level of cognitive and metacognitive strategies used during the learning process (i.e., patterns of self-regulated learning).

Chapter 9, dedicated to final conclusions, presents an overview of the results of the empirical studies included in the present dissertation, and their implications are discussed from the perspective of instructional design and educational applications.

Chapter 1
INSTRUCTIONAL TECHNOLOGY – THEORETICAL FRAMEWORK

1.1 Conceptual conceptions

Although for the people with no expertise in the educational field, the term *instructional technology* might only have a technical meaning (e.g., hardware components, etc), the instructional technology means more than those materials or equipment used in the instruction. They represent only the products of instruction, while the instructional technology is an applied field and, thus, involves a process often called instructional design (Lockee, Larson, Burton, & Moore, 2008).

The terms *educational technology, instructional design* and *instructional technology* are used interchangeable in literature (Lockee et al., 2008) and so we do in the present dissertation. Some authors (e.g., Kim, Lee, Merrill, Spector, & Van Merriënboer, 2008) claim that although these terms are interchangeable used, they have a slightly different meaning. While the term *educational technology* has a more general meaning, including all technologies that support any type of learning in any environment, the term *instructional technology* has a narrower meaning and involves only the technologies developed for attaining some specific, planned learning outcomes. One of the most representative definitions of instructional technology is the one given by the Association for Educational Communications and Technology (AECT - 1994), according to which the instructional technology is „ the theory and practice of design, development, utilization, management, and evaluation of the processes and resources for learning." (Seels & Richey, 1994).

Instructional design is the discipline which studies these technologies, and their development and use in order to support instruction and learning. Reigeluth (1983) defined instructional design as a „linking science" between the learning theory and the educational practice, with the main purpose of prescribing some instructional actions necessary to optimize the desired learning outcomes.

Kim et al. (2008) claimed that the study of the instructional design is represented by three distinct activities: (1). the development of tools and artifacts with the purpose to support learning; (2). the evaluation of the utility and efficacy of those tools in designing computer-based learning environments, and (3) the evaluation of the impact these tools have upon learning.

1.2 History of instructional technologies

Contrary to the general belief that the research, development and evaluation of the instructional technology began once the PCs started being used in the 1970s, it really took place long before that. Even from the early decades of the 20th century, instructional technology was constituted as a distinct field of research. The first research question was linked to the idea of enhancing learning with visual, and afterwards with audio-visual resources (for example the use of radio in instruction). As radio broadcasting grew in the 30s and the televison in the 50s, these mass media were easily accepted as methods of providing instruction both in schools and outside them.

In the 60s, the interest towards teaching machines that incorporate programmed instruction (based on behaviorist perspective), invaded the field. Thus, the research field of the instructional technology extended from the audio-visual technologies to all the other types of instructional technologies, including the psychological ones (for example, programmed instruction). In the 80s, the interest had changed again, this time moving towards the design of some instructional systems which presume the clever application of the instructional methods, a change brought to life by the new insights from the constructivist and cognitive perspectives.

As a result of the fact that in the 90s computers became pervasive, they have become the favourite way of supplying information/instruction. After the rapid global spread of the Internet after 1995, the computer networking started to have a function of communicating the information beside the one of storage and processing it. In the 21st century, the instructional technology focussed especially on the distance education, with the sole mission of helping people learn faster and more effective, in a less expensive manner.

1.3 Paradigmatic perspectives to instructional technologies

Learning and instructional theories are based on philosophical assumptions about *knowing* and *learning*, and these are implicit in the instructional design (Duffy & Jonassen, 1992). Over the years, instructional design has been characterized by radical changes both at the level of technology and the level of paradigms which underlie it. The paradigms which provide theoretical framework for designing instructional technologies are *behaviorism*, *cognitivism* and *constructivism*.

1.3.1. Behaviorism

Behaviorism emerged in the first half of the 20th century and is based on a associationist approach. From an ontological perspective, this paradigm is based on an objectivist philosophy: the world is real and exists outside of the individual (Duffy & Jonassen, 1992). According to the behaviorism, in order to know something, individuals must accomplish specific behaviours in the presence of specific stimuli (Schuh & Barab, 2008).

Programmed instruction represents an example of instructional design which facilitates learning by using reinforcement and feedback. In the case of programmed instruction, the instructional content is preplanned (based on the objective ontology), presenting the learners a plan of what needs to be learned. Teaching machines and the computer-assisted instruction,the descendants of programmed instruction, represent instructional technologies based on the reinforcement of the relationships between stimuli and responses. The essential aspect of these instructional technologies is represented by the content organisation so that the students might offer correct answers and benefit the reinforcement when they offer the correct answers (Saettler, 1995).

1.3.2. Cognitivism

Cognitivism emerged with the cognitive revolution in the 50s, emphasizing on the necessity to focus on the human mind. Cognitivism focus on mind, seeing it as an information processing system (the metaphor „mind-as-computer”), with the purpose of understanding the way knowledge is organised, encoded and retrieval.

Although the acquiring of knowledge structures underlie the cognitive perspective, as in behaviorsm, the rationalist epistemology (it considers that reason is the main source of knowledge) is the one that makes the distinction between behaviorism and cognitivism (Schuh & Barab, 2008). The unit of analysis of the cognitivism remains the individual, as in behaviorism, only it is not the behaviour that is analyzed, but the mental structures and the developed representations.

Gagné’s (1985) theory of instruction provides an exemplar within the cognitive perspective. This theory considers that during learning process, learners involve several capabilities, ierarchically organized, from simple to complex, and from particular to general. Gagné (1985) described five types of learning capabilities by which the learning can be facilitated: (1) intellectual skills; (2) verbal information; (3) cognitive strategies; (4) motor skills and (5) attitudes.

1.3.3. Constructivism

Constructivism emerged in 1990 as a alternative framework to the cognitive perspective. This paradigm states the existance of a real world that we experience (Duffy & Jonassen, 1992), so the ontological basis might as well be objectivist, but, because it is also states that this world cannot be directly know, the realism can also be the ontological base. In other words, like objectivism, constructivism considers that there is a real world which we experience, but the meaning of the world is imposed by us, it does not exist outside us (Duffy & Jonassen, 1992; Schuh & Barab, 2008). The individual remains unit of analysis of the constructivism, as in the case of cognitivism, but the focus is on the conceptual reorganization of the knowledge base, not on the extant structure of knowledge.

În ciuda criticilor primite (vezi Driscoll, 2005), constructivismul a avut un „ecou” puternic în domeniul *designului instrucţional*. Din perspectiva acestei paradigme, strategiile instrucţionale trebuie să respecte următoarele principii generale (Driscoll, 2005): (1) procesul de învăţare să aibă loc în cadrul unor medii complexe şi realiste (de ex., microlumi); (2) să fie promovate mediile de învăţare colaborative (de ex., forumuri de discuţii); (3) sprijinirea perspectivelor multiple asupra problemelor; (4) încurajarea perfecţionării prin învăţare; (5) susţinerea procesului de construire a cunoştinţelor.

Despite the critics (Driscoll, 2005), constructivism had a strong echo in the domain of instructional design. From this perspective, the instructional strategies must follow certain general principles (Driscoll, 2005): (1) the learning process must take place within complex and real environments (e.g., microworlds), (2) colaborative learning environments must be promoted, (3) multiple perspectives upon different problems must be supported, (4) mastering through learning should be encouraged, (5) the process of knowledge construction should be promoted.

Without a solid theoretical framework and a systematic application of the paradigms in the design and development of the computer-based learning environments, it is very likely they will not improve performance (Spector, 2008).

1.4 Cognitive load theory

The necessity to adapt instruction to the constraints of the learner’s cognitive system represented the main concern of the cognitive load theory, elaborated by Sweller et al. (Sweller, 1988; Sweller, Van Merriënboer, & Paas, 1998). The development of cognitive load theory started in the late 1970s, now being one of the most influential theories in the field of instructional design. Numerous studies found empirical support for the assumption that without taking into account the limitations of the human cognitive system, the effectiveness of instructional design is absolutely accidental (Sweller et al., 1998). In other words, the design of the instructional materials must be aligned with the limited cognitive processing resources of the learners, in order to prevent the cognitive load and improve learning (Paas & Van Merriënboer, 1994).

1.4.1. Basic assumptions of cognitive load theory

The fundamental assumptions of cognitive load theory can be divided in two categories: (a) general assumptions and (b) specific assumptions (Gerjets, Scheiter, & Cierniak, 2009).

(a) *At the general level*, cognitive load theory is based on the commonly accepted assumptions about human cognitive architecture, including the distinction between a limited working memory and a virtually unlimited long-term memory (see memory models elaborated by Atkinson and Shiffrin 1968; Baddeley 1999). From this perspective, the basic assumption is that the processing of instructional materials imposes a cognitive load which exceeds learners' working memory capacity, and as a result, interfere with learning.

(b) *At the specific level*, unique assumptions of cognitive load theory concern the differences between three types of cognitive load, namely, intrinsic, extraneous, and germane load (see Sweller et al. 1998). Cognitive load represents the mental resources which are allocated by the students to learn a particular material (Sweller & Chandler, 1994) or to perform a particular task (Sweller et al. 1998).

1. Extraneous cognitive load

One of the earliest versions of cognitive load theory focused on extraneous cognitive load only (Chandler & Sweller, 1991). This type of load is caused by the format of the instruction (Sweller 2005, Sweller et al. 1998), or by an inappropriate instructional design (Kalguya et al. 1998). A poor instructional design imposes a cognitive load because requires processes to overcome barriers imposed by this design. These processes are seen as irrelevant for learning because they are not directed to schema acquisition and schema automation (Sweller and Chandler 1994; Sweller 2005). From the cognitive load theory perspective, extraneous load interferes with learning and, thus, should be reduced as far as possible by eliminating irrelevant cognitive processes (Sweller et al, 1998).

2. Intrinsic cognitive load

Around 1993, another type of load was acknowledged, namely intrinsic cognitive load, which is imposed by the basic characteristics of the information, that is, the complexity of the information that must be processed (Sweller 1993). Complex materials are characterized by a high level of element interactivity, in this case, learners must to not only maintain information about these elements but also their interconnections simultaneously in working memory (Ayres, 2006; Gerjets et al., 2009). Both the element interactivity of the content and learners' prior knowledge determine the complexity of the information, and such as the intrinsic load (Sweller et al., 1998; Sweller, 2005).

3. Germane cognitive load

In 1998, Sweller et al.(1998) further augmented the cognitive load theory by introducing germane cognitive load. This type of load results from higher-level elaborative processes that go beyond the mere activation and memorization of information, being relevant to schema construction and schema automation. Germane load is caused by an adequate instructional design and is helpful for effective learning, as a result, it should be increased as far as possible.

Cognitive load theory assumes that intrinsic load, extraneous load and germane load are additive (Sweller et al., 1998).

Cognitive load theory assumes that principal mechanisms of learning are schema acquisition and schema automation (Sweller & Chandler, 1991; Sweller et al., 1998). In order to promote learning, the main purpose of the instructional strategies should be to reduce extraenous load, optimize intrinsic load, and increase germane load (Gejerts & Scheiter, 2003; Van Merriënboer & Sweller, 2005).

1.4.2 Measuring cognitive load

Mai multe studii au indicat că efortul mental investit de utilizatori constituie „esenţa" încărcării cognitive şi, prin urmare, efortul mental este adesea considerat un indicator fidel al încărcării cognitive (Paas, 1992; Paas et al., 2003).

There are three major methods of cognitive load measurement (Paas et al., 2003; Schnotz & Kürschner, 2007): physiological measures (papillary dilation or heart rate variability), subjective ratings (experienced difficulty and mental effort can be measured with subjective rating scales), and performance-based measures (dual task methodology; Brüncken, Plaas, & Leutner, 2003).

1.4.3 Limitations of cognitive load theory

Principalele critici aduse în acest sens se referă la modul de măsurare a conceptelor fundamentale ale teoriei încărcării cognitive şi la testarea asumpţiilor specifice (Schnotz & Kürschner, 2007).

Cognitive load theory has many conceptual, methodological and practical limitations, which need to be surmounted before the research can adequately test the predictions (Bannert 2002; Brünken et al. 2009; Horz and Schnotz 2009; Moreno 2006; Schnotz and Kürschner 2007). The main conceptual and methodological issues surrounds the lack of clarity of cognitive load concept itself and lack of standard, reliable, and valid measures for the constructs of the theory.

Chapter 4
PERSONALIZATION OF THE LEARNING TASKS TO THE LEARNERS' EXPERTISE LEVEL

4.1 Study 1: A methodological contribution

Adapting instruction to the individual student's progress seems a good way to reduce learners' cognitive load and improve learning results (Kalyuga & Sweller, 2005; Salden, Paas, & van Merriënboer, 2006). More specifically, in order to prevent a possible cognitive overload, the task difficulty and amount of support of each newly selected learning task should be adapted to the learners' expertise level and perceived mental effort (Corbalan, Kester, & van Merriënboer, 2006). According to adaptive models, the use of a computer program allows personalization of instruction by dynamically changing the instruction (i.e., task difficulty) as a response to input from the learners (i.e., performance scores and invested mental effort of each learning task).

Research using such adaptive program instruction has shown to lead to a more efficient training and higher transfer test performance compared to a non-adaptive program control (Camp, Paas, Rikers, & van Merriënboer, 2001; Corbalan et al., 2006; Kalyuga & Sweller, 2005; Salden, Paas, Broers, & van Merriënboer, 2004).

In the domain of Air Traffic Control, Camp et al. (2001) and Salden et al. (2004) compared a fixed, predetermined sequence of learning tasks with dynamic task selection which reflected a personalization of difficulty level of the tasks based on performance and mental effort scores (i.e., a measure of expertise level). They found that dynamic task selection yields more efficient transfer test performance compared to the fixed, predetermined sequence of learning tasks. Furthermore, in a study conducted by Salden et al. (2004) that compared two personalized methods (i.e., personalized efficiency and learner control) to yoked conditions revealed that personalized efficiency condition showed more effective training compared to the learner control condition, whereas the latter one proved to be more efficient than the personalized efficiency condition. Additionally, in Kalyuga and Sweller's study (2005) both the difficulty level and the support level for the next learning task were adapted to learner expertise. Results of their study showed that learners who received personalized support and difficulty obtained higher pre-to-post-test gains and higher cognitive efficiency than learners in a yoked control group.

These findings are consistent with the results obtained in the genetics domain by Corbalan, Kester, and van Merriënboer (2008) which showed that adaptive instruction including limited learner control (i.e., shared control) for both difficulty and support level based on the learners' growing level of competence and associated mental effort yields more effective and efficient learning. Additionally, the adaptive instruction including shared control increased learners' motivation (i.e., their task involvement) since the program ensured avoidance of overloading students' cognitive capacities and the limited given learner control was beneficial to their learning process.

4.1.1 Towards a personalized task selection model

Componentele modelelor instruirii personalizată cu ajutorul computerului (şi a celui propus de noi) sunt esenţiale pentru adaptarea nivelului de dificultate şi suport al sarcinilor la expertiza utilizatorilor şi vizează: (a) caracteristicile sarcinilor de învăţare; (b) caracteristicile sau profilul utilizatorilor, şi (c) componenta personalizării sau adaptării.

The personalized task selection model presented in this chapter aims at providing each individual learner the best next learning task based on her/his expertise level, thus yielding a personalized sequence of taks in a complex environment. The proposed model includes three components: (a) learning tasks characteristics, (b) learner characteristics, and (c) personalization.

Learning tasks characteristics include the level of complexity (i.e., from simple to complex, or from easy to difficult), embedded support (i.e., from full support to no support), and other task features (e.g., the surface features). According to 4C/ID model (Van Merriënboer, 1997), (1) learning tasks should be organized in easy-to-difficult categories or task classes, (2) learners should receive full support for the first learning task in each task class after which support is gradually reduced to none for the last learning tasks, and (3) learning tasks provide a high variability of practice.

In the proposed model, each of the five difficulty levels contained three support levels, differing with regard to the amount of embedded support and diminishing in a scaffolding process according to the completion strategy (van Merriënboer, 1997). The three levels of embedded support, ordered from high to no support are: (1) completion problems with high support which provided many, but not all solution steps (i.e., four out of five solution steps are worked out, learners have to complete the final step); (2) completion problems with low support that provided a few solution steps (i.e., three out of five solution steps), and (3) conventional problems that did not provide any support, learners had to solve all the sub-steps in the problem on their own.

The learner portofolio contains the information about the learners in terms of obtained performance and invested mental effort. The 4C/ID model indicates that in addition to performance, the amount of effort that a learner invests to reach this level of performance may be important. Since subjective rating scales have been repeatedly proven to be a reliable measure of cognitive load (for an overview see Paas, Tuovinen, Tabbers, & van Gerven, 2003), the current model utilized a subjective rating scale to measure mental effort. The perceived mental effort was measured after each learning task and after each pre-and post-test as well as after each far transfer test task on a 5-point rating scale, with values ranging from 1 (very low) to 5 (very high) (Paas, 1992).

The personalization component of the proposed model aims to prevent cognitive overload of the learners by dynamically adapting the level of task difficulty and embedded support to the expertise level. According to the 4C/ID assumptions, performance measures alone are not a sufficient basis for dynamic task selection, and may be improved by taking into account the effort that students invest in reaching this performance. Therefore, the dynamic process of task selection (in the proposed model) is based on the continuous assessment of the level of expertise of individual learners (after each learning task the learner portofolio is updated).

4.1.2 The learning environment developed on the basis of the personalized model

The aim of this study was to developed an personalized learning environment according to our model. The learning environment developed for the current study was a Web application written in PHP scripting language. A MySQL database connected to the learning environment contained all learning material and registered all the student interactions with the system: participants' competence and invested mental effort scores, their task selection choices, and time spent (in minutes) on each activity. Furthermore, this database contained a basic introduction to genetics, a pre- and post-test, a far transfer test, three motivational questionnaires, algorithm selection tables, and a glossary with the main genetics concepts used in the learning environment.

The basic components of the personalized learning environment are presented in Figura 1.

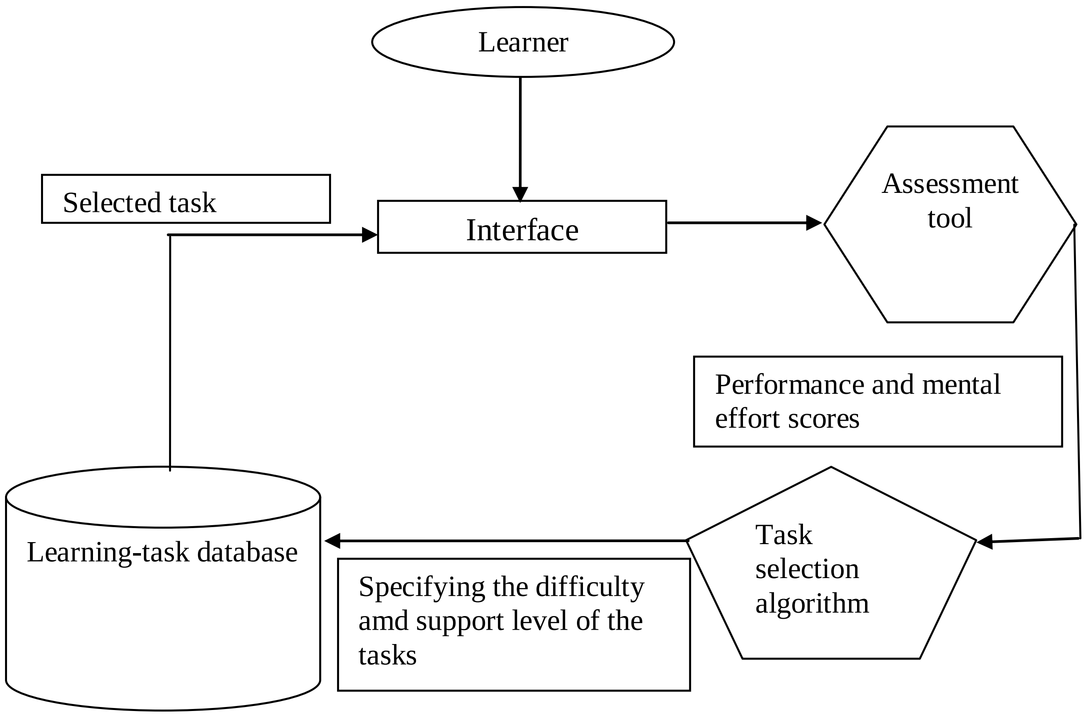


Fig. 1. *The basic components of the personalized learning environment*

Figure 2 presents the tasks that are represented in the learning-task database as a combination between five difficulty levels (i.e., from low to high), three levels of support (high, low and no support) and three tasks per support level with different surface features (*this was also the task-selection screen in learner control instruction*).

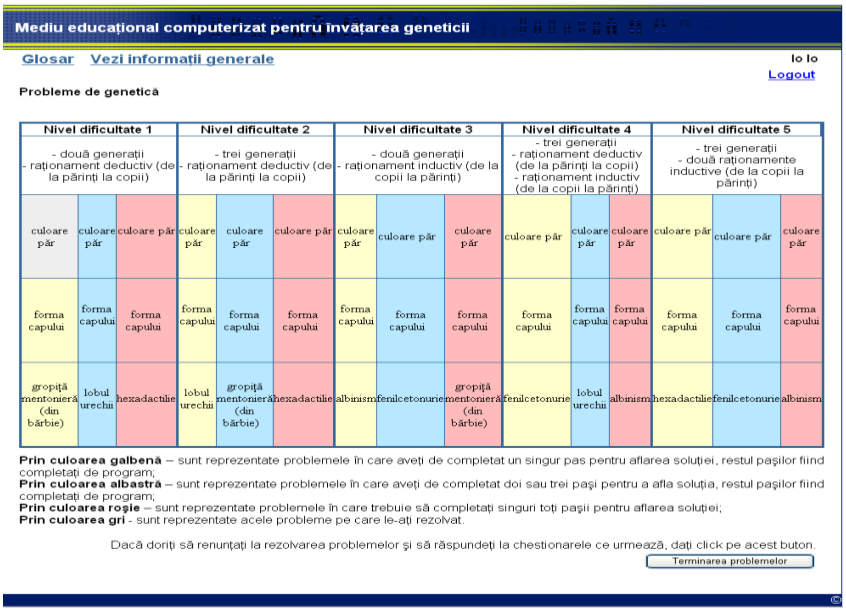


Figure 2. *Overview of database structure; this was also the task-selection screen.*

For the personalization of the instruction, the performance and invested mental effort scores were used as a variable for dynamic task selection, an approach used in other studies too (Camp et al., 2001; Corbalan et al, 2006; Salden et al., 2004). Based on these scores a task selection algorithm determined the appropriate difficulty and support level of the next learning task for each individual learner. The task selection algorithm for determining the difficulty and support level of the first learning task in the training phase using pre-test performance and associated mental effort is presented in Table 1, and task selection procedure for the remainder of the training phase using the performance and mental effort scores of the preceding solved learning task is presented in Table 2 (for completion problems with high support) and Table 3 (for completion problems with low support and conventional problems).

More specifically, the difficulty level of the first training problem would always be level 1 and the pre-test performance and associated mental effort scores determined the support level. Overall, most pre-test scores would lead to completion problems with high support (+1), some led to completion problems with low support (+2) and only a few led to conventional problems (+3).

Once working in the training phase, the selection algorithm determined the difficulty and support level of the next problem considering the support level the participants previously worked in. For instance, if a participant has successfully solved a completion problem with high support in difficulty level 1 by obtaining a performance score of 3 and a mental effort score of 1, s/he must jump 2 steps ahead, meaning that the amount of support increases two levels. Therefore, the learner will move to a conventional problem at the current difficulty level. For completion problems with high support, the mental effort scores determine changes in the support level within a certain difficulty level, since the performance score is preset to a fixed value (3).

Table 1 shows the selection decisions for completion problems with low support and conventional problems. The students receive a similar problem when their performance and corresponding mental effort scores are the same (+0) and they can jump to a higher or lower support level (+/-1 and +/-2) when these scores are different. If a learner solved a completion problem with low support obtaining a mean performance score of 5 and a mental effort score of 1, s/he must jump 3 steps ahead. But since there are less than three support levels available at the current difficulty level, the learner has to advance to a low support level of the next difficulty level. Therefore, only by obtaining the highest performance while investing the lowest mental effort can students jump between difficulty levels (+3). Similarly, participants can also drop to the previous difficulty level when obtaining the lowest performance (1) and the highest mental effort (5).

Tabelul 1. *Selection table indicating step size between pre-test and first learning task*

	Performance				
Mental effort	***1***	***2***	***3***	***4***	***5***
1	1	2	2	3	3
2	1	1	2	2	3
3	1	1	1	2	2
4	1	1	1	1	2
5	1	1	1	1	1

Tabelul 2. *Selection table indicating step size for completion problems with high support*

	Performance				
Mental effort	***1***	***2***	***3***	***4***	***5***
1	1	1	2	2	3
2	0	1	1	2	2
3	-1	0	0	1	1
4	-1	-1	0	0	1
5	-2	-1	-1	0	0

Tabelul 3. *Selection table indicating step size for completion problems with low support and conventional problems*

	Performance				
Mental effort	***1***	***2***	***3***	***4***	***5***
1	0	0	1	2	3
2	-1	0	0	1	2
3	-1	-1	0	0	1
4	-2	-1	-1	0	0
5	-3	-2	-1	-1	0

The selection tables 2 and 3 apply some additional rules to make the instruction encouraging for the learners: (1) if the learner completed all three available problems of a certain support level in a current difficulty level s/he will move to the next support level at the current difficulty level; (2) if the learner completed two successive problems of the same support level at a certain difficulty level , s/he can progress to the next support level at the current difficulty level; (3) the learner will finish the training after s/he successfully completed either one conventional problem at the highest difficulty level or after having worked through all conventional problems available in the highest difficulty level (i.e., difficulty level 5).

4.1.3 Discussion and conclusions

This chapter discussed a personalized task selection model which integrates the assumptions of the two-level model of adaptive instruction and of the four-component instructional design model (4C/ID; Van Merriënboer, 1997). The proposed model combines the strong points of both approaches and was therefore expected to make learning more effective (i.e., higher transfer test performance) and more efficient (i.e., a more favorable ratio between performance and time on task or mental effort). This personalized model allows for the dynamic selection of the learning tasks based on the learner's performance scores and invested mental effort, that is the expertise level of the learners.

There are two main differences between the proposed personalized model (and the learning environment developed according to this model) and the previous developed personalized models. First, the present model applies different measurement scales and another selection algorithm. The scales used in the proposed model are sensitive to the differences between the support level within the same complexity level of the tasks. As a result, the selection algorithm that is used for selecting a new learning task of a certain complexity and support level, is different for problems with high support and for problems with low support. Furthermore, the maximum jump size between complexity levels was decreased from four (Camp et al., 2001; Corbalan et al., 2006) to three in the implemented selection algorithm forcing a smoother increase or decrease in task complexity (see Salden et al., 2004). Secondly, unlike the previous personalized models in which the selection of the first training task is arbitrary, the support level of the first training problem would be adapted to the learners' expertise level (combination of performance and mental effort scores).

4.2 Formative evaluation of the computer-based learning environment developed on the basis of the model

The learning environment was pilot tested with 28 high school for functionality and usability assessment (formative evaluation). The results indicated that the program promotes learning and the provided content is suitable for target population.

Chapter 5
THE EFFECTS OF THE INTERNAL INSTRUCTIONAL CONTROL VS. EXTERNAL INSTRUCTIONAL CONTROL (ADAPTIVE AND NONADAPTIVE) ON EFFECTIVENESS AND LEARNING EFFICIENCY OF LEARNERS WITH DIFFERENT LEVELS OF EXPERTISE

5.1 Study 1

Aims and hypotheses

The purpose of the current study was to assess the effectiveness (i.e., training and test performance) and learning efficiency (i.e., test performance, its associated test mental effort and training time) of a non-adaptive program control, a full learner control, a limited learner control and an adaptive program control in learning genetics using students of different prior knowledge levels. The main research question entails what effects do these four types of instructional control, students' prior knowledge (i.e., high school, first year and second year college students), and the interaction between both factors have on learning outcomes and learning efficiency. It was hypothesized that the adaptive program control would yield higher performance and be more efficient than the other three conditions. Whereas the non-adaptive program instruction was expected to be insensitive to individual students' learning needs, the learner-controlled instruction might overload the students.

With regard to students' prior knowledge it was hypothesized that higher prior knowledge students (i.e., college students) would achieve higher performance and be more efficient than students with a low prior knowledge (i.e., high school students). Furthermore, it was expected that higher prior knowledge level students perceive their current learning state and instructional needs more accurately, and thus would be better able to manage their own instruction. Additionally, it was expected that the high prior knowledge students would spend more time-on-task due to engaging in deeper cognitive engagement and self-reflecting (see Chi, 2006) than the low prior knowledge students.

Method

Participants

Two hundred and sixty nine students (99 high school students, 117 first year college students, and 53 second year college students; 44 males and 225 females; M = 18.63 years, SD = 3.95) participated in this study. The high school students were novices and the college students were intermediate students with regard to the genetics domain used in this experiment. All participants were randomly assigned to one of the four experimental conditions: a non-adaptive program condition (n = 65, 25 high school students and 40 college students), a full learner control condition (n = 70, 25 high school students and 45 college students), a limited learner control condition (n = 68, 25 high school students and 43 college students), and an adaptive program control condition (n = 66, 24 high school students and 42 college students).

Materials

Electronic learning environment. The learning environment developed for this study was a Web application written in PHP scripting language. A MySQL database connected to the learning environment contained the learning material and registered student actions: performance and mental effort scores, problem selection choices, and time-on-task. Furthermore, this database contained a basic introduction to genetics, a pre-test and post-test, a far-transfer test, and a glossary with the main genetics concepts. The content of the instructional program was part of the regular biology curriculum for high school students and Neuropsychology curriculum for first year college students from Psychology.

The introduction included the main genetics concepts required for solving problems such as dominant and recessive genes, genotype, phenotype, homozygous and heterozygous gene pairs.

The *pre-test and post-test* consisted of the same ten multiple-choice questions on the subject of heredity (i.e., Mendel's Laws). The maximum score was 10 points, one point for each correct answer.

The participants received genetics problems represented in a database (see Figure 1) as a combination between five difficulty levels (i.e., from low to high), three levels of support (i.e., high, low, and no support) and three problems per support level with different surface features (i.e., aspects of the tasks that are not related to goal attainment such as eye color, hair shape). The selection of problems from the database of the 45 genetics problems (Figure 1) differed between the experimental conditions.

In the *non-adaptive program control* condition, participants received 15 problems with three randomly chosen problems of each support level within each of the five difficulty levels. These problems were presented in a predetermined simple to complex sequence, designed according to the 4C/ID model (Van Merriënboer, 1997).

In the *full learner control condition*, participants received an overview of all 45 problems with an indication of their difficulty and support level, and they could choose any problem to solve next. *The limited learner control condition* differed from the first in having to solve a conventional problem in each difficulty level before being allowed to start solving tasks from a higher difficulty level.

For the *adaptive program control condition* the performance and invested mental effort scores were used as a variable for dynamic problem selection (see chapter 5).

Far-transfer test. The far-transfer test consisted of five problems which differed structurally from the training problems and measured students' ability to apply the learned procedures to new learning situations. Specifically, participants had to solve problems on dihybrid crossings, problems involving sex-linkage and co-dominant genes (i.e., blood types). The transfer problems had distinctive solution steps, resulting in a maximum total score of 16. The reliability (Cronbach's alpha) of the pre-test, post-test, and far-transfer test was: .52, .69, and .75 respectively.

Mental effort. The perceived mental effort was measured after each problem during each phase of the study (i.e., pre-test, post-test, training, far-transfer test) on a 5-point rating scale adapted from Paas (1992), with values ranging from 1 (very low) to 5 (very high).

Learning efficiency. Learning efficiency was determined using the following formula derived from the original formula proposed by Paas and Van Merriënboer (1993; see also Tuovinen & Paas, 2004):

$$E = \frac{P + TT - ME}{\sqrt{3}}$$

In this formula, E = learning efficiency, P = test performance, TT = total training time, and ME = mental effort during test. To calculate learning efficiency, all variables were standardized before being entered into the formula.

Procedure

All participants were given a pre-test and a basic introduction before the training phase started. Participants were free to consult this basic introduction during the entire training session. Immediately after the training, participants received the post-test and far-transfer test, and mental effort was measured after each solved problem. Overall, the experiment lasted about two hours.

Results

All the analyses were done using ANOVAs with between-subjects factors (1) type of instructional control and (2) prior knowledge, and a significance level of .05 was used. Dependent variables were performance, mental effort, time on pre-test, time on training, time on post-test, and time on far-transfer test, total solved problems, total solved problems per difficulty and support level, and learning efficiency.

Table 4 provides an overview of the results during training and test phase for factor (1) and Table 5 provides an overview of the results for factor (2).

(1) Type of instructional control

An ANOVA showed significant differences for training performance, $F(3, 265) = 2.94$, $MSE = 3075.45$, $p < .05$, $\eta_p^2 = .03$ and time during training, $F(3, 265) = 13.57$, $MSE = 218.93$, $p < .0001$, $\eta_p^2 = .13$. Planned comparisons revealed that participants in the adaptive program condition attained higher performance scores ($t(265) = 2.59$, $p < .05$) than the participants in the non-adaptive condition and both learner control conditions. Furthermore, participants in the adaptive program condition spent more time on training ($t(265) = 5.06$, $p < .0001$) than the mean training time of participants in the non-adaptive condition and both learner control conditions. No effect on the invested mental effort during the training was found for type of instruction, $F(3, 265) = 1.37$, $MSE = 1.10$, *ns*.

With regard to the number of learning tasks that was completed during training, an ANOVA revealed a main effect for type of instruction, $F(3, 265) = 4.41$, $MSE = 19.16$, $p < .01$, $\eta_p^2 = .05$. Participants in the adaptive program condition solved more problems during training ($t(265) = 3.53$, $p < .0001$) than the participants in the non-adaptive condition and both learner control conditions.

With regard to total solved problems for each difficulty level, ANOVAs revealed significant differences for type of instruction on total solved problems for difficulty level 1, $F(3, 260) = 16.39$, $MSE = 6.16$, $p <.0001$, $\eta_p^2 = .16$; difficulty level 2, $F(3, 265) = 11.60$, $MSE = 5.46$, $p <.0001$, $\eta_p^2 = .12$; difficulty level 4, $F(3, 188) = 19.46$, $MSE = 1.69$, $p <.0001$, $\eta_p^2 = .24$, difficulty level 5, $F(3, 167) = 3.29$, $MSE = 1.36$, $p <.05$, $\eta_p^2 = .06$. Overall, participants in both learner control conditions solved more problems from lower difficulty levels (i.e., difficulty level 1) and fewer problems from higher difficulty levels (i.e., difficulty level 4) than participants in the adaptive program condition and the non-adaptive condition.

An ANOVA of total solved problems for each support level revealed a main effect for type of instruction on total solved completion problems with high support $F(3, 258) = 4.64$, $MSE = 7.05$, $p < .01$, $\eta_p^2 = .05$, and total solved completion problems with low support $F(3, 254) = 6.18$, $MSE = 3.61$, $p < .0001$, $\eta_p^2 = .07$. Overall, participants in both learner control conditions solved less completion problems with low support and conventional problems compared to participants in the adaptive program condition and the non-adaptive condition.

No significant differences in post-test and far transfer test performance, invested mental effort during the post-test and the far transfer test, time during the far transfer test (all Fs < 1), and time during the post-test ($F(3, 265) = 1.42$, $MSE = 28.39$, *ns*) were found.

(2) Prior knowledge

An ANOVA revealed significant differences on pre-test performance, $F(2, 266) = 18.28$, $MSE = 3.8$, $p < .0001$, $\eta_p^2 = .12$; invested mental effort, $F(2, 266) = 28.34$, $MSE = .59$, $p < .0001$, $\eta_p^2 = .18$; and pre-test time, $F(2, 266) = 13.67$, $MSE = 20.75$, $p < .0001$, $\eta_p^2 = .09$. High school students achieved lower pre-test performance scores ($t(266) = 5.29$, $p < .0001$) than first year college students and second year college students. Furthermore, second year college students achieved higher pre-test performance ($t(266) = 3.12$, $p < .0001$) compared to the mean of performance of high school students and first year college students. With regard to invested mental effort, planned comparisons showed that high school students experienced higher mental effort ($t(266) = -7.49$, $p < .0001$) than first year college students . Additionally, high school students spent less time on the pre-test ($t(266) = 2.30$, $p < .05$) than first year college students and second year college students. Furthermore, second year college students spend more time on the pre-test ($t(266) = 4.78$, $p < .0001$) than first year college students.

ANCOVAs revelead main effects of prior knowledge factor on training performance, $F(2, 265) = 15.13$, $MSE = 2551.96$, $p < .0001$, $\eta_p^2 = .10$; invested mental effort on the training, $F(2, 265) = 14.31$, $MSE = .70$, $p < .0001$, $\eta_p^2 = .10$; and training time, $F(2, 265) = 31.87$, $MSE = 151.29$, $p < .0001$, $\eta_p^2 = .19$. First year college students achieved higher training performance scores ($t(265) = 4.41$, $p < .0001$) than high school students, whereas second year college students achieved higher training performance scores ($t(265) = 3.69$, $p < .0001$) than the high school students and first year college students ($M = 116.26$, $SD = 48.26$). Furthermore, first year college students experienced a lower mental effort on training ($t(265) = -3.54$, $p < .0001$) than high school students, whereas second year college students experienced lower mental effort ($t(265) = 4.58$, $p < .0001$) than the high school students and first year college students.

ANOVAs showed significant main effects for prior knowledge on total solved problems for difficulty level 1, $F(2, 261) = 5.09$, $MSE = 7.02$, $p < .01$, $\eta_p^2 = .04$; and difficulty level 2, $F(2, 261) = 8.10$, $MSE = 5.61$, $p < .0001$, $\eta_p^2 = .06$. Overall, high school students solved more problems for lower difficulty levels (i.e., difficulty level 1) and fewer problems for higher difficulty levels (i.e., difficulty level 5).

With regard to the solved problems for each support level, an ANOVA revealed a main effect for prior knowledge level only for total completion problems with high support, $F(2, 259) = 12.40$, $MSE = 7.76$, $p < .0001$, $\eta_p^2 = .09$. First year college students solved less completion problems with high support ($t(259) = -3.65$, $p < .0001$) than the high school students, whereas second year college students solved less completion problems with high support ($t(259) = -3.55$, $p < .0001$) than the solved completion problems with high support of high school students and first year college students.

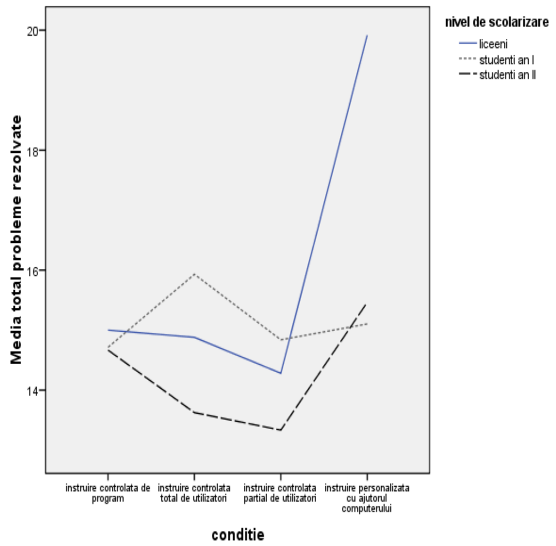
ANCOVA revealed a main effect on post-test performance, $F(2, 265) = 8.05$, $MSE = 4.23$, $p < .0001$, $\eta_p^2 = .06$, invested mental effort, $F(2, 265) = 17.46$, $MSE = .51$, $p < .0001$, $\eta_p^2 = .12$ and time spent on post-test, $F(2, 265) = 72.97$, $MSE = 13.05$, $p < .0001$, $\eta_p^2 = .36$. First year college students achieved higher post-test performance ($t(265) = 3.04$, $p < .01$) than high school students, whereas second year college students achieved higher post-test performance

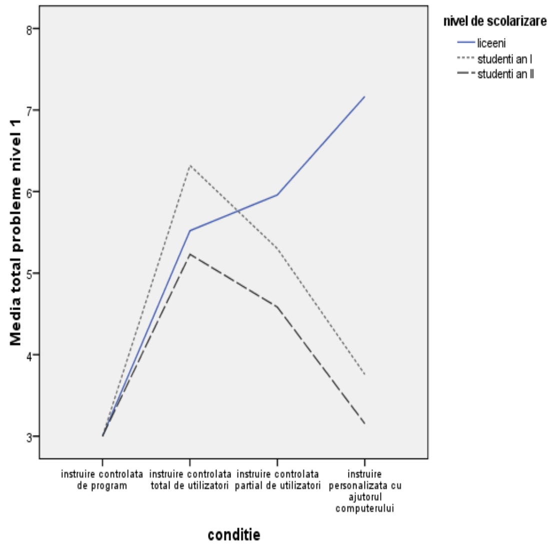
($t(265) = 2.89$, $p < .01$) than the mean score of high school students and first year college students. Furthermore, first year college students experienced lower mental effort during the post-test $t(265) = -3.34$, $p < .01$) than high school students, whereas second year college students experienced lower mental effort during the post-test ($t(265) = -4.93$, $p < .0001$) than the mean score of high school students and first year college students. Finally, first year college students spent more time on the post-test ($t(265) = 10.10$, $p < .0001$) than high school students, whereas second year college students spent more time during the post-test ($t(265) = 7.36$, $p < .0001$) than the mean score of high school students and first year college students.

Furthermore, an ANCOVA revealed a significant effect for prior knowledge on far transfer test performance, $F(2, 259) = 84.27$, $MSE = 5.23$, $p < .0001$, $\eta_p^2 = .39$, and time spent on the far transfer test $F(2, 265) = 146.67$, $MSE = 27.54$, $p < .0001$, $\eta_p^2 = .53$. First year college students achieved higher far transfer test performance ($t(258) = 10.78$, $p < .0001$) than high school students whereas second year college students achieved higher far transfer test performance ($t(258) = 4.21$, $p < .0001$) than the mean score of high school students and first year college students. Additionally, first year college students spent more time during the far transfer test ($t(265) = 15.56$, $p < .0001$) than high school students, whereas second year college students spent more time during the far transfer test ($t(265) = 8.30$, $p < .0001$) than the mean score of high school students and first year college students.

Using paired t-tests a significant gain from pre-to-post-test in performance ($t(268) = -7.51$, $p < .0001$) as well as a significant drop in mental effort ($t(268) = 8.52$, $p < .0001$) were found, indicating that learning did take place across all groups.

No significant interaction effects were found on performance, invested mental effort and time spent for the pre-test phase, training phase and the test phase (all *F*s < 1). Regarding the training phase, significant main effects were found on total solved problems, $F(6, 257) = 2.80$, $MSE = 18.14$, $p < .05$, $\eta_p^2 = .06$; completion problems with high support, $F(6, 250) = 2.64$, $MSE = 6.17$, $p < .05$, $\eta_p^2 = .06$; conventional problems, $F(6, 248) = 2.58$, $MSE = 2.98$, $p < .05$, $\eta_p^2 = .06$; on total solved problems for difficulty level 1, $F(6, 252) = 4.80$, $MSE = 5.44$, $p < .0001$, $\eta_p^2 = .10$; difficulty level 2, $F(6, 252) = 6.55$, $MSE = 4.38$, $p < .0001$, $\eta_p^2 = .14$, and difficulty level 3, $F(6, 238) = 2.86$, $MSE = 1.49$, $p < .05$, $\eta_p^2 = .07$. (see Figure 3).





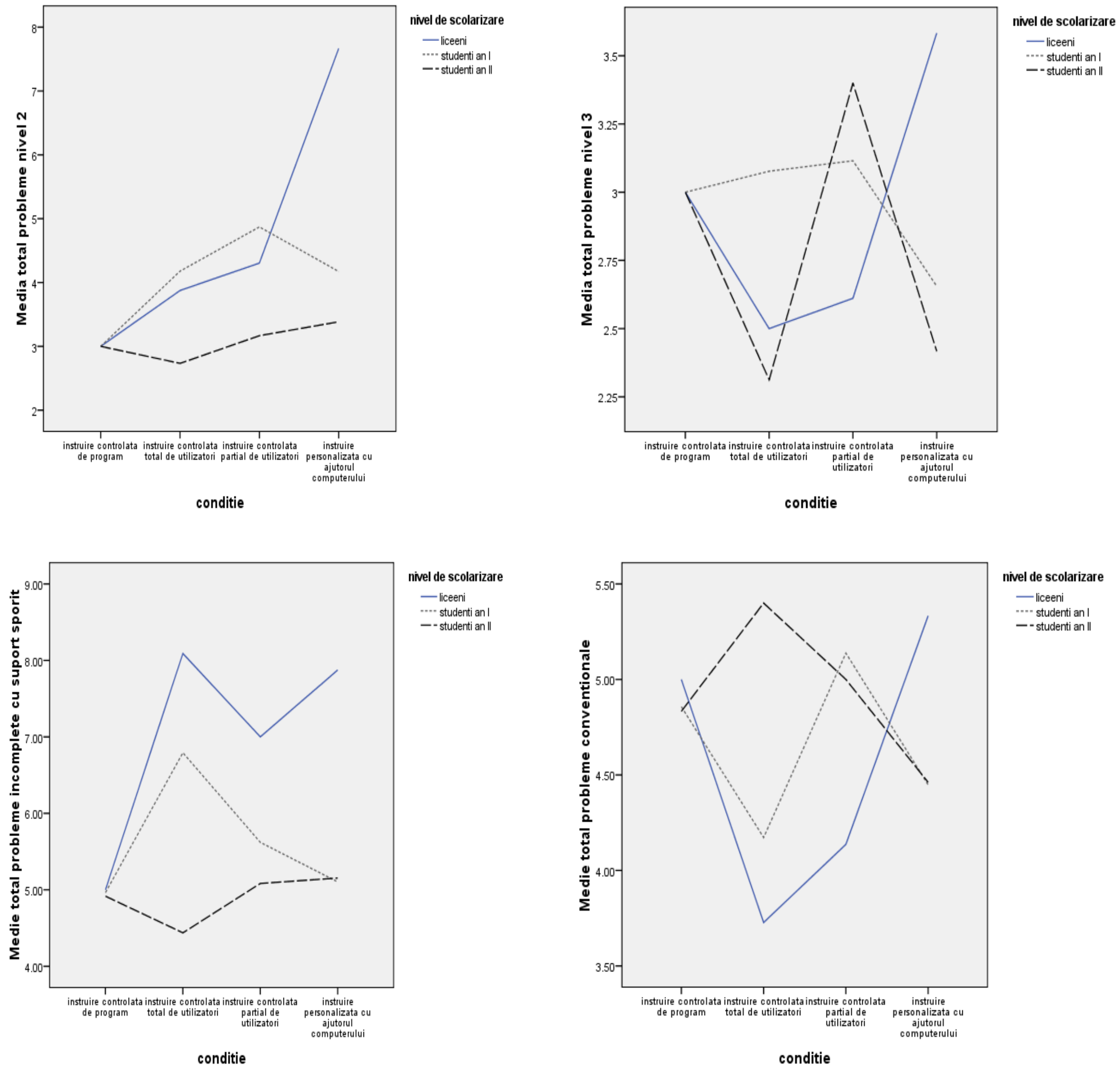


Figura 3. Graphical representation of the interaction between type of instruction and prior knowledge level on total solved problems, completion problems with high support, conventional problems, total solved problems for difficulty level 1, difficulty level 2, and difficulty level 3.

Using an ANOVA, a significant effect was found for learning efficiency related to the post-test scores, $F(3, 265) = 2.72$, $MSE = 1.70$, $p < .05$, $\eta_p^2 = .03$, and for learning efficiency related to the far transfer test scores, $F(3, 258) = 3.92$, $MSE = 1.57$, $p < .01$, $\eta_p^2 = .04$. for posttest performance, adaptive program condition was more efficient ($t(265) = 2.23$, $p < .05$) than the non-adaptive condition and both learner control conditions, and for far transfer test performance, adaptive program condition is more efficient ($t(258) = 2.96$, $p < .01$) than the non-adaptive condition and both learner control conditions.

An ANOVA revealed a significant effect of prior knowledge on learning efficiency for post-test scores, $F(2, 266) = 67.64$, $MSE = 1.16$, $p < .0001$, and for far transfer test scores $F(2, 259) = 88.84$, $MSE = .97$, $p < .0001$, $\eta_p^2 = .41$. For post-test performance, first year college students are more efficient ($t(266) = 10.16$, $p < .0001$) than high school students, whereas second year college students are more efficient ($t(266) = 6.04$, $p < .0001$) than the high school students and first year college students. Furthermore, for far transfer performance, first year college students are more efficient ($t(259) = 12.34$, $p < .0001$) than high school students , whereas second year college students are more efficient ($t(259) = 5.66$, $p < .0001$) than the high school students and first year college students.

Tabelul 4. *Overview of results from the pre-test and the training phase for factor type of instruction*

	Type of instruction							
	Non-adaptive program control		Full learner control		Limited learner control		Adaptive program control	
Dependent variables	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Pretest								
Time (min)	11.49	3.97	11.95	4.92	10.66	4.91	13.23	4.90
Mental effort	3.10	.86	3.08	.83	3.21	.84	3.04	.85
Performance	4.15	2.21	4.19	1.86	4.19	2.03	3.89	2.22
Training								
Total *N* of learning tasks	14.82	.83	15.03	5.33	14.37	5.46	16.92	4.06
Total solved steps	42.32	2.92	39.07	15.72	39.32	14.22	46.41	10.23
Time (min)	39.38	13.95	32.53	15.76	29.82	14.79	44.51	14.57
Mental effort	2.96	1.05	2.63	1.21	2.84	1.06	2.92	.83
Performance	127.20	37.70	117.26	71.16	114.04	61.54	139.85	43.13
Posttest								
Time (min)	6.20	4.42	7.83	5.38	7.71	5.38	7.72	6.00
Mental effort	2.73	.97	2.67	1.04	2.74	1.04	2.69	1.11
Performance	5.18	2.45	5.14	2.58	5.00	2.60	5.17	2.48
Learning efficiency	.01	1.27	-.21	1.36	-.39	1.28	.22	1.31
Far transfer								
Time (min)	11.13	7.42	12.67	8.05	12.50	8.08	13.37	8.24
Mental effort	4.01	.92	3.87	.97	3.96	.98	3.76	.98
Performance	3.95	3.02	3.93	2.87	3.60	2.81	4.04	3.06
Learning efficiency	-.05	1.22	-.22	1.34	-.42	1.19	.30	1.24

Tabelul 5. *Overview of results from the test phase for factor prior knowledge*

	Prior knowledge					
	High school students		First year college students		Second year college students	
Dependent variables	*M*	*SD*	*M*	*SD*	*M*	*SD*
Pretest						
Time (min)	9.92	4.39	12.90	4.78	13.02	4.34
Mental effort	3.52	.80	2.73	.76	3.18	.72
Performance	3.17	1.39	4.58	2.19	4.81	2.27
Training						
Total *N* of tasks	15.98	4.41	15.15	4.56	14.25	4.16
Total solved steps	42.00	12.59	41.79	12.87	2.47	.86
Time (min)	28.31	1.28	40.32	1.15	43.04	1.70
Mental effort	3.17	.09	2.73	.08	2.43	.12
Performance	101.60	5.29	133.60	4.73	146.70	7.03
Posttest						
Time (min)	3.80	.38	8.99	.34	10.52	.50
Mental effort	3.01	.08	2.65	.07	2.29	.10
Performance	4.46	.22	5.36	.19	5.84	.29
Learning efficiency	-.1.09	.98	.40	1.07	.65	1.25
Far transfer						
Time (min)	4.81	.54	16.43	.49	17.37	.73
Mental effort	3.98	.09	3.92	.08	3.72	.11
Performance	1.66	.24	5.17	.21	4.88	.31
Learning efficiency	-1.20	.80	.49	1.07	.50	1.07

Discussion

As predicted, the results show that the adaptive program control condition achieved higher training performance scores compared to the non-adaptive program control and learner control conditions. Therefore, adapting the difficulty and support of problems to the students' expertise level makes learning more effective (only for training) and efficient. Additionally, the adaptive program condition needed more time to complete the training than the other two experimental conditions. This difference in time could be attributed not only to the fact that the adaptive program condition solved significantly more problems, but possibly participants also noticed the relationship between their accuracy in solving the problems and the difficulty plus embedded support of the subsequent problems and consequently spent more time analyzing and self-reflecting (Corbalan et al., 2008).

Although the non-adaptive program control condition attained the same training performance as the learner control conditions, the former needed significantly more time to complete the training phase. A possible explanation could be that participants in the two learner control conditions solved more problems from lower difficulty levels, less problems from higher difficulty levels, and more completion problems with a high support than the non-adaptive program control condition. Not only did the learner control condition solve mostly easier problems, they also received more support in their problem solving than the non-adaptive program control condition.

Unfortunately, the higher training effectiveness of the adaptive program condition is not reflected in superior post-test or far-transfer performance. A possible explanation for the lack of higher test performance could be related to the difficulty levels the participants mostly worked in. The participants in the adaptive program control condition mostly worked in lower difficulty levels compared to the non-adaptive program control condition yet did not attain inferior post-test or far-transfer performance. More precisely, despite the fact that roughly 66% of the participants in the adaptive program control did not reach difficulty level 5 they did not do worse in terms of post-training performance. Another possible explanation could be related to the so-called 'perverse effects of help/ support'(Mircea Miclea, personal communication) or the acquisition of 'limited' schemas which interfere with the generation of new solutions for similar problems (Smith. et al., 1993).

Regarding learning efficiency, the results confirm that the adaptive program condition is more efficient than the other three experimental conditions. The inclusion of the training time in the 3D efficiency formula allows taking into account other differences besides those related to performance and invested mental effort. We chose to add the total training time instead of subtracting it as in Salden et al. study (2004) due to the fact that spending more time during training is considered to be beneficial in this study. This is in agreement with Chi (2006) who stated that experts spend a relatively great deal of time on solving learning tasks and self-reflection in comparison to novices.

Regarding the students' prior knowledge level, the prediction that the college students would outperform the high school students, spend more time-on-task and experience less mental effort was confirmed. While the same pattern was found for the second year college students over both first year college students and high school students, the differences between first and second year college students were relatively small.

The interaction effects found in this study show that the students' prior knowledge strongly affects the students learning path in the learner control and the adaptive program control conditions.

Chapter 6
EXPERTISE- RELATED DIFFERENCES IN TASK SELECTION: COMBINING EYE MOVEMENT, CONCURRENT AND CUED RETROSPECTIVE REPORTING

A series of studies indicated that low levels of prior knowledge may negatively affect learners potential to be aware of the task features that are relevant for the learning process (Quilici & Mayer, 2002). Corbalan et al. (2008) showed that low prior knowledge students typically focus on the more salient surface task features (e.g., cover stories that are irrelevant to understand how problems can be solved) rather than on the less salient structural task features (e.g., underlying problem-solving procedures that are relevant to understand how problems can be solved). Learners who do not possess or use appropriate schemas (i.e., one chunk of information, which increases the amount of information that can be held and processed in working memory), will not be able to recognize problem similarities on the basis of structural features (Chi, Feltovich, & Glaser, 1981; Quilici & Mayer, 1996, 2002). However, as learners' levels of knowledge in a particular domain increase, more useful schemas are constructed, which improve their ability to recognize structural task features (Quilici & Mayer, 2002) and consequently learning (Sweller, Chandler, Tierney, & Cooper, 1990).

Eye movement studies investigating how novices and experts perceive relevant versus irrelevant information have indicated that learners' attention allocation is indeed influenced by expertise. More specifically, it has been shown that with increasing domain knowledge, learners tend to focus more on task-relevant information (e.g., Van Gog & Scheiter, 2010). The tendency of experts to focus more on task-relevant features and less on salient, but irrelevant features can be seen as an example of the information-reduction hypothesis (Canham & Hegarty, 2010; Haider & Frensch, 1999; Jarodzka, Scheiter, Gerjets, & Van Gog, 2010). According to information-reduction hypothesis, improvements in task performance reveal that learners possess the necessary level of knowledge to discern between task features that need to be processed and those that do not.

Useful as eye movement data may be, they do not explain *why* learners focus their attention on certain areas for a certain amount of time and in a certain order (Kaakinen & Hyönä, 2005). In other words, eye tracking does not reveal any information about the success or failure of learners' ability to understand task-relevant information. In order to obtain a more comprehensive picture of the learning performance processes, eye movement data can be complemented with concurrent, retrospective or cued retrospective verbal protocols (cf. Van Gog et al., 2005).

The so-called cued retrospective reporting technique (Kaakinen & Hyönä, 2005; Van Gog et al., 2005; Van Gog et al., 2009) has been recognized as a valuable alternative for concurrent or restrospective reporting. Whereas "standard" retrospective reporting relies exclusively on memory processes, cued retrospective reports are less prone to omissions and constructions of actions. With this technique, records of eye movements and mouse/keyboard actions are used to stimulate retrospective verbal reports of a task performance process. Though this unburdens the learner from reporting what they are thinking during task performance, it does require stimulated memory-based recall.

Aims and hypotheses

The aim of the current study was to examine the differences in attention paid to relevant and irrelevant task-features during task selection processes between low and high prior knowledge learners by combining eye tracking measures, think-aloud and cued retrospective protocols (see e.g., Ericsson & Simon, 1993; Van Gog et al., 2005). Note that the cue consisted of a record of participants' eye movements as well as their actions on the computer screen (i.e., mouse/keyboard actions).

A prediction was that high prior knowledge students would focus on structural features during task selection as compared to low prior knowledge students, who would be more likely to focus on surface task features. The high prior knowledge students, by having at their disposal higher level schemas, were expected to be better able to discern which information is relevant to the task performance than low prior knowledge students. Furthermore, it was predicted that participants who were exposed to multiple examples of learning tasks (i.e., three task selections) would be more likely to select subsequently presented tasks based on their structural features than on their surface features. It was expected that in the later stages of processing irrelevant task information would become 'less salient'. Consequently, participants' eye fixations were expected to reveal a trade-off between surface features and structural features, indicating that more fixations would be made on structural features.

Also, it was expected that high prior knowledge students would verbalize more information, and implicitly would spend more time for verbalizing during both think-aloud and cued retrospective protocols than low prior knowledge students, and that their verbalizations would contain more relevant task information (i.e., structural features).

Method

Participants

Participants in the study were 30 students in first (n = 9), second (n = 10), third (n = 3) or fourth (n = 8) year of higher professional education. Four participants had to be excluded from the final analyses of the data due to technical difficulties. The remaining sample contained 26 students (12 females and 14 males) with a mean age of 21.15 years (SD = 2.34). All participants had normal or corrected-to-normal vision and all had at least some basic knowledge of Mendel's Laws, the topic of the study. The students received €10 for their participation.

Apparatus and Materials

Electronic learning environment. The learning environment consisted of a Web application written in PHP scripting language, and a MySQL database connected to it (based on Corbalan, Kester, & Van Merriënboer, 2011). The database contained 54 genetics completion tasks addressing Mendel's laws (i.e., inheritance tasks), which varied in terms of surface features (e.g., species type, traits), and structural features (to-be-completed solution steps). Completion tasks present a given state, a goal state, and a partial solution that must be completed by learners (Paas, 1992). In our study, completion tasks contained three to-be-completed solution steps and four steps that were already completed by the program. Table 6 shows all possible surface features and structural features of the genetics completion tasks (based on Corbalan et al., 2011).

Table 6.Composition of the Database with Learning Tasks *(based on Corbalan et al., 2011)*

Surface Task Feature		Structural Task Features
Species (species type)	Traits (part traits)	To-be-Completed Solution Steps
Humans (European/African/Asian)	Color (hair/eyes) Shape (hair/nose) Length (nose/lips)	(1) Determine the genotype of one parents based on information of the individual given (2) Determine the genotype of one parents based on the given percentage in her/his generation (3) Determine the genotype of one of the offspring of the first generation
Animals (dog/cat/guinea pig)	Color (fur/eyes) Shape (ear/fur) Length (tail/fur)	(4) Determine the genotype based on the information of the prior partner and related offspring (5) Draw a Punnett's square by combining the genotype of the parents
Plants (pea/corn/bean)	Color (flower/leaf) Shape (fruit/pod) Length (axis/fruit)	(6) Determine the genotype (and percentage) of the offspring (7) Determine the phenotype (and percentage) of the offspring

The selection screen always presented a set of four learning tasks, which contained a description of both surface features and to-be-completed steps (see Figure 4). Each set of learning tasks (i.e., three sets of learning tasks) represented a combination of low and high dissimilarity levels (i.e., in terms of surface and structural features), from which the learner selected and solved one task.

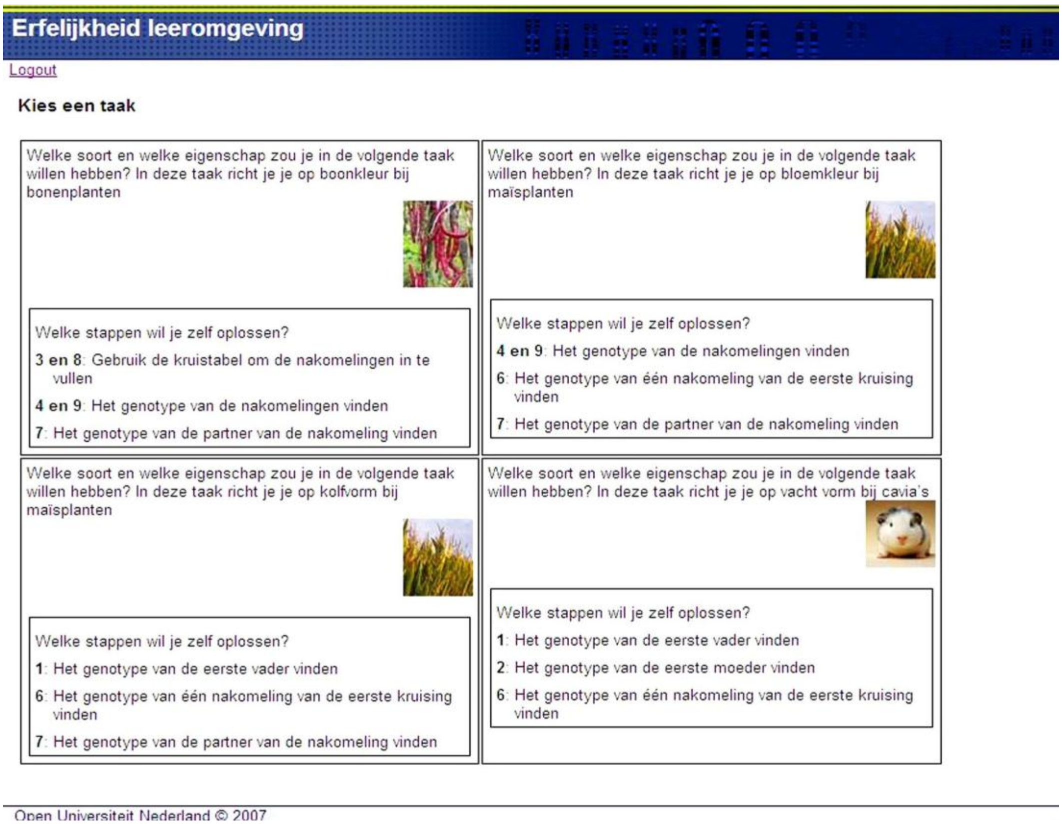


Figure 4. Example of a task-selection screen.

Eye tracking equipment. Participants' eye movements were recorded with a 50Hz Tobii 1750 eye tracking system, which is integrated into the stimulus PC monitor. Screen resolution of the stimulus PC was set at 1024 x 768 pixels, with a spatial accuracy better than 0.5 degrees. ClearView 2.7.1 software was used to record participants' eye movements and their keyboard and mouse actions, and to replay these recordings at half speed as a cue. This so-called "gaze replay" showed fixations, which represent gaze-points that fell within a radius of 50 pixels, and together had a minimal duration of 200 ms. The fixations were represented as a single red dot, which became larger with increasing fixation duration and smaller with decreasing fixation duration, and had a gaze trail of 1,000 ms (for an example screenshot of the gaze replay see Figure 5).

*Audio recordings***.** The verbal data were recorded with Audacity 1.2.6 software using a standard microphone attached to the stimulus PC.

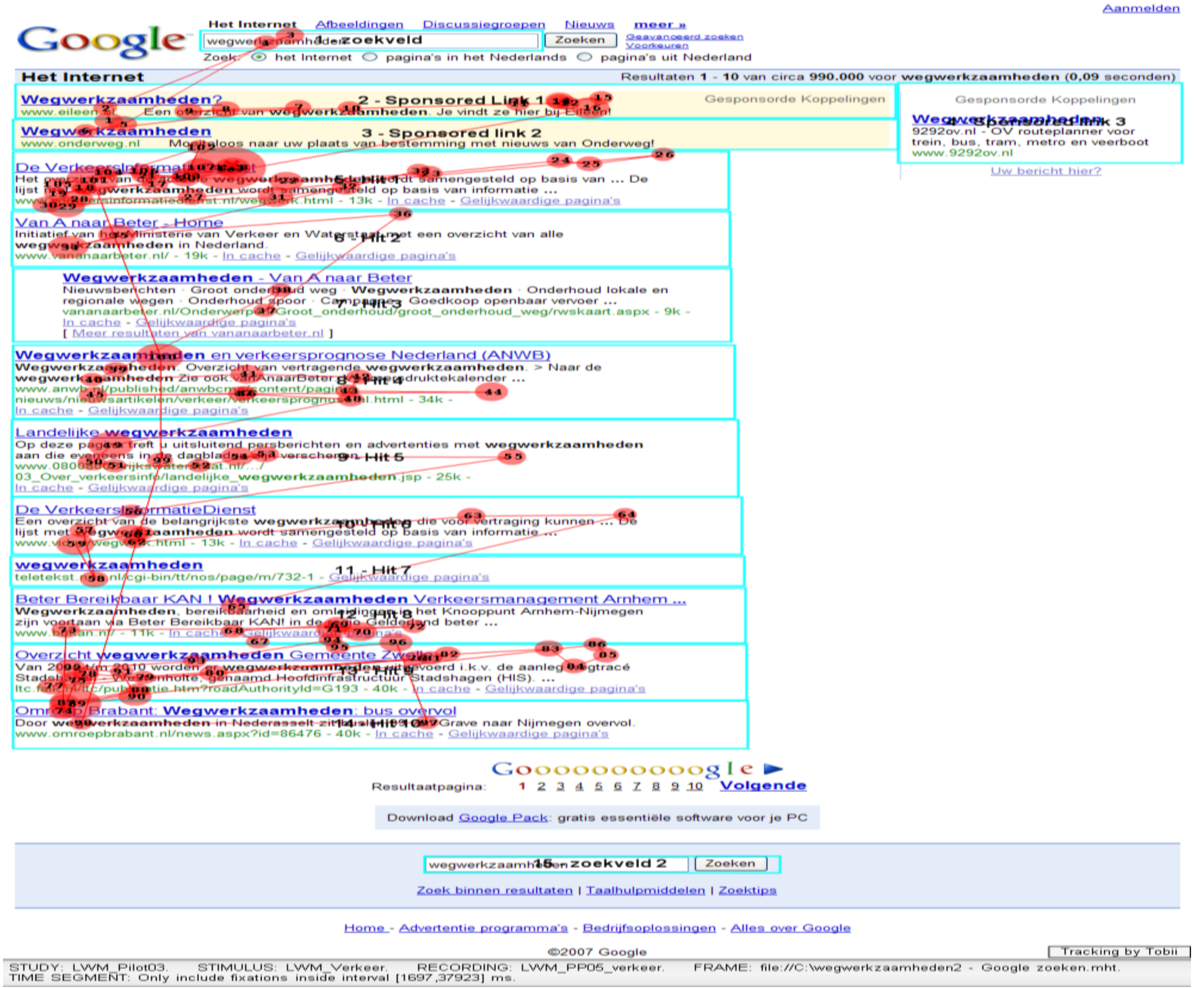


Figura 5. *Exemple of gaze reply during first warming-up task*

Verbal instructions. The instructions were formulated in line with the recommendations by Ericsson and Simon (1993; see also Van Gog et al., 2005).

Basic introduction. The basic introduction included the main genetics concepts required for solving completion tasks, and a worked-out example containing all the solution steps.

Pre-and post-test. The pre-test and post-test consisted of the same ten multiple-choice questions on the subject of heredity. The maximum score was 10 points, one point for each correct answer.

Warming-up tasks. Because learners vary in their ability to verbalize their own thoughts (Pressley & Afflerbach, 1995), two warming-up tasks were used to familiarize participants with the thinking aloud and cued retrospective reporting procedures. Although, those tasks were not related to the domain used (i.e., genetics), they required the participants to distinguish between relevant and irrelevant choices.

Procedure

The experiment was run in individual sessions of approximately 60 minutes. First, participants were given general instructions explaining the procedure and introducing the topic. They were asked to sign an agreement. The participants then started with the pre-test, for which they were given a total of eight minutes.

The pre-test was administered to all participants in order to assign participants in two groups: low and high prior knowledge students. Out of a possible ten points, participants' average pre-test score was 6.12 (*SD* = 2.53) with a median score of 6.50. Based on the median split we created two groups of equal size: low prior knowledge students ($n = 13$, age $M = 20.69$ years, $SD = 1.97$, 6 female, 7 male) and high prior knowledge students ($n = 13$, age $M = 21.62$ years, $SD = 2.66$, 6 female, 7 male). The high prior knowledge participants achieved an average score of 8.23 ($SD = 1.01$) on the pre-test, while the low prior knowledge students achieved an average score of 4.00 ($SD = 1.63$). The resulting independent samples *t* test was significant, $t(24) = 7.94$, $p < .001$, $d = 3.12$.

After completing the pre-test, participants were seated in front of the stimulus PC and the eye tracking system was calibrated. To familiarize participants with thinking aloud and cued retrospective procedures, they were given two warming-up tasks. When participants had finished the warming-up tasks, they received the basic introduction to read for ten minutes, and then started with the completion learning tasks. Before solving the learning tasks (i.e., three tasks), participants had to select one task from each set of tasks (i.e., a set contained four learning tasks), which represented a combination of low and high dissimilarity levels.

During the task selection process, participants were asked to think aloud, while during the task performance they had to complete the task in silence. Subsequently, all participants were exposed to the gaze replay and they were asked to provide the cued retrospective reports. The gaze replay was at half speed in order to allow participants to utter enough information about their thought processes.

Data analysis

Eye tracking data. To analyze participants' eye movements, eight areas of interest (AOIs) on the tasks features that were either relevant (i.e., structural features) or irrelevant to goal attainment (i.e., surface features) for each task selection were defined. AOIs were defined to determine whether and for which amount of time participants were looking at a specified area during the task selection process.

The dependent variables were the *fixation count,* the *gaze time,* and the *average fixation duration* (total fixation time divided by the number of fixations per AOI).

Verbal data. The concurrent reports obtained during the task selection process, and the cued retrospective reports obtained during the gaze replay were transcribed and analyzed with a coding scheme. The verbal protocols were analyzed to determine whether participants referred to either relevant (structural features) or irrelevant features (surface features) during task selection process. Therefore, the coding scheme was developed based on the participants' 'actions' during the task selection process ('reading', 'decision making', 'comparing the tasks', 'description of the tasks') and the task features types (surface features and structural features). Next to these, categories like 'reference to prior knowledge', 'picture', and 'rest' (i.e., other aspects) were included. The total number of words used during the thinking aloud and retrospection was counted.

Two raters familiarized with the experimental tasks coded 70 percent of the transcribed protocols with an inter-rater reliability of .72 (Cohen's kappa). Since the inter-rater reliability was sufficiently high (i.e., higher than .70; Van Someren, Barnard, & Sandberg, 1994), one rater scored the remaining protocols.

Results

Learning outcomes

Table 7 shows the descriptive statistics of the pre-test scores, training scores, post-test scores, pre-to-post-test gain, and time spent in the pre-test and post-test.

Table 7. *Means (M) and standard deviations (SD) for learning outcomes as a function of expertise*

Dependent variables	High prior knowledge students		Low prior knowledge students	
	M	*SD*	*M*	*SD*
Pre-test	8.23	1.01	4.00	1.63
Training performance	8.00	1.38	7.35	1.77
Post-test	8.92	.95	6.46	1.45
Pre-to-post-test gain	.69	1.11	2.46	2.11
Time on pretest (min)	7.00	1.15	6.15	1.52
Time on post-test (min)	5.31	1.70	5.62	1.39

Participants in the two conditions (i.e., high prior knowledge students and low prior knowledge students) did not differ significantly in terms of training performance, $t(24) = 1.05$, *ns.* A *t*-test on post-test scores showed that the high prior knowledge students attained higher post-test performance than the low prior knowledge students, $t(24) = 5.11$, $p < .001$, $d = 2.01$. No significant differences were found on time spent for the pre-test, $t(24) = 1.60$, *ns*, and post-test, $t(24) = -.51$, *ns*.

The high prior knowledge students gained less knowledge than the low prior knowledge students, $t(24) = - 2.68$, $p <.05$, $d = .36$. However, using paired *t*-tests a significant gain from pre-to-post-test in performance, $t(25) = -4.28$, $p <.0001$, $d = .72$, as well as a significant drop in time from pre-to-post-test, $t(25) = 3.59$, $p <.001$, $d = .77$, were found, indicating that learning did take place across both groups.

Eye tracking data

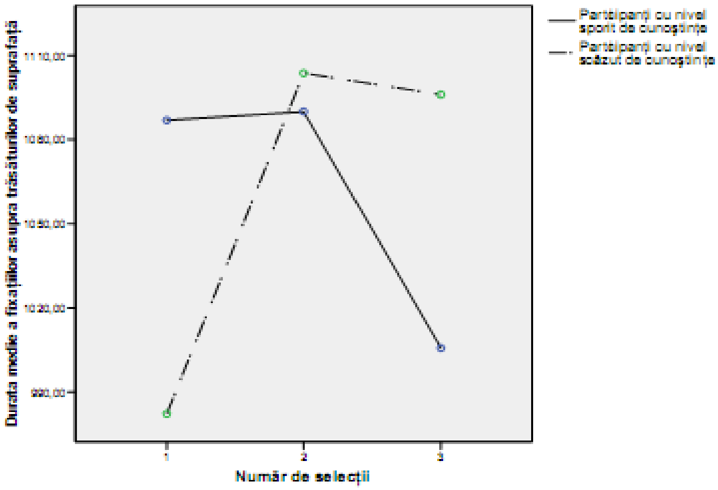
Regarding the number of fixations over surface features, a repeated measures ANOVA with expertise (i.e., high and low prior knowledge students) as the between subjects factor and number of task selections (i.e., first, second and third task selection) as within subjects factor was performed. Results showed a marginally effect of the number of task selections on fixation number over surface features, $F(2, 46) = 3.10$, $p = .055$, $\eta_p^2 = .12$, but no effect of expertise or interaction between expertise and number of task selections, $Fs < 1$. For factor number of task selections, planned contrasts revealed that the number of fixations over surface features was significantly lower for the third task selection compared to the first task selection, $F(1, 23) = 5.30$, $p < .05$, $\eta_p^2 = .19$, but was only marginally lower for the third task selection compared to the second task selection, $F(1, 23) = 3.96$, $p = .059$, $\eta_p^2 = .15$.

With respect to the number of fixations over structural features, ANOVA showed no significant main effect either for expertise or for number of task selections, and no interaction between expertise and number of task selections, $Fs < 1$.

An ANOVA on the duration of fixations over surface features revealed a significant main effect of number of task selections, $F(2, 46) = 3.48$, $p <.05$, $\eta_p^2 = .13$, but no effect of expertise or interaction between expertise and number of task selections, $Fs < 1$. The duration of fixations on surface features was significantly shorter in the third task selection than in the first task selection, $F(1, 23) = 5.01$, $p <.05$, $\eta_p^2 = .18$, and significantly shorter in the third task selection compared to the second task selection, $F(1, 23) = 4.40$, $p <.05$, $\eta_p^2 = .16$.

For the fixation duration over structural features, ANOVA revealed no significant main effect either for expertise or for number of task selections, *Fs* < 1, and no interaction between expertise and number of task selections, *F* < 1.

ANOVA revealed that there was a no significant effect of expertise, *F* < 1, and of number of task selections, $F(2, 36) = 1.31$, *ns*, on average fixation duration over surface features. A marginally significant interaction was found between expertise and number of task selections, $F(2, 36) = 3.04$, $p = .06$, $\eta_p^2 = .14$ (see figure 6). This marginal interaction showed that the average fixation duration over surface features was higher for the high prior knowledge students than for the low prior knowledge students in the first task selection, but lower for the high prior knowledge students than for the low prior knowledge students in the third task selection.



Finally, for the average fixation duration over structural features, the ANOVA showed no significant main effect of expertise or of number of task selections, *Fs* < 1. The interaction between expertise and number of task selections was also not significant, *F* < 1. Means and standard deviations for the eye movement parameters are displayed in Table 8.

Tabelul 8. *Means (M) and standard deviations (SD) for the eye tracking data as a function of expertise*

	High prior knowledge students				Low prior knowledge students			
	1st selection	2nd selection	3rd selection	Overall	1st selection	2nd selection	3rd selection	Overall
Eye tracking data	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Fixation number								
Surface features	72.69 (37.86)	62.85 (31.27)	57.77 (35.16)	64.44 (25.31)	67.67 (30.89)	66.42 (33.24)	45.50 (31.12)	59.86 (24.87)
Structural features	66.00 (63.99)	52.50 (49.25)	48.83 (49.99)	55.78 (42.50)	41.92 (46.18)	51.77 (62.72)	39.08 (45.99)	44.26 (46.01)
Fixation duration								
Surface features	19959.15 (12565.13)	16512.39 (9714.19)	14564.39 (11020.80)	17011.97 (8507.53)	19613.08 (14207.78)	20000.17 (13610.12)	12594.83 (10117.94)	17402.69 (10649.75)
Structural features	15488.33 (16192.85)	12719.42 (13160.60)	11955.58 (12665.70)	13387.78 (10861.32)	10686.08 (10775.31)	13498.31 (18070.30)	9582.77 (10809.41)	11255.72 (10938.00)
Average fixation duration								
Surface features	1086.88 (157.90)	1089.97 (142.52)	1005.63 (197.03)	1060.83 (131.64)	982.26 (238.03)	1103.63 (301.66)	1096.02 (350.80)	1060.64 (282.86)
Structural features	783.48 (214.60)	828.05 (246.98)	808.98 (205.09)	806.83 (216.28)	835.63 (99.71)	945.93 (285.76)	993.37 (304.21)	924.98 (216.92)

Verbal protocols

Because the numbers of the utterances in the response categories were unequal, nonparametric tests were used to analyze the verbal data. To test the effects of expertise (i.e., level of prior knowledge) on the categories produced in the thinking aloud and cued retrospective protocols, Mann-Whitney U tests were used. One-tailed significance is reported when a directional prediction is stated; otherwise two-tailed results are reported. Means and standard deviations of the main categories and subcategories are reported in Table 9.

On the main (sub)categories of both concurrent and cued retrospective protocols, Mann-Whitney U test was significant (two-tailed) only for a few (sub)categories. More specifically, the high prior knowledge students showed significantly less verbal utterances during concurrent reporting with respect to the category ‘comparing the tasks’ based on surface features (i.e., subcategory ‘within one selection moment’) compared to the low prior knowledge students, $U = 28.00$, $p < .01$. There was also a significant main effect of expertise on the category ‘comparing the tasks’ based on structural features (i.e., subcategory ‘within one selection moment’) from concurrent protocols, $U = 3.50$, $p < .05$. The high prior knowledge showed more verbal utterances during concurrent reporting with regard to the category ‘comparing the tasks’ based on structural features than the low prior knowledge students.

For the cued retrospective reporting, Mann-Whitney U test results were marginally significant only for two categories, ‘comparing the tasks’ based on surface features and ‘description of the tasks’ based on structural features (i.e., subcategory ‘like/dislike’). For high prior knowledge students, we found a marginally decrease in the use of category ‘comparing the tasks’ based on surface features, $U = 50.50$, $p = .08$ (see Table 9), but a marginally increase in the use of the category ‘description of the tasks’ based on structural features (i.e., subcategory ‘like/dislike’), $U = .0$, $p = .076$, compared to the low prior knowledge students.

With regard to the category ‘comparing the tasks’ based on surface features, during both concurrent and cued retrospective reporting, a strong trend was found, $U = 46.50$, $p = .05$ favouring the low prior knowledge students (see Table 9).

As shown in Table 10, most eye tracking parameters, especially the number and duration of fixations were positively correlated with the aggregated categories referring to surface and structural features of the verbal protocols. Notably, there were significant positive correlations for the number and duration of fixations over surface features with the variable indicating total surface features for both concurrent and cued retrospective protocols, as well as across verbal protocols.

Table 9. *Means (M) and standard deviations (SD) of the main (sub)categories as a function of expertise in the two verbal protocols*

	High prior knowledge students			Low prior knowledge students		
	TA[a]	CR[b]	Overall[c]	TA[a]	CR[b]	Overall[c]
Main sub(categories)	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Reading						
Surface features	13.85 (6.47)	15.77 (7.87)	29.54 (12.41)	9.77 (5.28)	18.23 (8.97)	28.00 (13.50)
Structural features	6.08 (3.85)	11.23 (10.38)	16.85 (13.51)	.33 (4.80)	10.91 (6.38)	16.91 (10.56)
Decision making						
Surface features	4.08 (3.15)	6.62 (3.88)	10.38 (6.80)	4.00 (2.35)	7.54 (3.62)	11.54 (4.98)
Structural features	2.43 (1.62)	2.91 (2.02)	4.08 (3.48)	1.80 (.84)	2.50 (1.52)	3.43 (2.51)
Comparing the tasks						
Surface features	2.67 (2.27)	7.00 (4.04)	9.46 (5.88)	3.69 (2.02)	10.54 (4.93)	14.23 (6.22)
Structural features	3.83 (3.71)	6.75 (6.18)	8.00 (8.90)	3.33 (3.27)	6.73 (7.09)	7.83 (9.54)
Description of the tasks						
Surface features	3.50 (2.59)	6.82 (5.51)	8.00 (7.52)	3.63 (3.74)	4.64 (6.31)	6.67 (9.01)
Structural features	3.33 (1.75)	3.71 (3.64)	5.75 (4.62)	2.17 (1.47)	2.40 (1.14)	3.57 (2.30)

[a] TA – thinking aloud protocol (i.e., concurrent reporting);
[b] CR – cued retrospective protocol;
[c] cumulated verbal protocols: TA and CR.

Table 10. *Correlations between the eye tracking parameters and the aggregated categories referring to surface and structural features of the verbal protocols*

	Aggregated categories of verbal protocols					
Eye tracking parameters	TA surface	CR surface	Total surface	TA surface	CR surface	Total surface
Fixation number						
Surface features	.44*	.47*	.49*	-.02	.17	.09
Structural features	.15	.34	.29	.69**	.72**	.74**
Fixation duration						
Surface features	.41*	.45*	.46*	-.13	.05	-.02
Structural features	.16	.32	.28	.65**	.66**	.69**
Average fixation duration						
Surface features	.25	.19	.23	-.64**	-.32	-.42
Structural features	-.74	-.38	-.55	-.35	-.31	-.32

Note: **p* < .05; ***p* < .0

Discussion

The results show that high prior knowledge students achieved higher post-test performance scores compared to low prior knowledge students. In terms of performance on training, no significant differences between high prior knowledge and low prior knowledge students were found.

No differences were found between high prior knowledge and low prior knowledge students with regard to the eye tracking data. More specifically, expertise (i.e., level of prior knowledge) did neither affect the number or duration of fixations nor the average fixation duration on both surface and structural features. The lack of differences between high and low prior knowledge students regarding the frequency and duration of fixations might be due to the fact that these eye tracking parameters indicate different things depending on the expertise level. For example, for high prior knowledge students, longer fixation durations might indicate productive involvement during learning, whereas for low prior knowledge students it could suggest unproductive processing (Schwonke, Berthold, & Renkel, 2009).

Although we found no differences in viewing behavior between groups over the three task selections, we did find a remarkable difference in participants' viewing behavior between those selections. The number and duration of fixations over surface features was significantly lower for the third task selection compared to the first task selection, and even compared to the second task selection (only marginally lower). This pattern of results was not found for the number or duration of fixations over structural features. These findings indicate that the participants' allocation of visual attention was less affected by surface features of the tasks when viewing tasks with the same format of presentation a second or third time.

However, high prior knowledge students differed in their verbal utterances made during concurrent reporting from low prior knowledge students in that they showed more verbal utterances with regard to the category 'comparing the tasks' based on structural features, but less utterances related to the category 'comparing the tasks' based on surface features. As indicated by the marginally significant effect of prior knowledge, during retrospection the verbal utterances related to the category 'description of the tasks' based on structural features (i.e., subcategory 'like/dislike') grow with increasing prior knowledge, whereas utterances referring to the category 'comparing the tasks' based on surface features decrease. Furthermore, the results from both concurrent and cued retrospective reporting revealed that high prior knowledge students showed less verbal utterances with respect to the category 'comparing the tasks' based on surface features than low prior knowledge students.

Finally, there is evidence of a correlation between increases in the perceptual processing of irrelevant or relevant task-features and increases in the number of statements referring to surface features, and structural features, respectively.

Chapter 9
CONCLUSIONS. APLICATIONS. FUTURE RESEARCH

The review of the literature, presented in the theoretical part of the dissertation, has outlined the fact that one of the major problems of the complex instructional designs is the control of the overload imposed on the learners' cognitive system (Paas, Renkl, & Sweller, 2003, 2004). From cognitive load theory perspective, in order to promote learning, the instructional designs have to decrease extraneous cognitive load and increase germane load (Kirschner, 2002).

The overarching goal of this dissertation is to control the cognitive load which impede learning, and this goal is reached in two ways: (a) using cognitive load (invested mental effort as input - together with the obtained performance- for the dynamic selection of the level of difficulty and support of the tasks which are about to be solved (in the case of personalized task selection model) and (b) assigning learners an active role in their own learning process (learner-controlled instruction; Paas, 2003).

A review of the main results and conclusions of this dissertation is given, following the suggestions of Van Gog et al. (2005) related to the implications for instructional design research as indicated by the relations between cognitive load theory assumptions and the framework of expert performance research.

1. Personalization of instruction

Chapter 4 instroduces a personalized task selection model which integrates the assumptions of the two-level model of adaptive instruction and the assumptions of the four-component instructional design model (4C/ID; Van Merriënboer, 1997) This personalized model combines the strong points of the above mentioned models and allows for dynamic selection of the appropriate learning tasks based on the learners' level of expertise (represented by the combination of the performance and invested mental effort).

The main purpose of this dynamic selection of the tasks is to prevent learners' cognitive load through a continous adaptation of the level of difficulty and support of the tasks to the learners'expertise. The utilization of invested mental effort as input for the process of the dynamic selection of the tasks is only at the beginning. Only few studies have explored the benefits of integrating the assumptions of cognitive load theory into the microadaptive models of instructional technologies upon learning. The model form the basis of the most of empirical studies described in this dissertation. In order to put this model into practice, we designed a computer-based learning environment for learning genetics and preliminary results were discussed. Chapter 4 also reports the results of a formative evaluation carried out with a twofold purpose: (a) to test the functionality and usability of the personalized learning environment and (b) to do the necessary changes in the interface as a result of the "field testing".

Unlike the previous developed learning environments, this learning environment applies different measurement scales and includes another selection algorithm for adapting the level of dificulty and support of the tasks to the learners' expertise. In this case the maximum jump size between complexity levels is decreased forcing a smoother increase or decrease in task complexity.

The results of the formative evaluation provides some preliminary evidence that the personalized learning environment is a promising approach to improve learning and efficiency in reaching the pre-established objectives.

2. Improving learning and performance

The experiments presented in chapter 5 tested the effects of prior knowledge (expertise level) and type of instructional control on performance and learning efficiency. The results of the first study in this chapter confirm the hypothesis that the adaptive program instruction has positive effects on the training effectiveness and learning efficiency, but this is not reflected in a superior post-test performance, a higher pre-to-post learning gain or higher transfer test performance. A possible explanation could be that the participants in the adaptive instruction have acquired 'restricted' cognitive schemes (as a result of "the perverse effect of the help") which only allow for a 'routine' completion of the steps (Van Merriënboer, 1997).

Although the participants in the non-adaptive condition attained the same training performance as the students in both learner control conditions, the non-adaptive condition needed significantly more time to complete the training phase. A possible explanation could be related to the fact that participants in the two learner control conditions chose to solve easier learning tasks (i.e., difficulty level 1 and 2), and more tasks with a high support (i.e., completion problems with high support). These results suggest the fact that learners who control their instruction have the tendency to minimize the effort involved in problem solving process rather than try to maximize this effort.

Regarding the students' prior knowledge level, the prediction that learners with a relatively higher prior knowledge (i.e., college students) would outperform lower prior knowledge students (i.e., high school students) on performance measures and efficiency was confirmed. In addition, college students spent more time on the training compared to high school students and their longer training time is assumed to be related to a deeper cognitive engagement and self-reflecting (see Chi, 2006).

Consistent with the literature on age differences in cognitive capacity which has found that adolescents demonstrate adult-like levels of maturity by the time they reach 15 or 16 (see Steinberg, Cauffman, Woolard, Graham, & Banich, 2009), it is unlikely that age differences between high school students and college students might affect the results regarding prior knowledge since after these ages cognitive performance does not change

Finally, the interaction effects found in this study show that the students' prior knowledge strongly affects the students learning path in the learner control and the adaptive program control conditions.

The second study described in chapter 5 is a replication of the previous study with the purpose of verifying predictions regarding the influence of the type of instructional control on test performance and learning efficiency in the context of increased level of learner expertise (inclusion of PhD students in the study). Contrary to the results of the first study (see also Mihalca et al., 2011), adapting the difficulty and support of the learning tasks for learners with a higher level of expertise would not make learning more effective (neither the training effectiveness) and efficient. These results support Lee and Lee'findings that differences between the different types of instructional control decrease whereas the learners' previously acquired knowledge increases.

3. *Cognitive structures*

The aim of the experiment presented in chapter 6 was to examine the differences between low and high prior knowledge learners in attention paid to relevant and irrelevant task-features during task selection processes by combining eye tracking measures, thinking-aloud and cued retrospective protocols. Contrary to our expectations, no differences were found between high prior knowledge and low prior knowledge students with regard to the eye tracking data. More specifically, learners’ expertise level did neither affect the number or duration of fixations nor the average fixation duration on both surface and structural features. However, the findings indicate that the participants’ allocation of visual attention was less affected by surface features of the tasks when viewing tasks with the same format of presentation a second or third time. In contrast, the number and duration of fixations over structural features in the first task selection were very similar to those in the last task selection, in other words the pattern of fixations on structural features was relative stable over the multiple viewings (i.e., the three tasks selections).

As indicated by the marginally significant effect of prior knowledge, during retrospection the verbal utterances related to the category ‘description of the tasks’ based on structural features (i.e., subcategory ‘like/dislike’) grow with increasing prior knowledge, whereas utterances referring to the category ‘comparing the tasks’ based on surface features decrease. Furthermore, the results from both concurrent and cued retrospective reporting revealed that high prior knowledge students showed less verbal utterances with respect to the category ‘comparing the tasks’ based on surface features than low prior knowledge students.

Furthermore, there is evidence of a correlation between increases in the perceptual processing of irrelevant or relevant task-features and increases in the number of statements referring to surface features, and structural features, respectively. The finding that the type of processing indicated by the participants’ verbal responses was related to the amount of processing time (indicated by eye tracking data) was in line with results of Kaakinen and Hyönä (2005).

In sum, the results of the present study suggests that combining different process measures, such as eye tracking, concurrent and cued retrospective reporting can provide a better understanding of the processes that underlying the selection decisions. As is suggested by this study, in addition to investigating the perceptual processing that occurs during task selection decisions, it is imperative to consider decision making from a cognitive perspective (i.e., verbal explanations of the task selections), because the results can differ.

To conclude, the results of this dissertation partially supported the idea that adapting instruction to the individual needs of the students makes training more effective and efficient yet had no effects on improving test performance. It seems necessary to conduct further studies in order to address the benefits and shortcomings of the types of instructional control used in this study, as well as explore the effects of feedback and advisory models to assist learners with their decisions.

BIBLIOGRAFIE

Alexander, P. A. (2003). The development of expertise: The journey from acclimation to proficiency. *Educational Researcher, 32,* 10-14.

Alexander, P. A., Jetton, T. L., & Kulikowich, J. M. (1995). Interrelationship of knowledge, interest, and recall: assessing the model of domain learning. *Journal of Educational Psychology*, *87*, 559–575.

Alexander, P. A., & Judy, J.E., (1988). The interaction of domain-specific and strategic knowledge in academic performance. *Review of Educational Research, 58,* 375-404.

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology*, *80*, 260-267.

Atkinson, J. W. (1974). Strength of motivation and efficiency of performance. In J. W. Atkinson & J. O. Raynor (Eds.), *Motivation and achievement*, (pp. 193-218). Washington, DC: Winston.

Atkinson, R. C. (1976). Adaptive instructional systems: Some attempts to optimize the learning process. In D. Klahr (Ed.), *Cognition and instruction.* New York: Wiley.

Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. In K. W. Spence & J. T. Spence (Eds.), *The psychology of learning and motivation* (vol. 2, pp. 89–195). London: Academic.

Atkinson, R. K., Renkl, A., & Merrill, M. M. (2003). Transitioning from studying examples to solving problems: Effects of self-explanation prompts and fading worked-out steps, *Journal of Educational Psychology, 95(4),* 774–783.

Atkinson, S. (1998). Cognitive style in the context of design and technology project work. *Educational Psychology: An International Journal of Experimental Educational Psychology*, *18(2),* 183-194.

Ayres, P. (2006). Using subjective measures to detect variations of intrinsic cognitive load within problems. *Learning and Instruction, 16,* 389-400.

Ayres, P., Sweller, J., & Clarke, T., (2005). The impact of sequencing and prior knowledge on learning mathematics through spreadsheet applications, *Educational Technology, Research and Development*, *53(3),* 15–24.

Azevedo, R., & Cromley, J. G (2004). Does training on self-regulated learning facilitate students' learning with hypermedia?. *Journal of Educational Psychology, 96(3),* 523–535.

Azevedo, R., Cromley, J. G., & Seibert, D. (2004). Does adaptive scaffolding facilitate students' ability to regulate their learning with hypermedia. *Contemporary Educational Psychology, 29*, 344–370.

Azevedo, R., Cromley, J. G., Winters, F. I., Moos, D. C., & Greene, J. A. (2005). Adaptive human scaffolding facilitates adolescents' self-regulated learning with hypermedia. *Instructional Science, 33,* 381–412.

Azevedo, R., Moos, D. C., Greene, J. A., Winters, F. I., & Cromley, J. G. (2008). Why is externally-facilitated regulated learning more effective than self-regulated learning with hypermedia?. *Educational Technology Research and Development, 56,* 45–72.

Baddeley, A. D. (1992). Working memory. *Science, 255,* 556-559.

Baddeley, A. D. (1999). *Essentials of human memory*. Hove, UK: Psychology.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman.

Barab, S. A., & Duffy, T. (2000). From practice fields to communities of practice. In D. Jonassen & S. M. Land (Eds.), *Theoretical foundations of learning environments* (pp. 25–56). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego-depletion: Is the active self a limited resource?. *Journal of Personality and Social Psychology, 74*, 1252–1265.

Băban, A. (2002). *Metodologia cercetării calitative*. Presa Universitară Clujeană, Cluj.

Becker, D. A. (1997). The effects of choice on auditors' intrinsic motivation and performance. *Behavioral Research in Accounting, 9,* 1–19.

Bell, B. S., & Kozlowski, S. W. J. (2002). Adaptive guidance: Enhancing self-regulation, knowledge, and performance in technology-based training. *Personnel Psychology, 55,* 267-306.

Benjamin, M., McKeachie, W. J., Lin, Y. G., & Holinger, D. P. (1981). Test anxiety: Deficits in information processing. *Journal of Educational Psychology*, *73*, 816-824.

Bickford, N. L. (1989). *The systematic application of principles of motivation to the design of printed instructional materials.* Unpublished doctoral dissertation. Florida State University, Florida.

Billings, K. (1982). Computer-assisted learning: A learner-driven model. In *The computer: extension of human mind*. Proceedings of the 3rd annual summer conference, University of Oregon. (ERIC Document Reproduction Service No. ED 219 863).

Blessing, S. B., & Anderson, J. R. (1996). How people learn to skip steps. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22,* 576–598.

Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher, 13,* 4–16.

Boekaerts, M. (1996). Self-regulated learning at the junction of cognition and motivation. *European Psychologist, 1(2),* 100-112.
Boekaerts, M. (1997). Self-regulated learning: A new concept embraced by researchers, policy makers, educators, teachers, and students. *Learning and Instruction, 7(2),* 161-186.
Boekaerts, M. (1999). Self-regulated learning: Where we are today. *International Journal of Educational Research, 31*, 445-457.
Boekaerts, M., Pintrich, P. R., & Zeidner, M. (2000). *Handbook of self-regulation.* San Diego, CA: Academic Press.
Boyatzis, R. E. (1998). *Transforming qualitative information: Thematic analysis and code development.* London: Sage
Bråten, I., & Olaussen, B. S. (2005). Profiling individual differences in student motivation: A longitudinal cluster-analytic study in different academic contexts. *Contemporary Educational Psychology, 30,* 359–396.
Bratfisch, O., Borg, G., & Dornic, S. (1972). *Perceived item-difficulty in three tests of intellectual performance capacity*. Report No. 29. Stockholm: Institute of Applied Psychology.
Brünken, R., Plass, J. L., & Leutner, D. (2003). Direct measurement of cognitive load in multimedia learning. *Educational Psychologist, 38*, 53–61.
Brünken, R., Plass, J., & Moreno, R. (2009). Current issues and open questions in cognitive load research. In J. Plass, R. Moreno & R. Brünken (Eds.), *Cognitive load theory*. New York: Cambridge University Press.
Brusilovsky, P. L. (1992). Intelligent tutor, environment and manual for introductory programming. *Educational and Training Technology International, 29(1),* 26-34.
Burger, J. M., & Cooper, H. M. (1979). The desirability of control. *Motivation and Emotion, 3,* 381-393.
Butler, D. L., & Winne, P. H. (1995). Feedback and self-regulated learning: A theoretical synthesis. *Review of Educational Research, 65*, 245–281.
Button, S. B., Mathieu, J. E., & Zajac, D. M. (1996). Goal orientation in organizational research: A conceptual and empirical foundation. *Organizational Behavior & Human Decision Processes, 67,* 26–48.
Camp, G., Paas, F., Rikers, R., & Van Merriënboer, J. J. G. (2001). Dynamic problem selection in air traffic control training: A comparison between performance, mental effort and mental efficiency. *Computers in Human Behavior, 17,* 575-595.
Campanizzi, J. A. (1978). Effects of locus of control and provision of overviews in a computer-assisted instruction sequence. *Association for Educational Data Systems (AEDS) Journal, 12(1)*, 21-30.
Camps, J. (2003). Concurrent and retrospective verbal reports as tools to better understand the role of attention in second language tasks. *International Journal of Applied Linguistics, 13*, 201-221.
Canham, M., & Hegarty, M. (2010). Effects of knowledge and display design on comprehension of complex graphics. *Learning and Instruction, 20,* 155-166.
Carrier, C. A., Davidson, G. V., Higson, V., & Williams, M. D. (1984). Selection of options by field independent and dependent children in a computer-based concept lesson. *Journal of Computer-Based Instruction, 11(2),* 49-54.
Carrier, C. A., Davidson, G. V., & Williams, M. D. (1985). Selection of instructional options in a computer-based coordinate concept lesson. *Educational Communications and Technology Journal, 33(3),* 199-212.
Carrier, C. A., Davidson, G. V., Williams, M. D., & Kalweit, C. M. (1986). Instructional options and encouragement effects in a microcomputer-delivered concept lesson. *Journal of Educational Research, 79(4),* 222-229.
Carrier, C. A., & Jonassen, D. H. (1988). Adapting courseware to accommodate individual differences. In D. Jonassen (Ed.). *Instructional designs for microcomputer courseware.* Mahwah, NJ: Lawrence Erlbaum Associates.
Carrier, C. A., & Williams, M. D. (1988). A test of one learner control strategy with students of differing levels of task persistence. *American Educational Research Journal, 25(2),* 285-306.
Chandler, P. & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction, 8,* 293-332.
Chandler, P., & Sweller, J. (1996). Cognitive load while learning to use a computer program. *Applied Cognitive Psychology, 10(2)*, 151–170.
Chi, M. T. H. (1997). Creativity: Shirring across ontological categories flexibly. In T. B. Ward, S. M. Smith, R. A. Finke & J. Vaid (Eds.). *Creative thought: An investigation of conceptual structures and processes* (pp. 209-234). Washington, DC: American Psychological Association.
Chi, M. T. H. (2000). Self-explaining: the dual processes of generating inference and repairing mental models. In R. Glaser (Ed.). *Advances in instructional psychology: Educational design and cognitive science* (Vol. 5, pp. 161–238). Mahwah, NJ: Erlbaum.
Chi, M. T. H. (2006). Two approaches to the study of experts 'characteristics. In K. A. Ericsson, N. Charness, P. Feltovich, & R. Hoffman (Eds.), *Cambridge handbook of expertise and expert performance* (pp. 21-30). Cambridge University Press.
Chi, M. T. H., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science, 13,* 145-182.

Chi, M. T. H., Feltovich, P., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science, 5,* 121-152.
Chi, M. T. H., & Glaser, R. (1985). Problem solving ability. In R. Sternberg (Ed.), *Human abilities: An information processing approach* (pp.227-250). San Francisco: Freeman.
Chi, M. T. H., Glaser, R., & Rees, E. (1982). Expertise in problem solving. In R. Sternberg (Ed.), *Advances in the psychology of human intelligence* (pp.7-75). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.
Clark, R. E. (1982). Antagonism between achievement and enjoyment in ATI studies. *Educational Psychologist, 17(2),* 92-101.
Clark, R. E. (1984). Research on student thought processes during computer-based instruction. *Journal of Instructional Development, 7(3),* 2-5.
Clarke, T., Ayres, P., & Sweller, J. (2005). The impact of sequencing and prior knowledge on learning mathematics through spreadsheet applications. *Educational Technology Research and Development, 53(3),* 15–24.
Cleary, T., & Zimmerman, B. J. (2001). Self-regulation differences during athletic practice by experts, non-experts, and novices. *Journal of Applied Sport Psychology, 13*, 61–82.
Cohen, J. (1988). *Statistical power analysis for the behavioral sciences.* Hillsdale, NJ: Erlbaum.
Como, L., & Snow, E. R. (1986). Adapting teaching to individual differences among learners. In M. C. Wittrock (Ed.), *Handbook of research on teaching* (3rd Ed.). New York: Macmillan.
Conati, C. (2002). Probabilistic assessment of user's emotions in educational games. *Journal of Applied Artificial Intelligence, 16,* 555-575.
Cooke, N. J. (1994). Varieties of knowledge elicitation techniques. *International Journal of Human-Computer Studies, 41*, 801-849.
Cooper, G., & Sweller, J. (1987). The effects of schema acquisition and rule automation on mathematical problem–solving transfer. *Journal of Educational Psychology, 79,* 347-362.
Corbalan, G., Kester, L., & Van Merriënboer, J. J. G. (2006). Towards a personalized task selection model with shared instructional control. *Instructional Science, 34,* 399-422.
Corbalan, G., Kester, L., & Van Merriënboer, J. J. G. (2008). Selecting learning tasks: Effects of adaptation and shared control on learning efficiency and task involvement. *Contemporary Educational Psychology, 33(4),* 733-756.
Corbalan, G., Kester, L., & Van Merriënboer, J. J. G. (2009). Dynamic task selection: Effects of feedback and learner control on efficiency and motivation. *Learning and Instruction, 19(6),* 455-465.
Corbalan, G., Kester, L., & Van Merriënboer, J. J. G. (2009). Combining shared control with variability over surface features: Effects on transfer test performance and task involvement. *Computers in Human Behavior, 25*, 290-298.
Corbalan, G., Kester, L., & Van Merriënboer, J. J.G. (2011). Learner-controlled selection of tasks with different surface and structural features: Effects on transfer and efficiency. *Computers in Human Behavior, 27(1),* 76-81.
Cordova, D. I., & Lepper, M. R. (1996). Intrinsic motivation and the process of learning: Beneficial effects of contextualization, personalization, and choice. *Journal of Educational Psychology, 88*, 715-730.
Corno, L., & Mandinach, E. (1983). The role of cognitive engagement in classroom learning and motivation. *Educational Psychologist, 18,* 88-100.
Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences, 24*, 87–114.
Cronbach, L. J. (1971). How can instruction be adapted to individual differences? In R. A.Weisgerber (Ed.), *Perspective in individualized learning*. Itasca, IL: Peacock.
Cronbach, L. J., & Snow, R. E. (1977). *Aptitudes and instructional methods: A handbook for research on interactions.* New York: Irvington.
Cummins, D. D. (1992). The role of analogical reasoning in the induction of problem categories. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18,* 1103-1124.
Dalton, D. W. (1990). The effects of cooperative learning strategies on achievement and attitudes during interactive video. *Journal of Computer-Based Instruction, 17(1),* 8-16.
De Croock, M. B. M., Van Merriënboer, J. J. G., & Paas, F. (1998). High vs. low contextual interference in simulation-based training of troubleshooting skills: Effects on transfer performance and invested mental effort. *Computers in Human Behavior, 14,* 249–267.
De Groot, E. V. (2002). Learning through interviews: Students and teachers talk about learning and schooling. *Educational Psychologist, 37*, 41–52.
De Jong, T. (2010). Cognitive load theory, educational research, and instructional design: Some food for thought. *Instructional Science, 38,* 105–134.
De Koning, B. B., Tabbers, H. K., Rikers, R. M. J. P., & Paas, F. (2010). Attention guidance in learning from complex animation: Seeing is understanding? *Learning and Instruction, 20,* 111-122.
Deci, E. L. (1980). *The psychology of self-determination.* Lexington, MA: Heath.

Deci, E. L., Connell, J. P., & Ryan, R. M. (1989). Self-determination in a work organization. *Journal of Applied Psychology, 74*, 580–590.

Deci, E. L., Eghrari, H., Patrick, B. C., & Leone, D. R. (1994). Facilitating internalization: The self-determination theory perspective. *Journal of Personality, 62,* 119-142.

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior.* New York: Plenum.

Denzin, N. K., & Lincoln, Y. S. (1994). Introduction: Entering the field of qualitative research. In N. K. Denzin & Y. S. Lincoln (Eds.), *Handbook of qualitative research* (pp. 1-17). Thousand Oaks, CA: Sage.

Dewey, J. (1902/1964). The child and the curriculum. In R. D. Archambault (Ed.), *John Dewey on education: Selected writings.* NewYork: Modern Library.

Duchowski, A. T. (2003). *Eye tracking methodology: Theory and practice.* London: Springer.

Duffy, T., & Jonassen, D. H. (1992). *Constructivism and the technology of instruction: A conversation*. Hillsdale. NJ: Lawrence Erlbaum.

Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development.* Philadelphia: Taylor & Francis.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95,* 256– 273.

Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L., & Midgley C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motivation* (pp. 75–146). San Francisco, CA: W. H. Freeman.

Eccles, J. S., Adler, T. F., & Meece, J. L. (1984). Sex differences in achievement: A test of alternate theories. *Journal of Personality and Social Psychology, 46(1),* 26–43.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology, 53*, 109–132.

Eccles, J. S., Wigfield, A., & Schiefele, U. (1998). Motivation to succeed. In W. Damon (Series Ed.) & N. Eisenberg (Vol. Ed.), *Handbook of child psychology* (Vol. 3, pp. 1017–1095). New York: Wiley.

Ericsson, K. A. (2002). Attaining excellence through deliberate practice: Insights from the study of expert performance. In M. Ferrari (Ed.), *The pursuit of excellence through education* (pp. 21-55). Hillsdale, NJ: Erlbaum.

Ericsson, K. A., & Kintsch, W. (1995). Long-term working memory. *Psychological Review, 102*, 211–245.

Ericsson, K. A., & Simon, H. A. (1993). *Protocol analysis: Verbal reports as data* (Rev. Ed.). Cambridge, MA: MIT Press.

Federico, P.-A. (1980). Adaptive instruction: Trends and issues. In R. E. Snow, P.-A. Federico, & W. E. Montague (Eds.), *Aptitude, learning and instruction, Vol. I: Cognitive process analyses of aptitude* (pp. 1-26). Mahwah, NJ: Lawrence, Erlbaum Associates.

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating rigor using thematic analysis: a hybrid approach of inductive and deductive coding and theme development. *International Journal of Qualitative Methods, 5(1),* 1-11.

Fincham, F., & Cain, K. (1986). Learned helplessness in humans: A developmental analysis. *Developmental Review, 6,* 25-86.

Fireman, G., Kose, G., & Solomon, M. J. (2003). Self-observation and learning: The effects of watching oneself on problem solving. *Cognitive Development, 18,* 339-354.

Fisher, M. D., Blackwell, L. R., Garcia, A. B., & Greene, J. C. (1975). Effects of student control and choice on engagement in a CAI arithmetic task in a low-income school. *Journal of Educational Psychology, 67(6),* 776-783.

Flowerday, T., & Schraw, G. (2003). Effect of choice on cognitive and affective engagement. *Journal of Educational Research, 96,* 207–215.

Flowerday, T., Schraw, G., & Stevens, J. (2004). The role of choice and interest in reader engagement. *The Journal of Experimental Education, 72,* 93–114.

Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. (1998). Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology, 83,* 218–233.

Frankola, K. (2001). Why online learners drop out. *Workforce, 80,* 53–60.

Fredrickson, B. (2001). The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions. *American Psychologist, 56,* 218–226.

Friend, C. L., & Cole, C. L. (1990). Learner control in computer-based instruction: A current literature review. *Educational Technology, 30(11),* 47-49.

Fry, J. P. (1972). Interactive relationship between inquisitiveness and learner control of instruction. *Journal of Educational Psychology, 63,* 459-465.

Garcia, T., & Pintrich, P. R. (1994). Regulating motivation and cognition in the classroom: The role of self-schemas and self-regulatory strategies. In D. H. Schunk & B. J. Zimmerman (Eds.), *Self-regulation of learning and performance: Issues and educational applications* (pp. 127-153). Hillsdale, NJ: Erlbaum.

Garcia, T., & Pintrich, P. R. (1996). Assessing student's motivation and learning strategies in the classroom context: The motivated strategies for learning questionnaire. In M. Birenbaum & F. Dochy (Eds.), *Alternatives in assessment of achievements, learning processes, and prior knowledge* (pp. 319-339). Boston: Kluwer Academic Publishers.

Gay, G. (1986). Interaction of learner control and prior understanding in computer-assisted video instruction. *Journal of Educational Psychology, 78,* 225-227.
Gerjets, P., & Scheiter, K. (2003). Goal configurations and processing strategies as moderators between instructional design and cognitive load: Evidence from hypertext-based instruction. *Educational Psychologist, 38,* 33–41.
Gerjets, P., Scheiter, K., & Cierniak, G. (2009). The scientific value of cognitive load theory: A research agenda based on the structuralist view of theories. *Educational Psychology Review, 21(1),* 43-54.
Gerjets, P., Scheiter, K., & Tack, W. H. (2000). Resource-adaptive selection of strategies in learning from worked-out examples. In L. R. Gleitman & A. K. Joshi (Eds.), *Proceedings of the 22nd Annual Conference of the Cognitive Science Society* (pp. 166-171). Mahwah, NJ: Erlbaum.
Gick, M., & Holyoak, J. (1987). The cognitive basis for knowledge transfer. In S. Cormier & J. Hagman (Eds.), *Transfer of learning: Contemporary research and applications* (pp. 9-46). San Diego, CA: Academic Press.
Glaser, R. (1977). *Adaptive education: Individual, diversity and learning*. New York: Holt.
Glaser, R., & Chi, M. (1988). Overview in M. Chi, R. Glaser, & M. Farr (Eds.), *The Nature of Expertise* (pp. xv-xxvii). Hillsdale, NJ: Erlbaum.
Goetyfried, L., & Hannafin, M. J. (1985). The effects of locus of CAI control strategies on the learning of mathematics rules. *American Educational Research Journal*, *22(2),* 273-278.
Goldman, S. R. (1991). On the derivation of instructional applications from cognitive theories: Commentary on Chandler and Sweller. *Cognition and Instruction, 8(4),* 333-342.
Gray, S. H. (1987). The effect of sequence control on computer assisted learning. *Journal of Computer-Based Instruction, 14(2),* 54-56.
Haider, H., & Frensch, P. A. (1999). Eye movement during skill acquisition: More evidence for the information reduction hypothesis. *Journal of Experimental Psychology: Learning, Memory and Cognition, 25,* 172-190.
Hannafin, M. J. (1984). Guidelines for using locus of instructional control in the design of computer-assisted instruction. *Journal of Instructional Development*, *7(3),* 6-10.
Hannafin, M. J., & Colamaio, M. E. (1987). The effects of variations in lesson control and practice on learning from interactive video. *Educational Communications and Technology Journal, 35(4),* 203-212.
Hannafin, R. D., & Sullivan, H. J. (1995). Learner control in full and lean CAI programs. *Educational Technology Research and Development*, 43(1), 19-30.
Hannafin, R. D., & Sullivan, H. J. (1996). Learner preferences and learner control over amount of instruction, *Journal of Educational Psychology*, *88,* 162-173.
Hintze, H., Mohr, H., & Wenzel, A.(1988). Students' attitudes towards control methods in computer-assisted instruction. *Journal of Computer Assisted Learning, 4(1),* 3-10.
Hyönä, J. (2010). The use of eye movements in the study of multimedia learning. *Learning and Instruction, 20,* 172-176.
Iyengar, S. S., & Lepper, M. (2000). When choice is demotivating: Can one desire too much of a good thing?. *Journal of Personality and Social Psychology, 79,* 995-1006.
Jarodzka, H., Scheiter, K., Gerjets, P., & Van Gog, T. (2010). In the eyes of the beholder: How experts and novices interpret dynamic stimuli. *Learning and Instruction, 20,* 146-154.
Järvelä, S., & Salovaara, H. (2004). The interplay of motivational goals and cognitive strategies in a new pedagogical culture a context-oriented and qualitative approach. *European Psychologist, 9(4),* 232–244.
Järvelä, S., Veermans, M., & Leinonen, P. (2008). Investigating student engagement in computer-supported inquiry: A process-oriented analysis. *Social Psychology of Education, 11(3),* 299-322.
Järvenoja, H., & Järvelä, S. (2005). How students describe the sources of their emotional and motivational experiences during the learning process: A qualitative approach. *Learning and Instruction, 15(5),* 465–480.
Johansen, K. J., & Tennyson, R. D. (1983). Effect of adaptive advisement on perception in learner-controlled, computer-based instruction using a rule-learning task. *Educational Communications and Technology Journal, 31(4),* 226-236.
Johnson-Laird, P. N. (1983). *Mental models: Towards cognitive science of language, inference and consciousness.* Cambridge, England: Cambridge University Press.
Judd, W. A. (1972). *Learner-controlled computer-based instruction*. Paper presented at the International School on Computers in Education, Pugniochiuso, Italy. (ERIC Document Reproduction Service No. ED 072635).
Just, M. A., & Carpenter, P. A. (1980). A theory of reading: from eye fixations to comprehension. *Psychological Review, 87,* 329-355.
Kaakinen, J. K., & Hyönä, J. (2005). Perspective effects on expository text comprehension: Evidence from think-aloud protocols, eyetracking, and recall. *Discourse Processes, 40,* 239-257.
Kaakinen, J. K., Hyönä, J., & Keenan, J. M. (2002). Perspective effects on on-line text processing. *Discourse Processes, 33,* 159-173.
Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instruction. *Educational Psychology Review*, *19(4),* 509–539.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist, 38*, 23-32.
Kalyuga, S., Chandler, P., & Sweller, J. (2000). Incorporating learner experience into the design of multimedia instruction. *Journal of Educational Psychology, 92(1),* 126-136.
Kalyuga, S., Chandler, P., & Sweller, J. (2001). Learner experience and efficiency of instructional guidance. *Educational Psychology, 21(1)*, 5–23.
Kalyuga, S., Chandler, P., Tuovinen, J., & Sweller, J. (2001). When problem solving is superior to studying worked examples. *Journal of Educational Psychology, 93*, 579–588.
Kalyuga, S., & Sweller, J. (2004). Measuring knowledge to optimize cognitive load factors during instruction. *Journal of Educational Psychology, 96,* 558–568.
Kalyuga, S., & Sweller, J. (2005). Rapid dynamic assessment of expertise to improve the efficiency of adaptive e-learning. *Educational Technology, Research and Development*, *53,* 83-93.
Kanfer, R., & Ackerman, P. L. (1989). Motivation and cognitive abilities: an integrative/ aptitude-treatment approach to skill acquisition. *Journal of Applied Psychology, 74,* 657–690.
Kashihara A., Hirashima T., & Toyoda, J. (1995). A cognitive load application in tutoring. *Journal of User Modeling and User-Adapted Interaction, 4(4),* 279-303.
Katz, I., & Assor, A. (2007). When choice motivates and when it does not. *Educational Psychology Review*, *19(4),* 429-442.
Keller, J. M. (1979). Motivation and instructional design: A theoretical perspective. *Journal of Instructional Development, 2(4),* 26-34.
Keller, J. M. (1983a). *Development and use of the ARCS model of motivational design*. Enschede, The Netherlands: Toegepaste Onderwijskunde, Technische Hogeschool Twente.
Keller, J. M. (1983b). Motivational design of instruction. In C. M. Reigeluth (Ed.), *Instructional-design theories and models: An overview of their current status* (pp. 386-436). Hillsdale, NJ: Lawrence Erlbaum Associates.
Keller, J. M. (1987a). Strategies for stimulating the motivation to learn. *Performance and Instruction Journal*, *26*(8), 1-7.
Keller, J. M. (1987b). The systematic process of motivational design. *Performance and Instruction Journal*, *26*(9/10), 1-8.
Keller, J. M. (1987c). Development and use of the ARCS model of instructional design. *Journal of Instructional Development, 10(3),* 2-10.
Keller, J. M. (1999). Motivational systems. In H. Stolovitch & E. Keeps (Eds.), *Handbook of human performance technology* (2nd Ed.). San Francisco: Tossey-Bass Inc. Publishers.
Keller, J. M., & Kopp, T. W. (1987). Application of the ARCS model to motivational design. In C. M. Reigeluth (Ed.), *Instructional theories in action: Lessons illustrating selected theories* (pp. 289 -320). New York: Lawrence Erlbaum, Publishers.
Keller, J. M., & Suzuki, K. (1988). Use of the ARCS motivation model in courseware design. In D. H. Jonassen (Ed.), *Instructional designs for microcomputer courseware*. Hillsdale N.J: Lawrence Erlbaum Associates.
Keller, J. M., & Suzuki, K. (2004). Learner motivation and e-learning design: a multinationally validated process. *Journal of Educational Media, 29(3),* 229-239.
Kernan, M. C., Heimann, B., & Hanges, P. J. (1991). Effects of goal choice, strategy choice, and feedback source on goal acceptance, performance, and subsequent goals. *Journal of Applied Social Psychology, 21*, 713–733.
Kinzie, M. B. (1990). Requirements and benefits of effective interactive instruction: Learner control, self-regulation, and continuing motivation. *Educational Technology, Research and Development, 38,* 5-21.
Kinzie, M. B., & Sullivan, H. J. (1989). Continuing motivation, learner control, and CAI. *Education Technology Research and Development, 37(2),* 5-14.
Kinzie, M. B., Sullivan, H. L., & Berdel, R. L. (1988). Learner control and achievement in science computer-assisted instruction. *Journal of Educational Psychology, 80(3),* 299-303.
Kirschner, P. A. (2002). Cognitive load theory: Implications of cognitive load theory on the design of learning. *Learning and Instruction, 12*, 1–10.
Klein, J. D., & Freitag, E. T. (1992). Training students to utilize self-motivational strategies. *Educational Technology, 32(3),* 44-48.
Klein, J. D., & Keller, J. M. (1990). Influence of student ability, locus of control, and type of instructional control on performance and confidence. *Journal of Educational Research, 83(3),* 140-146.
Koch, B., Münzer, S., Seufert, T., & Brünken, R. (2009). *Testing the additivity hypothesis of cognitive load theory*: *Combined variation of modality and seductive details in a self-paced multimedia instruction.* Paper presented at the 3rd International Cognitive Load Theory Conference, Heerlen, The Netherlands.
Kopcha, T. J., & Sullivan, H. (2007). Learner preferences and prior knowledge in learner-controlled computer-based instruction. *Educational Technology, Research and Development*, *56,* 265-286.
Kostons, D., Van Gog, T., & Paas, F. (2009). How do I do? Investigating effects of expertise and performance-process records on self-assessment. *Applied Cognitive Psychology*, *23*, 1256-1265.

Kozma, R. B., & Russell, J. (1997). Multimedia and understanding: Expert and novice responses to different representations of chemical phenomena. *Journal of Research in Science Teaching, 34(9),* 949–968.
Kulik, J. A. (1982). Individualized systems of instruction. In H. E. Mitzel (Ed.), *Encyclopedia of educational research (5th Ed.).* New York: Macmillan.
Langer, E. (1975). The illusion of control. *Journal of Personality and Social Psychology, 32,* 311–328.
Lansdale, M., Underwood, G., & Davies, C. (2010). Something overlooked? How experts in change detection use visual saliency. *Applied Cognitive Psychology, 24,* 213-225.
Lawless, K. A., & Brown, S. W. (1997). Multimedia learning environments: Issues of learner control and navigation. *Instructional Science, 25,* 117-131.
Lee, H., Plass, J. L., & Homer, B. D. (2006). Optimizing cognitive load for learning from computer-based science simulations. *Journal of Educational Psychology, 98,* 902–913.
Lee, J., & Park, O. (2008). Adaptive instructional systems. In J. M. Spector, M. D. Merrill, J. Van Merriënboer, & M. P. Driscoll (Eds.), *Handbook of research on educational communications and technology*, 3rd Ed., (pp. 469-484). Lawrence Erlbaum Associates.
Lee, S. S., & Lee, Y. H. K. (1991). Effects of learner-control versus program-control strategies on computer-aided learning of chemistry problems: for acquisition or review? *Journal of Educational Psychology, 83,* 491-498.
Lee, S. S., & Wong, S. C.-H. (1989). Adaptative program vs. learner control strategy on computer-aided learning of gravimetric stoichiometry problems. *Journal of Research on Computing in Education, 21(4),* 367-379.
LeFevre, J. A., & Dixon, P. (1986). Do written instructions need examples? *Cognition and Instruction, 3,* 1-30.
Lepper, M. R. (1985). Microcomputers in education: Motivational and social issues. *American Psychologist, 40(1),* 1-18.
Lewin, K. (1938). *The conceptual representation and the measurement of psychological forces.* Durham, NC: Duke University Press.
Lin, Y.-G., & McKeachie, W. J. (1999, August). *College student intrinsic and/or extrinsic motivation and learning.* Paper presented at the Annual Conference of the American Psychological Association, Boston, MA.
Lohman, D. F. (1986). Predicting mathemathanic effects in the teaching of higher-order thinking skills. *Educational Psychologist*, *21,* 191–208.
Lowe, R. K. (2003). Animation and learning: selective processing of information in dynamic graphics. *Learning and Instruction, 13,* 157-176.
MacGregor, S. K. (1988). Instructional design for computer-mediated text systems: Effects of motivation, learner control, and collaboration on reading performance. *Journal of Experimental Education, 56(3),* 142-147.
Marcus, N., Cooper, M., & Sweller, J. (1996). Understanding instructions. *Journal of Educational Psychology, 88,* 49-63.
Margueratt, D. (2007). *Improving learners motivation through enhanced instructional design.* Unpublished master's thesis. Athabasca University, Athabasca, Canada.
Markland, D., & Hardy, L. (1997). On the factorial and construct validity of the Intrinsic Motivation Inventory: Conceptual and operational concerns. *Research Quarterly for Exercise and Sport, 68,* 20-32.
Martens, R. L., Gulikers, J., & Bastiaens, T. (2004) The impact of intrinsic motivation on e-learning in authentic computer tasks. *Journal of Computer Assisted Learning, 20,* 368–376.
Mawer, R. F., & Sweller, J. (1982). Effects of subgoal density and location on learning during problem solving. *Journal of Experimental Psychology: Learning, Memory and Cognition, 8,* 252-259.
Mayer, R. E. (1976). Some conditions of meaningful learning for computer programming: Advance organizers and subject control of frame order. *Journal of Educational Psychology, 68(2),* 143-150.
Mayer, R. E. (1989). Models for understanding. *Review of Educational Research, 59,* 43–64.
Mayer, R. E., & Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. *Educational Psychologist, 38,* 43-52.
Means, T. B., Jonassen, D. H., & Dwyer, R. M. (1997). Enhancing relevance: Embedded ARCS strategies vs. purpose. *Educational Technology, Research and Development, 45(1),* 5–18.
Merrill, M. D. (1975). Learner control: beyond aptitude-treatment interactions. *AV Communication Review, 23(2),* 217-226.
Merrill, M. D. (1983). Component display theory. In C. M. Reigeluth. (Ed.), *Instructional-design theories and models* (pp. 279-334). Hillsdale, NJ: Erlbaum.
Merrill, M. D. (1984). What is learner control? In R. K. Bass & C. D. Dills (Eds.), *Instructional development: The state of the art II.* Dubuque, IA: Kendall/Hunt (ERIC Document Reproduction Service No. ED298905).
Merrill, M. D. (2002). First principles of instruction. *Educational Technology Research and Development, 50(3),* 43-59.
Merrill, M. D. (2002). Instructional strategies and learning styles: Which takes precedence?. In R. A. Reiser & J. V. Dempsey (Eds.), *Trends and issues in instructional technology.* Upper Saddle River, NJ: Merrill Prentice Hall.
Mihalca, L., Salden, R. J. C. M., Corbalan, G., Paas, F., & Miclea, M. (2011). Effectiveness of cognitive-load based adaptive instruction in genetics education. *Computers in Human Behavior, 27,* 82-88.

Milheim,W. D. (1989, February). *Perceived attitudinal effects of various types of learner control in an interactive video lesson.* Paper presented at the annual meetings of the Association for Educational Communications and Technology, Dallas, TX. (ERIC Document Reproduction Service No. ED 308 828)

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63,* 81–97.

Mischel, W., & Shoda, Y. (1995). A cognitive-affective system theory of personality: Reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. *Psychological Review, 102*, 246–268.

Moller, A. C., Deci, E. L., & Ryan, R. M. (2006). Choice and ego-depletion: The moderating role of autonomy. *Personality and Social Psychology Bulletin, 32*, 1024–1036.

Moller, L. (1993). *The effects of confidence building strategies on learner motivation and achievement*. Unpublished doctoral dissertation, Purdue University, West Lafayette.

Moos, D. C., & Azevedo, R. (2008). Self-regulated learning with hypermedia: The role of prior domain knowledge. *Contemporary Educational Psychology, 33*, 270–298.

Moreno, F. J., Reina, R., Luis, V., & Sabido, R. (2002). Visual search strategies in experienced and inexperienced gymnastic coaches. *Perceptual and Motor Skills, 95*, 901-902.

Moreno, R. (2010). Cognitive load theory: more food for thought. *Instructional Science, 38(2),* 135-141.

Morrison, G. R., Ross, S. M., & Baldwin, W. (1992). Learner control of context and instructional support in learning elementary school mathematics. *Educational Technology, Research and Development*, *40,* 5-13.

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle?. *Psychological Bulletin, 126*, 247–259.

Muraven, M., Baumeister, R. F., & Tice, D. M. (1999). Self-control as limited resource: Regulatory depletion patterns. *Journal of Personality and Social Psychology, 74,* 774–789.

Murphy, P. K., & Alexander, P. A. (2002). What counts? The predictive powers of subject-matter knowledge, strategic processing, and interest in domain-specific performance. *The Journal of Experimental Education, 70(3),* 197–214.

Naime-Diefenbach, B. (1991). *Validation of attention and confidence as independent components of the ARCS motivational model.* Unpublished doctoral dissertation, Florida State University, Tallahassee.

Niemiec, R. P., Sikorski, C., & Walberg, H. J. (1996). Learner-control effects: A review of reviews and a meta-analysis. *Journal of Educational Computing Research, 15(2),* 157-174.

Overskeid, G., & Svartdal, F. (1996). Effects of reward on subjective autonomy and interest when initial interest is low. *The Psychological Record, 46*, 319–331.

Paas, F. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach. *Journal of Educational Psychology, 84*, 429-434.

Paas, F., & Kester, L. (2006). Learner and information characteristics in the design of powerful learning environments. *Applied Cognitive Psychology*, *20(3)*, 281–285.

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, *38*, 1-4.

Paas, F., Renkl, A., & Sweller, J. (2004). Cognitive load theory: Instructional implications of the interaction between information structures and cognitive architecture. *Instructional Science, 32*, 1-8.

Paas, F., Tuovinen, J. E., Tabbers, H. K., & Van Gerven, P. W. M. (2003). Cognitive load measurement as a means to advance cognitive load theory. *Educational Psychologist*, *38*, 63-71.

Paas, F., Tuovinen, J. E., Van Merriënboer, J. J. G., & Darabi, A. A. (2005). A motivational perspective on the relation between mental effort and performance: Optimizing learner involvement in instruction. *Educational Technology Research and Development, 53(3),* 25-34.

Paas, F., & Van Merriënboer, J. J. G. (1993). The efficiency of instructional conditions: An approach to combine mental effort and performance measures. *Human Factors*, *35*, 737-743.

Paas, F., & Van Merriënboer, J. J. G. (1994a). Instructional control of cognitive load in the training of complex cognitive tasks. *Educational Psychology Review, 6*, 51-71.

Paas, F., & Van Merriënboer, J. J. G. (1994b). Variability of worked examples and transfer of geometrical problem-solving skills: A cognitive load approach. *Journal of Educational Psychology*, *86*, 122-133.

Paas, F., Van Merriënboer, J. J. G., & Adam, J. J. (1994). Measurement of cognitive load in instructional research. *Perceptual and Motor Skills, 79,* 419–430.

Paris, S. G., & Oka, E. (1986). Children's reading strategies, metacognition and motivation. *Developmental Review, 6,* 25-86.

Paris, S. G., & Winograd, P. (1990). How metacognition can promote academic learning and instruction. In B. F. Jones & L. Idol (Eds.), *Dimensions of tinking and cognitive instruction* (pp. 15-51) Hillsdale, NJ: Erlbaum.

Park, O., & Lee, J. (2003). Adaptive instructional systems. In D. H. Jonassen (Ed.), *Handbook of research on educational communications and technology*, 2nd Ed. (pp. 651-684). Mahwah, NJ: Lawrence Erlbaum Associates.

Park, O., & Tennyson, R. D. (1980). Adaptive design strategies for selecting number and presentation order of examples in coordinate concept acquisition. *Journal of Educational Psychology, 72,* 362–370.

Park, O., & Tennyson, R. D. (1986). Computer-based response-sensitive design strategies for selecting presentation form and sequence of examples in learning of coordinate concepts. *Journal of Educational Psychology, 78,* 23–28.

Parker, L. E., & Lepper, M. R. (1992). Effects of fantasy contexts on children's learning and motivation: Making learning more fun. *Journal of Personality and Social Psychology, 62,* 625–633.

Patall, E. A., Cooper, H., & Robinson, J. C. (2008). The effects of choice on intrinsic motivation and related outcomes: A meta-analysis of research findings. *Psychological Bulletin, 134(2),* 270-300.

Patton, M. Q. (1990). *Qualitative evaluation and research methods (2nd Ed.)*. Newbury Park, CA: Sage.

Patton, M. Q. (2002). *Qualitative research & evaluation methods (3rd Ed.).* Thousand Oaks, CA: Sage.

Pekrun, R. (1992). The impact of emotions on learning and achievement: Towards a theory of cognitive/motivational mediators. *Applied Psychology, 41*, 359–376.

Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic emotions in students' self-regulated learning and achievement: a program of qualitative and quantitative research. *Educational Psychologist, 37(2),* 91-105.

Perry, N. P., Van de Kamp, K. O., Mercer, L. K., & Nordby, C. N. (2002). Investigating teacher-student interactions that foster self-regulated learning. *Educational Psychologist, 37*, 5–15.

Peterson, L. & Peterson, M. (1959). Short-term retention of individual verbal items. *Journal of Experimental, Psychology, 58*, 193–198.

Peterson, P. L., Janicki, T. C., & Swing, S. (1981). Ability X treatment interaction effects on children's learning in large-group and small-group approaches. *American Educational Research Journal, 18,* 453–473.

Pintrich, P. R. (1988a). A process-oriented view of student motivation and cognition. In J. S. Stark & L. Mets (Eds.), *Improving teaching and learning throught research: New directions for institutional research* (Vol.57, pp. 65-79). San Francisco: Jossey-Bass.

Pintrich, P. R. (1988b). Student learning and college teaching. In R.E. Young & K. E. Eble (Eds.), *College teaching and learning: preparing for new commitments. New directions for teaching and learning* (Vol. 33, pp. 71-86). San Francisco: Jossey-Bass.

Pintrich, P. R. (1989). The dynamic interplay of student motivation and cognition in the college classroom. In M. L. Maehr & C. Ames (Eds.), *Advances in motivation and achievement: Motivation-enhancing environments* (Vol. 6, pp. 117–160). Greenwich, CT: JAI.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research*, *31*, 459–470.

Pintrich, P. R. (2000a). Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. *Journal of Educational Psychology, 92*, 544–555.

Pintrich, P. R. (2000b). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). San Diego, CA: Academic Press.

Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology, 95,* 667–686.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82,* 33-40.

Pintrich, P. R., & Schrauben, B. (1992). Students' motivational beliefs and their cognitive engagement in classroom academic tasks. In D. H. Schunk & J. L. Meece (Eds.), *Student perceptions in the classroom* (pp.149–183). Hillsdale, NJ: Erlbaum.

Pintrich, P. R., & Schunk, D. H. (2002). *Motivation in education: Theory, research, and applications* (2nd Ed.). Upper Saddle River, NJ: Prentice Hall.

Pintrich, P. R., & Zusho, A. (2002). The development of academic self-regulation: The role of cognitive and motivational factors. In A. Wigfield & J. Eccles (Eds.), *Development of achievement motivation* (pp.249–284). San Diego, CA: Academic Press.

Pirolli, P., & Recker, M. (1994). Learning strategies and transfer in the domain of programming. *Cognition and Instruction, 12*, 235-275.

Pollock, E., Chandler, P., & Sweller, J. (2002). Assimilating complex information. *Learning and Instruction, 12,* 61-86.

Pollock, J. C., & Sullivan, H. J. (1990). Practice mode and learner control in computer-based instruction. *Contemporary Educational Psychology, 15(3),* 251-260.

Pressey, S. L. (1926). A simple apparatus which gives tests and scores and teaches. *School and Society, 23,* 373–376.

Pressey, S. L. (1927). A machine for automatic teaching of drill material. *School and Society, 25,* 1–14.

Pressley, M., & Afflerbach, P. (1995). *Verbal protocols of reading: The nature of constructively responsive reading.* Hillsdale, NJ: Erlbaum.

Quilici, J. L., & Mayer, R. E. (1996). Role of examples in how students learn to categorize statistics word problems. *Journal of Educational Psychology, 88,* 144-161.

Quilici, J. L., & Mayer, R. E. (2002). Teaching students to recognize structural similarities between statistics word problems. *Applied Cognitive Psychology, 16,* 325-342.

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin, 124,* 372-422.

Reeve, J. (1996). *Motivating others.* Needham Heights, MA: Allyn & Bacon.

Reeve, J., Nix, G., & Hamm, D. (2003). Testing models of the experience of self-determination in intrinsic motivation and the conundrum of choice. *Journal of Educational Psychology, 95,* 375–392.

Reigeluth, C. M. (1999). The elaboration theory: Guidance for scope and sequence decisions. In C. M. Reigeluth (Ed.), *Instructional design theories and models: A new paradigm of instructional theory,* vol. II, (pp. 424–453). Erlbaum, Mahwah, NJ.

Reigeluth, C. M., & Stein F. S. (1983). The elaboration theory of instruction In C. M. Reigeluth (Ed.), *Instructional-design theories and models* (pp. 335-382). Hillsadale, NJ: Erlbaum.

Reingold, E. M., Charness, N., Pomplun, M., & Stampe, D. M. (2001). Visual span in expert chess players: Evidence from eye movement. *Psychological Science, 12,* 48-55.

Reiser, R. A. (1987). Instructional technology: A history. In R. M. Gagné (Ed.), *Instructional technology*: *Foundations* (pp. 11-48). Mahwah, NJ: Lawrence Erlbaum Associates.

Reisslein, J., Atkinson, R. K., Seeling, P., & Reisslein, M. (2006). Encountering the expertise reversal effect with a computer-based environment on electrical circuit analysis. *Learning and Instruction, 16,* 92-103.

Renkl, A. (1997). Learning from worked-out examples: A study on individual differences. *Cognitive Science, 21,* 1–29.

Renkl, A. (1999). Learning mathematics from worked-out examples: Analyzing and fostering self-explanations. *European Journal of Psychology of Education, 14,* 477-488.

Renkl, A. (2002). Learning from worked-out examples: Instructional explanations supplement self-explanations. *Learning and Instruction, 12,* 149-176.

Renkl, A., & Atkinson, R. K. (2001, August). *The effects of gradually increasing problem-solving demands in cognitive skill acquisition.* Paper presented at the 9th Conference of the European Association for Research on Learning and Instruction (EARLI), Fribourg, Switzerland.

Renkl, A., & Atkinson, R. K. (2003). Structuring the transition from example study to problem solving in cognitive skill acquisition: A cognitive load perspective. *Educational Psychologist, 38,*15-22.

Renkl, A., Atkinson, R. K., & Maier, U. H. (2000). From studying examples to solving problems: Fading worked-out solution steps helps learning. In L. Gleitman & A. K. Joshi (Eds.), *Proceeding of the 22nd Annual Conference of the Cognitive Science Society* (pp. 393–398). Mahwah, NJ: Lawrence Erlbaum Associates.

Renkl, A., Atkinson, R. K., Maier, U. H., & Staley, R. (2002). From example study to problem solving: Smooth transitions help learning. *Journal of Experimental Education, 70,* 293–315.

Ross, S. M., & Morrison, G. R. (1986). Adaptive instructional strategies for teaching rules in mathematics. *Educational Communication and Technology Journal, 30,* 67–74.

Ross, S. M., & Morrison, G. R. (1988). Adapting instruction to learner performance and background variables. In D. H. Jonassen (Ed.), *Instructional designs for microcomputer courseware* (pp. 227–243). Mahwah, NJ: Lawrence Erlbaum Associates.

Ross, S. M., Morrison, G. R., & O'Dell, J. K. (1988). Obtaining more out of less text in CBI: Effects of varied text density as a function of learner characteristics and control strategy. *Educational Communications and Technology Journal, 36(3),* 131-142.

Ross, S. M., Morrison, G. R., & O'Dell, J. K. (1989). Uses and effects of learner control of context and instructional support computer-based instruction. *Educational Technology, Research and Development, 37,* 29-39.

Ross, S. M., & Rakow, E. A. (1981). Learner control versus program control as adaptive strategies for selection of instructional support on math rules. *Journal of Educational Psychology, 73(5),* 745-753.

Ross, T. C. (1989). Distinguishing types of superficial similarities: Different effects on the access and the use of earlier problems. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15,* 456-468.

Rossett, A., & Gautier-Downes, J. (1991). *A handbook of job-aids.* San Diego, CA: Pfeiffer

Rothen, W., & Tennyson, R. D. (1978). Application of Bayes' theory in designing computer-based adaptive instructional strategies. *Educational Psychologist, 12,* 317–323.

Rotter, J. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs, 80(1),* 1–28.

Ryan, R. M. (1982). Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. *Journal of Personality and Social Psychology, 43,* 450–461.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development and well-being. *American Psychologist, 55*, 68–78.

Ryan, R. M., Mims, V., & Koestner, R. (1983). Relation of reward contingent and interpersonal context to intrinsic motivation: A review and test using cognitive evaluation theory. *Journal of Personality and Social Psychology, 45*, 736-750.

Salden, R. J. C. M., Paas, F., Broers, N. J., & Van Merriënboer, J. J. G. (2004). Mental effort and performance as determinants for the dynamic selection of learning tasks in Air Traffic Control training. *Instructional Science, 32*, 153-172.

Salden, R. J. C. M., Paas, F., & Van Merriënboer, J. J. G. (2006). Personalized task selection in Air Traffic Control: Effects on training efficiency and transfer. *Learning and Instruction, 16,* 350-362.

Salden, R. J. C. M., Paas, F., & Van Merriënboer, J. J. G. (2006). A comparison of approaches to learning task selection in the training of complex cognitive skills. *Computers in Human Behavior, 22,* 321-333.

Salomon, G. (1983). The differential investment of mental effort in learning from different sources. *Educational Psychologist, 18(1),* 42-50.

Salomon, G., & Gardner, H. (1986). The computer as educator: Lessons from television research. *Educational Researcher, 15(1),* 13-19.

Savelsbergh, E. R., de Jong, T., & Ferguson-Hessler, M. G. M. (2002). Situational knowledge in physics: The case of electrodynamics. *Journal of Research in Science Teaching, 39(10),* 928-951.

Scandura, J. M. (1983). Instructional strategies based on the structural learning theory. In C. M. Reigeluth (Ed.), *Instructional-design theories and models: An overview of their current status* (pp. 213–249). Mahwah, NJ: Lawrence Erlbaum Associates.

Scheiter, K., & Gerjets, P. (2007). Learner control in hypermedia environments. *Educational Psychology Review, 19,* 285-307.

Scheiter, K., Gerjets, P., Vollmann, B., & Catrambone, R. (2009). The impact of learner characteristics on information utilization strategies, cognitive load experienced, and performance in hypermedia learning. *Learning and Instruction, 5,* 387-401.

Scheiter, K., & Van Gog, T. (2009). Using eye tracking in applied research to study and stimulate the processing of information from multi-representational sources. *Applied Cognitive Psychology, 23,* 1209-1214.

Schiefele, U. (1991). Interest, learning, and motivation. *Educational Psychologist, 26,* 299–323.

Schnackenberg, H. L., & Sullivan, H. J. (2000). Learner control over full and lean computer-based instruction under differing ability levels. *Educational Technology, Research and Development, 48,*19-35.

Schnotz, W., & Kürschner, C. (2007). A reconsideration of cognitive load theory. *Educational Psychology Review, 19(4),* 469-508.

Schraw, G., Flowerday, T., & Reisetter, M. F. (1998). The role of choice in reader engagement. *Journal of Educational Psychology, 90,* 705–714.

Schunk, D. H. (1985). Self-efficacy and school learning. *Psychology in the Schools, 22,* 208-223.

Schunk, D. H. (1989). Self-efficacy and achievement behaviors. *Educational Psychology Review, 1(3),* 173-208.

Schunk, D. H., & Zimmerman, B. J. (1994). *Self-regulation of learning and performance : Issues and educational applications.* Hillsdale, NJ: Erlbaum.

Schwartz, B. (2000). Self-determination: The tyranny of freedom. *American Psychologist, 55,* 79–88.

Schwonke, R., Berthold, K., & Renkl, A. (2009). How multiple external representations are used and how they can be made more useful. *Applied Cognitive Psychology, 23,* 1227-1243.

Segers, M., Dochy, F., & Cascallar, E. (2003). *Optimizing new modes of assessment: In search of qualities and standards.* Dordrecht, The Netherlands: Kluwer.

Seidel, R. J., & Park, O. (1994). An historical perspective and a model for evaluation of intelligent tutoring systems. *Journal of Educational Computing Research, 10,* 103–128.

Seufert, T., & Brünken, R. (2006). Cognitive load and the format of instructional aids for coherence formation. *Applied Cognitive Psychology, 20,* 321–331.

Shute, V. J., & Psotka, J. (1995). Intelligent tutoring systems: Past, present and future. In D. H. Jonassen (Ed.), *Handbook of research on educational communications and technology.* New York: Scholastic.

Shute, V. J., & Towle, B. (2003). Adaptive e-learning. *Educational Psychologist, 38(2),* 105–114.

Shute, V. J., & Zapata-Rivera, D. (2008). Adaptive technologies. In J. M. Spector, M. D. Merrill, J. Van Merriënboer, & M. P. Driscoll (Eds.), *Handbook of Research on Educational Communications and Technology*, 3rd Ed., (pp. 277-294). Lawrence Erlbaum Associates.

Shyu, H. Y., & Brown, S. W. (1992). Learner control versus program control in interactive videodisc instruction: What are the effects in procedural learning? *International Journal of Instructional Media, 19,* 85-96.

Singhanayok, C., & Hooper, S. (1998). The effects of cooperative learning and learner control on students' achievement, option selections, and attitudes. *Educational Technology, Research and Development, 46(2),* 17-32.
Skinner, B. F. (1954). The science of learning and the art of teaching. *Harvard Educational Review, 24*, 86–97.
Skinner, B. F. (1958). The teaching machines. *Science, 128*, 969–977.
Snow, R. E. (1980). Aptitude, learner control, and adaptive instruction. *Educational Psychologist, 15,* 151-158.
Snow, R. E. (1986). Individual differences and the design of educational program. *American Psychologist, 41,* 1029–1039.
Snow, R. E. (1989). Toward assessment of cognitive and conative structures in learning. *Educational Researcher, 18(9),* 8-14.
Snow, R. E. (1989). Aptitude–treatment interaction as a framework for research on individual differences in learning. In P. L. Ackerman, R. J. Sternberg, & R. Glaser (Eds.), *Learning and individual differences. Advances in theory and research* (pp. 13–59). New York: W. H. Freeman.
Snow, R. E. (1994). Abilities in academic tasks. In R. J. Sternberg & R. K. Wagner (Eds.), *Mind in context: Interactionist perspectives on human intelligence* (pp. 3–37). Cambridge, U. K.: Cambridge University Press.
Snow, R. E., & Swanson, J. (1992). Instructional psychology: Aptitude, adaptation, and assessment. *Annual Review of Psychology, 43*, 583–626.
Song, S. H., & Keller, J. M. (1999, February). *The ARCS model for developing motivationally-adaptive computer-assisted instruction.* Paper presented at the Association for Educational Communications and Technology, Houston, TX.
Song, S. H., & Keller, J. M. (2001). Effectiveness of motivationally adaptive computer-assisted instruction on the dynamic aspects of motivation. *Educational Technology, Research and Development, 49*, 5-22.
Stark, R., Mandl, H., Gruber, H., & Renkl, A. (2002). Conditions and effects of example elaboration. *Learning and Instruction, 12(1),* 39-60.
Steele-Johnson, D., Beauregard, R. S., Hoover, P. B., & Schmidt, A. M. (2000). Goal orientation and task demand effects on motivation, affect, and performance. *Journal of Applied Psychology, 85,* 724– 738.
Steinberg, E. R. (1977). Review of student control in computer-assisted instruction. *Journal of Computer-Based Instruction, 3*, 84-90.
Steinberg, E. R. (1989). Cognition and learner control: A literature review, 1977-1988. *Journal of Computer-Based Instruction, 16*, 117-121.
Steinberg, L., Cauffman, E., Woolard, J., Graham, S., & Banich, M. (2009). Are adolescents less mature than adults? Minors' access to abortion, the juvenile death penalty, and the alleged APA ''flip-flop*''. American Psychologist, 67,* 583–594.
Sternberg, R. J. (1997). *Thinking styles*. New York: Cambridge University Press.
Stone, N. (2000). Exploring the relationship between calibration and self-regulated learning. *Educational Psychology Review, 12*, 437–475.
Sweller, J. (1983). Control mechanisms in problem solving. *Memory and Cognition, 11*, 32-40.
Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*, 257–285.
Sweller, J. (1993). Some cognitive processes and their consequences for the organisation and presentation of information. *Australian Journal of Psychology, 45,* 1–8.
Sweller, J. (1999). *Instructional design in technical areas*. Melbourne: ACER.
Sweller, J. (2004). Instructional design consequences of an analogy between evolution by natural selection and human cognitive architecture. *Instructional Science, 32*, 9–31.
Sweller, J. (2005). Implications of cognitive load theory for multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (pp. 19–30). New York: Cambridge University Press.
Sweller, J. (2005). The redundancy principle in multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (pp. 159-167). New York: Cambridge University Press.
Sweller, J., & Chandler, P. (1991). Evidence for cognitive load theory. *Cognition and Instruction, 8,* 351–362.
Sweller, J., & Chandler, P. (1994). Why some material is difficult to learn. *Cognition and Instruction, 12(3),* 185–233.
Sweller, J., Chandler, P., Tierney, P., & Cooper, M. (1990). Cognitive load as a factor in the structuring of technical material. *Journal of Experimental Psychology: General, 119*, 176-192.
Sweller, J., & Levine, M. (1982). Effects of goal specificity on means-ends analysis and learning. *Journal of Experimental Psychology: Learning, Memory and Cognition, 8*, 463-474.
Sweller, J., Mawer, R. F., & Howe, W. (1982). Consequences of history-cued and means-end strategies in problem solving. *American Journal of Psychology, 95,* 455–483.
Sweller, J., Mawer, R., & Ward, M. (1983). Development of expertise in mathematical problem solving. *Journal of Experimental Psychology General, 12,* 639–661.
Sweller, J., & Sweller, S. (2006). Natural information processing systems. *Evolutionary Psychology, 4*, 434–458.
Sweller, J., Van Merriënboer, J. J. G., & Paas, F. (1998). Cognitive architecture and instructional design. *Educational Psychology Review, 10*, 251-296.

Taylor, K. L., & Dionne, J. P. (2000). Accessing problem-solving strategy knowledge: The complementary use of concurrent verbal protocols and retrospective debriefing. *Journal of Educational Psychology, 92*, 413-425.
Taylor, S. (1989). *Positive illusions: Creative self-deception and the healthy mind.* New York: Basic Books.
Tennyson, R. D., & Buttrey, T. (1980). Advisement and management strategies as design variables in computer-assisted instruction. *Educational Communication and Technology Journal, 28,* 169-176.
Tennyson, R. D., & Christensen, D. L. (1988). MAIS: An intelligent learning system. In D. Jonassen (Ed.), *Instructional designs for micro-computer courseware* (pp. 247-274). Mahwah, NJ: Lawrence Erlbaum Associates
Tennyson, R. D., & Park, O.-C. (1984). Computer–based adaptative instructional systems: A review of empirically based models. *Machine-Mediated Learning, 1(2),* 129-153.
Tennyson, R. D., Park, O.-C., & Christensen, D. L. (1985). Adaptative control of learning time and content sequence in concept learning using computer-based instruction. *Journal of Educational Psychology, 77(4),* 481-491.
Thorndike, E. L. (1911). *Individuality*. Boston, MA: Houghton Mifflin.
Thorndike, E. L. (1913). *The psychology of learning: Educational psychology II.* New York: Teachers College Press.
Tobias, S. (1976). Achievement-treatment interactions. *Review of Educational Research, 46*, 61–74.
Tobias, S. (1985). Test anxiety: Interference, defective skills, and cognitive capacity. *Educational Psychologist, 20*, 135-142.
Tobias, S. (1987). Learner characteristics. In R. Gagné (Ed.), *Instructional technology: Foundations. Mahwah*, NJ: Lawrence Erlbaum Associates.
Tobias, S. (1989). Another look at research on the adaptation of instruction to student characteristics. *Educational Psychologist, 24,* 213–227.
Tobias, S. (1994). Interest, prior knowledge, and learning. *Review of Educational Research, 64,* 37–54.
Tobias, S., & Federico, P. A. (1984). Changing aptitude-achievement relationships in instruction: A comment. *Journal of Computer-Based Instruction, 11*, 111–112.
Tuovinen, J. E., & Paas, F. (2004). Exploring multidimensional approaches to the efficiency of instructional conditions. *Instructional Science, 32,* 133–152.
Tuovinen, J. E., & Sweller, J. (1999). A comparison of cognitive load associated with discovery learning and worked examples. *Journal of Educational Psychology, 91,* 334–341.
Turner, J. C., & Patrick, H. (2008). How does motivation develop and how does it change? Reframing motivation research. *Educational Psychologist, 43,* 119-131.
Underwood, G., Chapman, P., Brocklehurst, N., Underwood, J., & Crundall, D. (2003). Visual attention while driving: Sequences of eye fixations made by experienced and novice drivers. *Ergonomics, 46*, 629-646.
Van Gog, T., Ericsson, K. A., Rikers, R. M. J. P., & Paas, F. (2005). Instructional design for advanced learners: Establishing connections between the theoretical frameworks of cognitive load and deliberate practice. *Educational Technology Research and Design, 53*(3), 73–81.
Van Gog, T., Kester, L., Nievelstein, F., Giesbers, B., & Paas, F. (2009). Uncovering cognitive processes: Different techniques that can contribute to cognitive load research and instruction. *Computers in Human Behavior, 25,* 325-331.
Van Gog, T., Kostons, D., Azevedo, R., Paas, F. (2010). *Enhancing the effectiveness of self-regulated learning: A cognitive load perspecitve*. Manuscript submitted for publication.
Van Gog, T., Paas, F., & Van Merriënboer, J. J. G. (2004). Process-oriented worked examples: Improving transfer performance through enhanced understanding. *Instructional Science*, *32*, 83– 98.
Van Gog, T., Paas, F., & Van Merriënboer, J. J. G. (2005). Uncovering expertise-related differences in troubleshooting performance: Combining eye movement and concurrent verbal protocol data. *Applied Cognitive Psychology, 19,* 205–221.
Van Gog, T., Paas, F., & Van Merriënboer, J. J. G. (2006). Effects of process-oriented worked examples on troubleshooting transfer performance. *Learning and Instruction, 16,* 154-164.
Van Gog, T., Paas, F., Van Merriënboer, J. J. G., & Witte, P. (2005). Uncovering the problem-solving process: Cued retrospective reporting versus concurrent and retrospective reporting. *Journal of Experimental Psychology: Applied, 11,* 237–244.
Van Gog, T., & Scheiter, K. (2010). Eye tracking as a tool to study and enhance multimedia learning. *Learning and Instruction, 20,* 95-99.
Van Gerven, P. W. M., Paas, F., Van Merriënboer, J. J. G., & Schmidt, H. G. (2004). Memory load and the cognitive pupillary response in aging. *Psychophysiology, 41*, 167–174.
VanLehn, K., & Jones, R. M. (1993). Better learners use analogical problem solving sparingly. In P. E. Utgoff (Ed.), *Machine Learning: Proceedings of the Tenth Annual Conference.* San Mateo, CA: Morgan Kaufmann.
VanLehn, K., & Jones, R. M. (1993). Learning by explaining examples to oneself: A computational model. In S. Chipman & F A. L. Meyrowitz (Eds.) *Foundations of knowledge acquisition: Cognitive models of complex learning.* Boston: Kluwer Academic Publishing.

Van Merriënboer, J. J. G. (1997). *Training complex cognitive skills: A four component instructional design model*. Englewood Cliffs, NJ: Educational Technology Publications.

Van Merriënboer, J. J. G., & Ayres, P. (2005). Research on cognitive load theory and its design implications for e-learning. *Educational Technology Research and Development, 53(3),* 5–13.

Van Merriënboer, J. J. G., Clark, R. E., & de Croock, M. B. M. (2002). Blueprints for complex learning: The 4C/ID-model. *Educational Technology, Research and Development*, *50 (2),* 39-64.

Van Merriënboer, J. J. G., & de Croock, M. B. M. (1992). Strategies for computer-based programming instruction: Program completion vs. program generation. *Journal of Educational Computing Research, 8*, 365-394.

Van Merriënboer, J. J. G., de Croock, M. B. M., & Jelsma, O. (1997). The transfer paradox: Effects of contextual interference on retention and transfer performance of a complex cognitive skill. *Perceptual and Motor Skills, 84*, 784-786.

Van Merriënboer, J. J. G., Kirschner, P. A., & Kester, L. (2003). Taking the load off a learner's mind: Instructional design for complex learning. *Educational Psychologist*, *38*, 5–14.

Van Merriënboer, J. J. G., & Paas, F. (1989). Automation and schema acquisition in learning elementary computer programming: Implications for the design of practice. *Computers in Human Behavior, 6*, 273–289.

Van Merriënboer, J. J. G., Schuurman, J. G., de Croock, M. B. M., & Paas, F. (2002). Redirecting learners' attention during training: Effects on cognitive load, transfer test performance and training efficiency. *Learning and Instruction, 12,* 11-37.

Van Merriënboer, J. J. G., Sluijsmans, D., Corbalan, G., Kalyuga, S., Paas, F., & Tattersall, C. (2006). Performance assessment and learning task selection in complex learning environments. In J. Elen & R.E. Clark (Eds.), *Handling complexity in learning environments: Theory and research,* Elsevier Ltd.

Van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review, 17*, 147-177.

Van Someren, M. W., Barnard, Y. F., & Sandberg, J. A. C. (1994). *The think aloud method: A practical guide to modeling cognitive processes.* London: Academic Press.

Visser, J., & Kelier, J. M (1990). The clinical use of motivational messages: An inquiry into the validity of the ARCS model of motivational design. *Instructional Science, 19*, 467-500.

Volet, S. E. (1997). Cognitive and affective variables in academic learning: The significance of direction and effort in students' goals. *Learning and Instruction, 7(3),* 235-254.

Wang, M. (1980). Adaptive instruction: Building on diversity. *Theory into Practice*, *19,* 122–128.

Weiner, B. (1990). History of motivational researcher in education. *Journal of Educational Psychology, 82,* 616–622.

Weinstein, C. E., & Mayer, R. E. (1986). The teaching of learning strategies. In M. C. Wittrock (Ed), *Handbook of research on teaching* (pp. 315-327), New York: Macmillan.

Wigfield, A. (1994). Expectancy: Value theory of achievement motivation—A developmental perspective. *Educational Psychology Review, 6,* 49–78.

Wigfield, A., & Eccles, J. (1989). Test anxiety in elementary and secondary school students. *Educational Psychologist*, *24*, 159-183

Wigfield, A., & Eccles, J. S. (2000). Expectancy: Value theory of motivation. *Contemporary Educational Psychology, 25*, 68–81.

Wigfield, A., Eccles, J. S., Yoon, K. S., Harold, R. D., Arbreton, A., Freedman-Doan, C., et al. (1997). Changes in children's competence beliefs and subjective task values across the elementary school years: A 3-year study. *Journal of Educational Psychology, 89,* 451–469.

White, B. Y., Shimoda, T. A., & Frederiksen, J. R. (1999). Enabling students to construct theories of collaborative inquiry and reflective learning: Computer support for metacognitive development. *International Journal of Artificial Intelligence in Education*, *10,* 151-182.

Williams, M. D. (1993). A comprehensive review of learner-control: The role of learner characteristics. In M. R. Simonson & A. Dristen (Eds.), *Proceedings of the Annual Conference of the Association for Educational Communications and Technology* (pp. 1083-1114). New Orleans, LA: Association for Educational Communications and Technology.

Williams, M. D. (1996). Learner-control and instructional technologies. In D. H. Jonassen (Ed.), *Handbook of research on educational communications and technology* (pp. 957-982). New York: Simon & Schuster Macmillan.

Williams, S. (1998). An organizational model of choice: A theoretical analysis differentiating choice, personal control, and self-determination. *Genetic, Social & General Psychology Monographs, 124,* 465–492.

Wilson, B. G., & Jonassen, D. H. (1989). Hypertext and instructional design: Some preliminary guidelines. *Performance Improvement Quarterly*, *2(3),* 34-49.

Winne, P. H. (1995). Self-regulation is ubiquitous but its forms vary with knowledge. *Educational Psychologist, 30(4),* 223-228.

Winne, P. H. (2001). Self-regulated learning viewed from models of information processing. In B. J. Zimmerman and D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives*, 2nd Ed. (pp. 153-189). Mahwah, NJ: Lawrence Erlbaum Associates.

Winne, P. H., & Hadwin, A. F. (1997). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky & A. C. Graesser (Eds.), *Metacognition in educational theory and practice.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In P. Pintrich, M. Boekaerts, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 531-566). Orlando, FL: Academic Press.

Wolters, C. (1999). The relation between high school students' motivational regulation and their use of learning strategies, effort, and classroom performance. *Learning and Individual Differences, 11,* 281–299.

Workman, M. (2004). Performance and perceived effectiveness in computer-based and computer-aided education: do cognitive styles make a difference? *Computers in Human Behavior, 20(4)*, 517-534.

Zimmerman, B. J. (1989). A social cognitive view of self-regulated learning. *Educational Psychology, 81,* 329–339

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. Pintrich & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press: San Diego, CA.

Zimmerman, B. J. (2001). Theories of self-regulated learning and academic achievement: An overview and analysis. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives*, 2nd Ed. (pp. 1–38). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Zimmerman, B. J. (2002). Achieving academic excellence: A self-regulatory perspective. In M. Ferrari (Ed.), *The pursuit of excellence through education* (pp. 85-110). Hillsdale, NJ: Erlbaum.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45(1),* 166–183.

Zimmerman, B. J., & Bandura, A. (1994). Impact of self-regulatory influences on writing course attainment. *American Educational Research Journal, 31,* 845–862.

Zimmerman, B. J., & Kitsantas, A. (1997). Developmental phases in self-regulation: Shifting from process goals to outcome goals. *Journal of Educational Psychology, 89,* 29–36.

Zimmerman, B. J., & Kitsantas, A. (1999). Acquiring writing revision skill: Shifting from process to outcome self-regulatory goals. *Journal of Educational Psychology, 91,* 1–10.

Zuckerman, M. (1971). Dimensions of sensation seeking. *Journal of Consulting and Clinical Psychology, 36(1),* 45-52.

Zuckerman, M., Porac, J., Lathin, D., Smith, R., & Deci, E. (1978). On the importance of self-determination for intrinsically-motivated behavior. *Personality and Social Psychology Bulletin, 4,* 443–446.