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The time on task effect in reading and problem solving is moderated by item difficulty and ability: Insights from computer-based large-scale assessment

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Abstract

Computer-based assessment can provide new insights into behavioral processes of task completion that cannot be uncovered by paper-based instruments. Time presents a major characteristic of the task completion process. Psychologically, time on task has two different interpretations, suggesting opposing associations with task outcome: Spending more time may be positively related to the outcome as the task is completed more carefully. However, the relation may be negative if working more fluently, and thus faster, reflects higher ability level. Using a dual processing theory framework, the present study argues that the validity of each assumption is dependent on the relative degree of controlled versus routine cognitive processing required by an item, as well as a person's acquired ability. A total of 1020 persons participated in the German field test of the Programme for the International Assessment of Adult Competencies (PIAAC), aged 16 to 65 years. Test takers completed computer-based reading and problem solving items. As revealed by linear mixed models, in problem solving, which required controlled processing, the time on task effect was positive and increased with item difficulty. In reading items, which required more routine processing, the time on task effect was negative and the more negative the easier an item was. In problem solving, the positive time on task effect decreased with increasing ability level. In reading, the negative time on task effect increased with increasing ability level. These results suggest that time on task has no uniform interpretation but is a function of item difficulty and individual ability.

Keywords: computer based assessment, time on task, automatic and controlled processing, reading literacy, problem solving

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There are two fundamental observations on human performance: The result obtained on a task and the time taken (e.g., Ebel, 1953). In educational assessment, the focus is mainly on the task outcome, behavioral processes that led to the result are usually not considered. One reason may be that traditional assessments are paper-based and, hence, are not suitable for collecting behavioral process data at the item level (cf., Scheuermann & Björnsson, 2009). However, computer-based assessment – besides other advantages, like increased construct validity (e.g., Sireci & Zenisky, 2006) or improved test design (e.g., van der Linden, 2005) – can provide further insights into the task completion process. This is because in computer-based assessment, log file data can be recorded by the assessment system that allows for the researcher to derive theoretically meaningful descriptors of the task completion process. The present study draws on log file data from an international computer-based large scale assessment to address the question of how time on task is related to the task outcome.

Time on task is an important characteristic of the solution process indicating the duration of perceptual, cognitive and psycho-motorical activities. From a measurement point of view, the usefulness of time on task and the task outcome respectively depend on the items' difficulty. In easy items assessing basic abilities, individual differences will mainly occur in response latencies while accuracy will be consistently high. Following this logic, a number of assessment tools that address constructs like naming speed (e.g., Nicolson & Fawcett, 1994), visual word recognition (e.g., Balota, Cortese, Sergent-Marshal, Spieler, & Yap, 2004), or number naming speed (e.g., Krajewski & Schneider, 2009) make use of response times. In contrast, in more difficult items the accuracy of a result is of interest, e.g in assessments of reading comprehension (e.g., van den Broek, & Espin, 2012), or problem solving (e.g., Greiff et al., 2013; Klieme, 2004; Mayer, 1994;

Wirth & Klieme, 2003). In these ability assessments, time on task usually is not taken into account. Nevertheless, both the task result and time on task constitute task performance regardless of the task's difficulty.

In ability assessments, the relationship between time on task and task result (accuracy or correctness) can be conceived in two ways. On the one hand, taking more time to work on a item may be positively related to the result as the item is completed more thoroughly. On the other hand, the relation may be negative if working faster and more fluently reflects a higher ability level. The present study addresses these contradictory predictions and aims at clarifying the conditions of their validity by jointly analyzing task success and time on task data from the computer-based Programme for the International Assessment of Adult Competencies (PIAAC, cf. Schleicher, 2008). Thus, we take advantage of the fact that computer-based assessment renders data available on a large scale that was previously available only through small scale experimenting (i.e., response times). Data such as response times on the level of individual items can serve to answer basic research questions (such as clarifying relation of time on task and task result in different domains). Furthermore, the data can enhance educational assessment.

Time on task

Time on task is understood as the time from task onset to task completion. Thus, if the task was completed orderly, it reflects the time taken to become familiar with the task, to process the materials provided to solve the task, to think about the solution, and to give a response. In assessment items requiring the participant to interact with the stimulus through multiple steps, time on task can be further split into components, for instance, reflecting the time taken to process a single page from a multi-page stimulus. To model time on task, two different approaches have been suggested (cf. van der Linden, 2007, 2009). First, time is considered an indicator of a (latent) construct, for example, reading speed (Carver, 1992) or reasoning speed

(Goldhammer & Klein Entink, 2011). Here, response and time data are modeled using separate measurement models. Second, within an explanatory item response model, time is used as a predictor to explain differences in task success (cf. Roskam, 1997). In the present study, this second approach is used to investigate the relation between time on task and task success. Task success (dependent variable) can be perceived as a function of time on task (independent variable) because the individual is able to control time spent on completing a task to some extent, which in turn may affect the probability of attaining the correct result (cf. van der Linden, 2009).

Relation of time on task to task success

When investigating the relation between time on task and task success, the well-known speed-accuracy trade-off which is usually investigated in experimental research (cf. Luce, 1986) has to be considered. Trade-off means that for a given person working on a particular item, accuracy will decrease as the person works faster. The positive relation between time on task and task success, as predicted by the speed-accuracy trade-off, is a within-person phenomenon that can be expected for any task (e.g., Wickelgren, 1977). However, when switching from the within-person level to a population, the relation between time on task and task success might show a different pattern, for instance, a negative relation although *within* each person the speed-accuracy compromise remains as the positive relation between time on task and task success (cf. van der Linden, 2007). Consequently, at the population level findings on the relation of time on task with task success may be heterogeneous. One line of research modeling time on task as an indicator of speed provides speed-ability correlations of different directions and strengths across domains. For example, for reasoning, positive correlations between ability (measured through task success) and slowness (measured through time on task) were found (e.g., Goldhammer & Klein Entink, 2011, Klein Entink, Fox, & van der Linden, 2009), for arithmetic zero correlations (van der Linden, Scrams, & Schnipke, 1999), whereas for basic abilities to operate a computer's graphical user

interface a negative relation was demonstrated (Goldhammer, Naumann & Keßel, 2013), as was for basic reading tasks such as phonological comparison and lexical decision (Richter, Isberner, Naumann, & Kutzner, 2012).

These results suggest that the time on task effect might be moderated by item difficulty. A comparison of items across studies reveals that in difficult items, task success is positively related to time on task, whereas in easy items like basic interactions with a computer interface, the relation is negative. Independent evidence for this line of reasoning comes from research suggesting that item difficulty within a given domain affects the association between time on task and task success. Neubauer (1990) investigated the correlation between the average response time and the test score for figural reasoning items and found a zero correlation. However, for item clusters of low, medium and high difficulty he found negative, zero and positive correlations, respectively. Similarly, in a recent study by Dodonova and Dodonov (2013), the strength of the negative correlation between response time and accuracy in a letter sequence task tended to decrease with increasing item difficulty.

Time on task effects and dual processing theory

An explanation for the heterogeneity of associations between time on task and task success may be provided by dual processing theory that distinguishes between automatic and controlled mental processes (cf. Fitts & Posner, 1967; Schneider & Chein, 2003; Schneider & Shiffrin, 1977). Automatic processes are fast, proceduralized and parallel; they require little effort and operate without active control or attention, whereas controlled processes are slow, serial, require attentional control, and can be alternated quickly. Tasks are amenable to automatic processing due to learning only under consistent conditions, that is, rules for information processing including related information processing components and their sequence are invariant (Ackerman, 1987). Learning under consistent conditions can be divided into three stages (cf.

Ackerman & Cianciolo, 2000; Fitts & Posner, 1967). The first stage when the individual acquires task knowledge and creates a production system (cf. ACT theory, Anderson & Lebiere, 1998), is characterized by controlled processing. Automatic processing becomes more apparent in the second stage and dominates in the third stage. Thus, task performance is slow and error prone at the beginning of learning, but speed and accuracy increase as the strength of productions is increased through practice (Anderson, 1992).

Consequently in domains and tasks that allow for automatic processing, a negative association between time on task and task success is expected. Well-practiced task completion is associated with both fast and correct responses. In contrast, a positive association is expected in domains and tasks that do not allow for a transition from controlled to automatic processing due to inconsistent processing rules and variable sequences of information processing. Taking more time to work carefully would positively impact task success. In line with this reasoning, Klein Entink et al. (2009) showed that test effort in a reasoning test, that is, the extent to which a test taker cares about the result, is positively related to test taking slowness (measured through time on task) which itself is positively related to ability (measured through task success).

Notably, dual-processing theory suggests a dynamic interaction of automatic and controlled processing in that the acquisition of higher level cognition is enabled by and builds upon automatic subsystems (Shiffrin & Schneider, 1977). Basically, tasks within and between domains are assumed to differ with respect to the composition of demands that necessarily require controlled processing and those that can pass into automatic processing (Schneider, & Fisk, 1983). Similarly, for a particular task individuals are assumed to differ in the extent to which the task-specific information processing elements that can be automatized are actually automatized (e.g., Carlson, Sullivan, & Schneider, 1989). In the following two sections, we

describe in detail how automatic and controlled processes may interact in the two domains considered, reading and problem solving.

Time on Task in Reading

Reading a text demands a number of cognitive component processes and related abilities. Readers have to identify letters and words. Syntactic roles are then assigned to words, sentences are parsed for their syntax and their meaning is extracted. Coherence must be established between sentences, and a representation of the propositional text base must be created as well as a situation model of the text contents, integrated with prior knowledge (Kintsch, 1998). In addition, cognitive and meta-cognitive regulations might be employed. When text contents are learned, strategies of organization and elaboration will aid the learning process.

These different cognitive component skills allow for a transition from controlled to automatic processing to different degrees. Processes such as phonological recoding, orthographic comparison or the retrieval of word meanings from long-term memory are slow and error-prone in younger readers, but become faster and more accurate as reading skill acquisition progresses (Richter, Isberner, Naumann, & Neeb, 2013). Indeed, theories of reading such as the lexical quality hypothesis (Perfetti, 2007) claim that reading ability rests on reliable as well as quickly retrievable lexical representations. In line with this, text comprehension is predicted by the speed of access to phonological, orthographic and meaning representations (e.g. Richter et al., 2012, 2013). Beyond the word level, the speed of semantic integration and local coherence processes are equally positively related to comprehension (e.g. Naumann, Richter, Flender, Christmann, & Groeben, 2007; Naumann, Richter, Christmann & Groeben, 2008; Richter et al., 2012). As shown by longitudinal studies, accuracy in reading assessments during primary school approaches perfection whereas reading fluency reflecting reading performance per time unit continues to

increase across years of schooling (cf. Landerl & Wimmer, 2006). The high accuracy rates suggest that reading is already well automatized during primary school.

Following this line of reasoning, in reading tasks a negative time on task effect might be expected. A number of reading tasks however require attentional cognitive processing to a substantial degree as well. For instance, readers might need to actively choose which parts of a text to attend to when pursuing a given reading goal (e.g. Gräsel, Fischer, & Mandl, 2001; Naumann et al., 2007, 2008; Puntambekar & Stylianou, 2005; OECD, 2011, ch. 3). In the case of a difficult text, strategies such as re-reading or engaging in self-explanations (e.g. Best, Rowe, Ozuru, & McNamara, 2005; McKeown, Beck, & Blake, 2009) are needed for comprehension. Also in skilled readers, such processes require cognitive effort (Walczyk, 2000), and effort invested in strategic reading positively predicts comprehension (e.g. Richter, Naumann, Brunner & Christmann, 2005; Sullivan, Gnedsdilov, & Puntambekar, 2011). This however will involve longer time spent on task.

At the bottom line, this means that in easy reading tasks, the potentially automatic nature of reading processes at the word, sentence and local coherence level leads to a negative time on task effect (e.g. when reading a short and highly coherent linear text). As reading tasks become more difficult and readers need to engage in strategic and thus controlled cognitive processing, the negative time on task effect will be diminished or reversed.

Time on task in problem solving

Problem solving is required in situations where a person cannot attain a goal by using routine actions or thinking due to barriers or difficulty (e.g., Funke & Frensch, 2007; Mayer, 1992; Wirth & Klieme, 2003). Problem solving requires higher-order thinking, finding new solutions and sometimes interaction with a dynamic environment (Klieme, 2004; Mayer, 1994). In the present study, a specific concept of problem solving as defined for the PIAAC study is

taken into account; it refers to solving information problems in technology-rich environments. That is, technology-based tools and information sources (e.g., search engines, web pages) are used to solve a given problem by “storing, processing and communicating symbolic information” (OECD, 2009a, p. 8). Information problems in this sense (e.g., finding information on the web fulfilling multiple criteria to take a decision) cannot be solved immediately and routinely. They require to develop a plan consisting of a set of properly arranged sub-goals, and to perform corresponding actions through which the goal state can be reached (e.g., identifying the need for information to be obtained from the web, defining an appropriate web search query, scanning the search engine results page, checking linked web pages for multiple criteria, collecting and comparing information from selected web pages and making use of it in the decision to be taken). This differs, for instance, from solving logical or mathematical problems where complexity is determined by reasoning requirements but not primarily by the information that needs to be accessed and used (OECD, 2009a). Cognitive and metacognitive aspects of problem solving as assessed in PIAAC include setting up appropriate goals and plans to achieve the goal state. This includes monitoring the progress of goal attainment, accessing and evaluating multiple sources of information and making use of this information (OECD, 2009a, p. 11).

Problem solving is a prototype of an activity that relies on controlled processing. Controlled processing enables an individual to deal with novel situations for which automatic procedures and productions have not yet been learned. Otherwise the situation would not constitute a problem. Accordingly, Schneider and Fisk (1983) describe skilled behavior in problem solving and strategy planning as a function of controlled processing. Notably, problem solving ability may also benefit from practice. The development of fluent component skills at the level of sub-goals enables problem solvers to improve their strategies optimizing the problem solving process (see e.g., Carlson, Khoo, Yaure, & Schneider, 1990).

(Complex) problem solving performance in general can be conceived as consisting of knowledge acquisition including problem representation and the application of this knowledge to generate solutions (cf. Funke, 2001; Greiff et al., 2013). Wirth and Leutner (2008) identified two simultaneous goals in the knowledge acquisition phase, that is, generating information through inductive search, and integrating this information into a coherent model. Successful problem solvers move more quickly from identification to integration and thus will be able to invest time in advanced modeling and prediction (which provides the basis for successful knowledge application), rather than in low-level information processing.

Problem solving in technology-rich environments assumes two concepts, accessing information and making use of it, that seem similar to knowledge acquisition and application. However, there are differences in that, for instance, retrieving information (e.g., by means of a search engine) is not comparable with an inductive search for rules governing an unknown complex system. Nevertheless, the various notions of problem solving assume successive steps of controlled information processing which may benefit from fluent component skills.

Therefore, a positive effect of time on task on task success is expected for problem solving. Taking sufficient time allows for all serial steps to planned sub-goals to be processed, as well as more sophisticated operations to be used and properly monitored regarding progress. Particularly for weak problems solvers, spending more time on a task may be helpful to compensate a lack of automaticity in required subsystems (e.g., reading or computer handling processes).

Research goal and hypotheses

Our general research goal was to determine the conditions that influence the strength and direction of the time on task effect. To achieve this goal, we used the computer-based assessment

of reading and problem solving in the international large-scale study PIAAC including log file data generated by the assessment system.

From a dual processing framework, we derived the general hypothesis that the relative degree of controlled versus automatic cognitive processing as required by an item, as well as the test taker's acquired ability level, determines the strength and direction of the time on task effect. The following three hypotheses address time on task effects across domains, item properties, and person characteristics. The fourth hypothesis aims at validating the interpretation of the time on task effect in problem solving by splitting up the global time on task into components that represent different steps of task solution and information processing.

Hypothesis 1: Time on task effect across domains. We expected a positive time on task effect for problem solving in technology rich environments items. A negative time on task effect was expected for reading literacy items because in reading items, a number of component cognitive processes are apt for automatization. Problem solving in contrast by definition must rely on controlled processing to a substantial degree in each item.

Hypothesis 2: Time on task effect across items. Within domains we expected the time on task effect to be moderated by item difficulty. Easy items can be assumed to be completed substantially by means of automatic processing whereas difficult items evoking more errors require a higher level of controlled processing. Accordingly, we expected a positive time on task effect in problem solving to be accelerated with increasing item difficulty, and a negative time on task effect in reading to diminish with increasing item difficulty. Besides item difficulty, we looked at the cognitive operations involved in each item, as specified by the PIAAC assessment framework. We took this step as differences in difficulty, and therefore in the time on task effect, may be due to the presence or absence of specific cognitive operations.

Hypothesis 3: Time on task effect across persons. For a given item, individuals are assumed to differ in the extent to which the information processing elements that are amenable to automatic processing are actually automatized. Highly skilled individuals are expected to be in command of well automatized procedures within task solution sub-systems that are apt to automatization (such as decoding in reading or using shortcuts to perform basic operations in a computer environment). We therefore expect the time on task effect to vary across persons. On the one hand, we predict that the time on task effect gets more positive for less skilled persons since they are expected to accomplish tasks with higher demands of controlled and strategic processing than skilled persons. For example, poor readers may rely on compensatory behaviors and strategies especially when completing difficult items (see Walczyk, 2000). On the other hand, for skilled persons we expect the inverse result, that is, due to a higher degree of routinized processing the positive time on task effect gets less positive and more negative, respectively.

Hypothesis 4: Decomposing time on task effect at task level. Computer-based assessment and especially the exploitation of log file data can help to further understand the task completion process. By moving from the global process measure of time on task to the underlying constituents, we can further validate the interpretation of the time on task effect. This is especially true for tasks requiring a complex sequence of stimulus interactions that can be reconstructed from a log file, giving insight into the accuracy and timing with which sub-goals were being completed. In the present study, items assessing problem solving in technology-rich environments are highly interactive, requiring the operation of simulated computer and software environments or navigation in simulated web environments. For a particular item, we expect that a positive time on task effects is confined to the completion of steps that are crucial for a correct solution, while for others the effect is assumed to be negative. If this were the case, it would corroborate our assumption that it is the need for strategic and controlled allocation of cognitive

resources that produces a positive time on task effect in problem solving or very difficult reading items.

Method

Sample

The PIAAC study initiated internationally by the Organisation for Economic Co-operation and Development (OECD, cf. Schleicher, 2008) is a fully computer-based international comparative study assessing the competence levels of adults in 2011/12. For the present study, data provided by GESIS - Leibniz Institute for the Social Sciences from the German PIAAC field test in 2010 was used. The target population consisted of all non-institutionalised adults between the ages of 16 and 65 years (inclusive) who resided in Germany at the time of sample selection and were enrolled in the population register. For the field test in Germany, a three-stage sampling was used with probability sample of communities and individuals in five selected federal states. The within-household sample included in the present study comprised N = 1020 individuals completing the computer-based PIAAC assessment. Of these, 520 were male (50.98%) and 458 female (44.90%). For 42 participants no gender information was available (4.12%). The average age was 39.40 years (SD = 13.30).

Instrumentation

Reading literacy. The PIAAC conceptual framework for reading literacy is based on conceptions of literacy from the International Adult Literacy Survey (IALS) conducted in the 1990s and the Adult Literacy and Life Skills Survey (ALL) conducted in 2003 and 2006 (see OECD, 2009b). It was extended for PIAAC to cover reading ability in the information age by including abilities of reading in digital environments. More than half of the reading items were taken from the former paper-based adult literacy assessments IALS and ALL to link PIAAC results back to these studies. New items simulating digital (hypertext) environments were

developed to cover the broadened construct including abilities of reading digital texts. The items cover the cognitive operations “access and identify information”, “integrate and interpret information”, and “evaluate and reflect information” (see OECD, 2009b). The majority of items include print-based texts as used in previous studies (e.g., newspapers, magazine, books). Items representing the digital medium include, for instance, hypertext, environments such as message boards and chat rooms. Items also varied with respect to the context (e.g., work/occupation, education and training), and whether they included continuous texts (e.g., magazine articles), non-continuous texts (e.g., tables, graphs), or both.

In the PIAAC field test 23 reading units with 72 items were administered. For the present study, only those 49 items were used that entered the main study. To respond, participants were required to highlight text, to click a (graphical) element of the stimulus, to click a link, or to select a check box. As a sample, Figure 1 (upper panel) presents a screenshot from the first item of the unit “Preschool Rules”. Respondents were asked to answer the question shown on the left side of the screen by highlighting text in the list of preschool rules on the right side. The question was to figure out the latest time that children should arrive at preschool. Thus, readers were required to access and identify information, the context was personal and print text was presented.

Problem solving in technology-rich environments. This construct refers to using information and communication technology (ICT) to collect and evaluate information, to communicate and perform practical tasks such as organizing a social activity, deciding between alternative offers, or judging the risks of medical treatments (OECD, 2009a). The framework (OECD, 2009a) defines multiple item characteristics which formed the basis for instrument development. The cognitive operations to be covered by the items were goal setting and progress monitoring, planning and self-organizing, acquiring and evaluating information, and making use

of information. The technology dimensions included hardware devices (e.g., desktop or laptop computers), software applications (e.g., file management, web browser, Email, spreadsheet), various commands and functions (e.g. buttons, links, sort, find) and multiple representations (e.g., text, numbers and graphics). Moreover, item development aimed at the variation of the task's purpose, (e.g., personal, work/occupation), intrinsic complexity (e.g., the minimal number of actions required to solve the problem, the number of constraints to be satisfied), as well as the explicitness of the problem (implicit, explicit).

As defined by the framework (OECD, 2009a), items were developed in a way that they varied in the number of required cognitive operations (e.g., acquiring and evaluating information), the number and kind of actions that have to be taken to solve the item in a computer environment, the inclusion of unexpected outcomes or impasses, and the extent to which the tasks are open-ended. A more difficult item simulating real-life problem solving would require several cognitive operations, multiple actions in different environments, unexpected outcomes, and the planning of multiple sub-goals which may depend on each other. A corresponding sample task would be one in which the problem solver has to do a web search on the internet to access information, integrate and evaluate information from multiple online sources by using a spread sheet, and then to create a summary of the information to be presented at school by using a presentation software.

Fourteen units including 24 items were administered in the PIAAC field test. Of these items, only 13 were selected for the main study. For the present study, all available items were considered to increase reliability. After excluding items with poor discrimination and items for which no score could be derived, 18 items were left. In the context of international large-scale assessments further items may be dropped, especially if they show differential item functioning (DIF) across participating countries. However, as we only used national data and did not aim at

comparing countries, there was no need to consider item-by-country interactions. To give a response, participants were required to click buttons, menu items, or links, to select from drop-down menus, to drag and drop, etc. in simulated computer environments.

As a sample, Figure 1 (lower panel) presents a screenshot from the item “Job Search”. Regarding cognitive operations, participants have to access and evaluate information and monitor criteria for constraint satisfaction within a simulated job search. Thus, the task’s purpose is occupational. Starting from a search engine results page, the task is to find all the sites that do not require users to register or pay a fee and to bookmark these sites. Regarding the explicitness of the problem, instructions do not directly tell participants the number of sites they must locate but evaluation criteria are clearly stated. To solve the item, single actions of evaluation have to be repeated for each web site; for a target page, multiple constraints need to be satisfied. Both characteristics determine intrinsic complexity. As regards software applications and related commands, the item is situated in a simulated web environment that includes tools and functionality similar to those found in real-life browser applications, that is, clickable links, back and forward buttons of the browser, and a bookmark manager which allows to create, view and change bookmarks. The opening page presents the task description on the left side, and the results of the web search engine, that is, clickable links and brief information about the linked page, on the right side of the screen. From this search engine results page participants have to access the hypertext documents connected via hyperlinks to locate and bookmark those websites that meet the search criteria.

Design and procedure

A rotation design was used to form 21 booklets resulting in an effective sample size for reading literacy of 113 to 146 responses per item and for problem solving in technology-rich environments of 140 to 191 responses per item.

Data was collected in computer assisted personal interviews. Interviewers went to the participants' households to conduct the interview in person. First, participants completed a background questionnaire, and then the interviewer handed the notebook to the participant for completion of the cognitive items. There was no global time limit, that is, participants could take as long as they needed. Participants only completed the computer-based items if they were sufficiently ICT-literate, which was tested by ICT items requiring basic operations such as highlighting text by clicking and dragging. In case of non-sufficient ICT literacy, a paper-based assessment was administered. In the computer-based part participants were randomly assigned to booklets including reading literacy, numeracy, and problem solving items. For the present study, only data from the computer-based assessment of reading literacy and problem solving was included.

Statistical Analyses

Modeling Approach. The Generalized Linear Mixed Model (GLMM) framework (e.g., Baayen, Davison, & Bates, 2008; De Boeck et al., 2011; Doran, Bates, Bliese, & Dowling, 2007) was used to investigate the role of time on task in reading and problem solving (Hypotheses 1 to 3). A linear model consists of a component η_{pi}, representing a linear combination of predictors determining the probability of person p for solving the item i correctly. The predictors' weights are called effects. Modeling mixed effects means to include both random effects and fixed effects. Fixed effects are constants across units or groups of a population (e.g., items, persons, class rooms), whereas random effects may vary across units or groups of a population (cf. Gelman, 2005). The generalized version of the linear mixed model accommodates also categorical response variables. In measurement models of item response theory (IRT), for instance, the effect of each item i on the probability to obtain a correct response is typically estimated as a fixed effect representing the item's difficulty or easiness. The effect of person p is

usually modeled as random, that is, as an effect which may vary across persons and for which the variance is estimated. The variance of this random effect represents the variability of ability across persons.

The GLMM incorporating both random effects, **b**, and fixed effects, **β**, can be formulated as follows: $\boldsymbol{\eta} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{b}$ (e.g., Doran et al., 2007). In this model, **X** is a model matrix for predictors with fixed weights included in vector **β**, and **Z** is a model matrix for predictors with random weights included in vector **b**. The distribution of the random effects is modeled as a multivariate normal distribution, $\mathbf{b} \sim N(\mathbf{0}, \boldsymbol{\Sigma})$ with **Σ** as the covariance matrix of the random effects. The continuous linear component η_{pi} is linked to the observed ordered categorical response Y_{pi} (correct vs. incorrect) by transforming the expected value of the observed response, that is, the probability to obtain a correct response π_{pi}. When using the log-transformed odds ratio (log-odds), the logit link function follows: $\eta_{pi} = \ln(\pi_{pi}/(1-\pi_{pi}))$ (cf. De Boeck et al., 2011).

In the present study to address the research question of whether the strength of the time on task effect is correlated with the easiness of items, both the effects of persons and items were defined as random intercepts (cf. random person random item model, cf. De Boeck, 2008). A fixed intercept, β_0, is estimated additionally, which is the same for all participants and items.

A baseline model M0 was obtained by specifying an item response model (1PL or Rasch model) with item and person as random intercepts and by adding the time on task as person-by-item predictor with a fixed effect β_1. Model M0 serves as parsimonious reference model that is compared with more complex models including further fixed and/or random effects: η_{pi} = (intercept β_0) + (individual ability b_{0p}) + (relative easiness b_{0i}) + β_1 (time on task t_{pi}).

In the following analyses, this model is systematically extended by adding further predictors. For example, the predictor (time on task t_{pi}) with the random weight b_{1i} is added, providing the variance of the by-item adjustment b_{1i} to the fixed time on task effect β_1. As the by-

item adjustment, b_{1i}, and item easiness, b_{0i}, are tied to the same observational unit, that is, item i, their association is also estimated. This correlation can be used to test whether the strength of the time on task effect linearly depends on item difficulty (as claimed by Hypothesis 2). Figure 2 shows the path diagram of model M1, which is model M0 extended by the predictor (time on task t_{pi}) with a random weight across items, b_{1i} (cf. the graphical representations of GLMMs by De Boeck & Wilson, 2004). The other models under consideration can be derived in a similar fashion by adding random effects adjusting the time on task effect by cognitive operation (model M2), by person (model M3) or by item and person (model M4).

To clarify whether the introduction of further random components into the model significantly improves model fit, model comparison tests were conducted. For comparing nested models, the likelihood ratio (LR) test was used which is appropriate for inference on random effects (Bolker et al., 2009). The test statistic, that is, twice the difference in the log-likelihoods, is approximately χ^2 distributed with degrees of freedom equal to the number of extra parameters in the more complex model. The LR test is problematic when the null hypothesis implies the variance of a random effect to be zero, this means that the parameter value is on the boundary of the parameter space (boundary effect, cf. Baayen, et al., 2008; Bolker, et al., 2009; De Boeck et al., 2011). Using the χ^2 reference distribution increases the risk of type II errors; therefore, the LR test has to be considered as a conservative test for variance parameters.

For the analysis at the task level (Hypothesis 4), logistic regression was used to predict task success by the time taken on individual steps of the task completion sequence.

Interpreting the effect of time on task in the GLMM. The “fundamental equation of RT modeling” (van der Linden, 2009, p. 259) assumes that the response time of person p when completing item i depends both on the person’s speed τ_p and the item’s time intensity λ_i. Accordingly, the expected value of the (log-transformed) response time can be defined as

follows: $E(\ln(t_{pi})) = \lambda_i - \tau_p$ (cf. van der Linden, 2009). This implies that the effect of time on task reflects both the effect of the person and the item component.

When the effect of time on task is introduced as an overall fixed effect β_1, as in model M0, this effect would reflect the association between time on task and the log-odds ratio of the expected response. This association could not be interpreted in a straightforward way, as it depends not only on the correlation between underlying person-level parameters, that is ability and speed, but also on the correlation of corresponding item parameters, that is difficulty and time intensity (see van der Linden, 2009). However, when modeling the effect of time on task as an effect random across items (Hypothesis 1), groups of items supposed to be homogenous (Hypothesis 2), or individuals (Hypothesis 3), the influences from the item and person level can be disentangled.

A time on task effect random across items is obtained by introducing the by-item adjustment b_{1i} to the fixed time on task effect β_1. The time on task effect by item results as $\beta_1 + b_{1i}$. Thereby, time on task is turned into a person-level covariate varying between items. That is, given a particular item with certain time intensity, variation in time on task is only due to differences in persons' speed (plus residual). This allows us to interpret time on task as an item-specific speed parameter predicting task success above and beyond individual ability.

A by-person random time on task effect means to adjust the fixed time on task effect β_1 by the person-specific parameter b_{1p}, resulting in the time on task effect $\beta_1 + b_{1p}$. Given a particular person working at a certain speed level, variation in time on task is only due to differences in the items' time intensity (plus residual). This means that time on task can be conceived as an item-level covariate that is specific to persons and predicts task success above and beyond item easiness.

Trimming of time data. As a preparatory step for data analysis, the (between-person) time on task distribution of each item was inspected for outliers. The middle part of a time on task distribution was assumed to include the observations that are most likely to come from the cognitive processes of interest. To exclude extreme outliers in time on task and to minimize their effect on analyses, observations 2 standard deviations above (below) the mean were replaced by the value at 2 standard deviations above (below) the mean. As even a single extreme outlier can considerably affect mean and standard deviation, time on task values were initially log-transformed which means that extremely long time on task values were pulled to the middle of the distribution. With this trimming approach 4.79% of the data points in reading literacy and 4.67% in problem solving were replaced. Transforming a covariate may have an impact on estimated parameters of the linear mixed model (for linear transformations see e.g. Morrell, Pearson, & Brant, 1997). Therefore, we conducted the analyses also without log-transforming the time on task variable. As we obtained the same result pattern, we report the analyses with log transformation only. Results obtained with the un-transformed data are available from the first author upon request.

Statistical Software. For estimating the presented GLMMs, the lmer function of the R package lme4 (Bates, Maechler, & Bolker, 2012) was applied. The R environment (R Core Team, 2012) was also used to conduct logistic regression analyses.

Results

Difficulty of items

To compare the difficulty of problem solving items and reading literacy items, the baseline model M0 was tested for both domains without the time on task effect. For reading literacy, an intercept of $\beta_0 = .61$ ($z = 3.21$, $p < .01$) was obtained; it represents the marginal log-odds for a correct response in an item of average easiness completed by a person of average ability; the

corresponding probability was 64.68 %. For problem solving, the result was β_0 = -.72 (z = -2.37, p < .01) indicating that the probability of a correct response was on average only 32.68 %, that is, problem solving items were much harder than reading literacy items. Figure 3 shows the densities of the estimated item easiness parameters for reading literacy items (upper panel) and problem solving items (lower panel). Item easiness values were obtained by adding the intercept β_0 and the random item intercept (relative easiness b_{0i}). The proportion of correct responses, p, ranged for reading literacy from 12.41% to 96.92%, and for problem solving from 11.86% to 77.49%.

Time on task effect by domain (Hypothesis 1)

For testing Hypothesis 1 and Hypothesis 2, model M0 was extended to model M1 by adding the by-item random time on task effect b_{1i}: η_{pi} = (intercept β_0) + (individual ability b_{0p}) + (relative easiness b_{0i}) + β_1 (time on task t_{pi}) + b_{1i} (time on task t_{pi}).

To address Hypothesis 1 regarding the time on task effect by domain, the fixed time on task effects β_1, as specified in model M1 (see also Fig. 2), were compared between reading literacy and problem solving

Reading Literacy. Table 1 provides an overview of the results. For reading literacy, a negative and significant time on task effect of β_1 = -.61 (z = -4.90, p < .001) was found. Thus, for a reading literacy item of average difficulty, correct responses were associated with shorter times on task whereas incorrect responses were associated with longer times on task.

Problem Solving. For problem solving, a positive and significant time on task effect of β_1 = .56 (z = 2.30, p = .02) was estimated. Thus, for a problem solving item of average difficulty correct responses were associated with longer times on task and vice versa. These findings give support to Hypothesis 1.

Time on task effect by item (Hypothesis 2)

If the assumption holds that item difficulty moderates the time on task effect, a relation between item easiness and the strength of the time on task effect should be observable within a domain. To test Hypothesis 2, the variances of the by-item adjustments to the fixed time on task effects and their correlations with item easiness, as estimated through model M1, were inspected for both domains under consideration.

Reading Literacy. For reading literacy, the variability of the by-item adjustment was estimated to be $Var(b_{1i}) = .55$. This means that for reading literacy, the time on task effect varied across items. Most importantly the by-item time on task effect and intercept were negatively correlated, $Cor(b_{0i}, b_{1i}) = -.39$. That is, the overall negative time on task effect became even stronger in easy items but was attenuated in hard items. The upper left panel in Figure 4 illustrates how the time on task effect in reading literacy was adjusted by item. To test whether the model extension improved the model's goodness of fit, we compared the nested models M0 and M1. The difference test showed that model M1 fitted the data significantly better than model M0, χ^2 (2) = 77.65, $p < .001$. To test whether the correlation parameter was actually needed to improve model fit, that is, to test the significance of the correlation, model M1 was compared to a restricted version (model M1r), which did not assume a correlation between by-item time on task effect and by-item intercept. The model difference test suggested that the unrestricted version of model M1 had a better fit to the data than the restricted version, χ^2 (1) = 5.16, $p = .02$. Thus, the negative correlation between the by-item adjustment of the time on task effect and the random item intercept (i.e., item easiness) was also significant.

Problem Solving. For problem solving, the variance of the by-item adjustment to the fixed effect of time on task was estimated as $Var(b_{1i}) = .89$. Thus, for problem solving in technology rich environments, the time on task effects varied across items. The correlation between the by-item adjustment to the time on task effect and item easiness was negative as for reading literacy,

Cor(b_{0i}, b_{1i}) = -.61. That is, the overall positive time on task effect became even stronger in hard-to-solve items, but was attenuated in easy-to-solve items. Figure 4 (upper right panel) illustrates how the time on task effect in problem solving was adjusted by item. The model difference test, comparing the nested models M0 and M1, clearly showed that adding the random time on task effect in model M1 improved the model fit, χ^2 (2) = 73.99, p <. 001. Moreover, comparing model M1 with a restricted version (model M1r) without a correlation between the by-item time on task effect and the random item intercept revealed that the correlation was significant, χ^2 (1) = 6.50, p = .01.

All together, these results give clear support to Hypothesis 2. In a domain where task solution cannot rely on automatic processes such as problem solving, the already positive time on task effect was substantially increased in items that were especially difficult. In a domain where rapid automatic processing can account for a substantial part of the task solution process such as reading, an already negative time on task effect became even stronger in easier items, but diminished in more difficult items.

Time on task effect by cognitive operation

An alternative explanation for the variability of the time on task effect between items refers to differences in the required cognitive operations. That is, items being homogeneous with respect to cognitive operations would show similar time on task effects. To test whether the presence of different cognitive operations as detailed by the respective frameworks affects the time on task effect, we extended model M0 to the following model M2 by introducing the cognitive operation c required in an item as a categorical item-level predictor and as a factor moderating the time on task effect: η_{pi} = (intercept β_0) + (individual ability b_{0p}) + (relative easiness b_{0i}) + β_1 (time on task t_{pi}) + (cognitive operation b_{0c}) + b_{1c} (time on task t_{pi}).

Reading Literacy. For reading literacy, the PIAAC framework assumes three broad aspects of cognitive operation, “access and identify information”, “integrate and interpret information”, and “evaluate and reflect information”. In a first step, we tested an explanatory item response model with random person and item effects as well as the effect of cognitive operation. For the three aspects of cognitive operations, the intercepts of 1.07 (z = 4.72, p <. 01), .00 (z = .00, p = 1.00), and .08 (z = .19, p = .85) were estimated. The probabilities of a correct response corresponding to these intercepts were 74.50%, 50.01%, and 51.96%. Access items were thus relatively easy, whereas integrate and evaluate items show quite the same level of medium difficulty; by introducing cognitive operation as explanatory variable of item easiness, the variance of item easiness, $Var(b_{0i})$, decreased from 1.52 to 1.24, which corresponds to R^2 = .20.

To investigate whether the influence of time on task on task success varies across cognitive operations, model M2 was tested. The obtained variance of the by-cognitive operation adjustment to the time on task effect was only $Var(b_{1c})$ = .003. Moreover, the correlation with the corresponding intercept was $Cor(b_{0c}, b_{1c})$ = -1.00 indicating overparameterization of the model. Model M2 was compared with a restricted model including no time effect varying across cognitive operation (model M2r); there was no significant improvement of model fit, χ^2 (2) = .79, p = .67. Thus, the time on task effect did not vary across cognitive operations.

Problem Solving. The time on task effect was not further investigated with respect to cognitive operations for two reasons. First, there was only a small set of 18 items available. Second, each of the problem solving items explicitly included multiple cognitive operations from a set of four dimensions, that is, goal setting and progress monitoring, planning and self-organizing, acquiring and evaluating information, and making use of information, as defined by the PIAAC assessment framework (OECD, 2009a, p. 10). Given the constraints of a large-scale

assessment PIAAC only aimed at an overall indicator of problem solving. Our analyses would require a more fine-grained measure with a broad set of indicators for the various underlying cognitive operations. Although for each item one operation is assumed to be dominant, other operations might also be involved. For instance, the PIAAC framework maps the sample item "Job search" to the cognitive operations of access and evaluating information as well as monitoring criteria for constraint satisfaction. There were only two more items that showed a comparable set of assumed cognitive operations, whereas in other items the requirement of accessing information was combined with a different additional demand, for example, communicating information. Thus, it was not possible to form subgroups with a sufficient number of items being homogenous in the assumed composition of required cognitive operations.

Time on task effect by person (Hypothesis 3)

On the person level, we assumed that the effect of time on task varies across the individual ability level. To test Hypothesis 3, we extended model M0 to model M3 by adding a random time on task effect, b_{1p}, representing the variation across individuals: η_{pi} = (intercept β_0) + (individual ability b_{0p}) + (relative easiness b_{0i}) + β_1 (time on task t_{pi}) + b_{1p} (time on task t_{pi})

Reading Literacy. For reading literacy, the variance of the by-person adjustment was *Var*(b_{1p}) = .14. Thus, for reading literacy, the time on task effects varied across persons. Most importantly, a correlation between the by-person time on task effect and by-person intercept of *Cor*(b_{0p}, b_{1p}) = -.65 was estimated. That is, the overall negative time on task effect became stronger in able readers, but was attenuated in poor readers. The bottom left panel in Figure 4 illustrates how the time on task effect adjusted by person linearly decreases in more able persons. To clarify whether the liberal model M3 better fitted the data, we compared the nested models M0 and M3. The model difference test revealed that model M3 fitted the data significantly better than model M0, χ^2 (2) = 15.09, p < .01.To test whether the correlation parameter is required to

improve model fit, that is, to test the significance of the correlation, model M3 was compared with a restricted version (model M3r) without the correlation between by-person time on task effect and intercept. The model difference test revealed that model M3 without restrictions was the better fitting model, χ^2 (1) = 12.85, $p < .01$.

Problem Solving. Similar results were obtained for problem solving. The variance of the by-person adjustment to the fixed effect of time on task was $Var(b_{1p}) = .22$. Thus, for problem solving in technology rich environments, the time on task effect varied across persons. The correlation between the by-person adjustment of the time on task effect and the by-person intercept (individual ability) was again negative and substantial, $Cor(b_{0p}, b_{1p}) = -.79$. That is, the overall positive time on task effect became even stronger in poor problem solvers, but was attenuated in able problem solvers (see the bottom right panel in Figure 4). The difference test comparing model M3 including the random time on task effect with the baseline model M0 was almost significant, χ^2 (2) = 5.98, $p = .05$. Finally, comparing model M3 with a restricted version (model M3r) without a correlation between by-item time on task effect and intercept revealed that the correlation was significant, χ^2 (1) = 5.98, $p = .01$.

Integrated model - Time on task effect by item difficulty and individual ability level

As assumed in Hypotheses 2 and 3, the previous results indicate that item difficulty and individual ability level have an influence on the strength and direction of the time on task effect. The final model M4 integrates both the by-item and the by-person adjustments to the time on task effect. The results found for models M1 and M3 were perfectly reproduced in the following model M4: η_{pi} = (intercept β_0) + (individual ability b_{0p}) + (relative easiness b_{0i}) + β_1 (time on task t_{pi}) + b_{1i} (time on task t_{pi}) + b_{1p} (time on task t_{pi})

Reading Literacy. For reading literacy, the time on task effect was estimated to be $\beta_1 = -.69$ ($z = -5.16$, $p < .01$). The variance of the by-item adjustment to the time on task effect was

Var(b_{1i}) = .64, and of the by-person adjustment it was *Var*(b_{1p}) = .23, that is, the time on task effect varied across both reading items and readers. Moreover, the time on task effect varied systematically in that the adjustments were linearly related to item easiness and individual ability level respectively, as expected. The correlation between easiness of reading items and by-item adjustment was *Cor*(b_{0i}, b_{1i}) = -.52, and the correlation between individual ability and by-person adjustment was *Cor*(b_{0p}, b_{1p}) = -.78.

The curves in Figure 5 (upper panel) indicate how for a given reader and reading item the probability for a correct response depends on time on task. The range of the time on task axis represents the empirical range of time on task in the selected items. The slope of the curves resulted from adding up the time on task effect and the adjustments to the time on task effect by item and by person. When considering a proficient reader (ability level of b_{0p} = 1.61) and an easy reading item (easiness of b_{0i} = 1.89), that is, a reading situation of low demand, the negative effect of -.69 became much stronger, resulting in a negative time on task effect of -1.90 (‘plus’ line). However, in a situation of high demand, where a difficult reading item (easiness of b_{0i} = -.77) was completed by a poor reader (ability level of b_{0p} = -1.79), the curve’s slope was no longer negative but even slightly positive, that is, .55 (‘triangle’ line). In situations of medium demand, that is, a poor reader completes an easy item or an able reader completes a difficult item, the curves’ slopes are in between.

Problem Solving. In the integrated model a positive time on task effect of β_1 = .56 (z = 2.26, p = .02) was obtained. The variance of the by-item adjustment to the time on task effect was *Var*(b_{1i}) = .91, and of the by-person adjustment it was *Var*(b_{1p}) = .11. The correlation between easiness of problem solving items and the by-item adjustment to the time on task effect was *Cor*(b_{0i}, b_{1i}) = -.52, and the correlation between individual ability level and the by-person adjustment to the time on task effect was *Cor*(b_{0p}, b_{1p}) = -.78.

The bottom panel in Figure 5 shows the probability to obtain a correct response as a function of the time on task for two selected items completed by two selected persons. In a situation of high demand where a difficult item (easiness of b_{0i} = -3.44) is completed by a poor problem solver (ability level of b_{0p} = -1.66), the positive time on task effect of .56 becomes much stronger and was estimated as 1.69 (‘triangle’ line). However, in the situation of low demand, that is, a proficient problem solver (ability level of b_{0p} = 2.63) completing an easy item (easiness of b_{0i} = -.67), the time on task effect decreases dramatically and becomes even negative and was estimated as -.62 (‘plus’ line). If the demand is medium, that is, a less able person completes an easy item or an able person completes a difficult item, the curves’ slopes are in-between.

Taken together, these results indicate that positive time on task effects are observed especially in highly demanding situations, where not so skilled readers or problem solvers are confronted with difficult item. Presumably, they can partly compensate for task demands by allocating cognitive resources. If this interpretation holds true, differential time on task effects should be observable on a within-task level as well. Specifically, if it is the strategic allocation of processing time that drives a positive time on task effect in problem solving items, and difficult reading items being encountered by poor readers, on a within-task level the positive time on task effect should be confined to the processing of task-relevant parts of the stimulus. We tested this hypothesis as a last step.

Decomposing the time on task effect at the task level (Hypothesis 4)

Using fine-grained time information extracted from log files, we decomposed the global time on task into several components that reflect particular steps of task solution. This was done at the task level for the problem solving item “Job search” which required to screen a search engine results page (see Fig. 1, lower panel), and to visit multiple linked web pages. Two of five web pages in this item meet the criteria specified in the instruction and have to be bookmarked to

obtain a correct response. In Hypothesis 4, spending more time on the two target pages was expected to indicate strategic behavior associated with a higher probability of successful task completion. In contrast, a negative effect was assumed for spending time on the search engine results page which did not provide any hints about the target pages. For the time spent on non-target pages, also a negative effect was expected.

First, logistic regression was used to predict the task success by time on task. The sample size for this analysis was N = 182. This analysis revealed a non-significant time on task effect of -.29 (z = -.59, p = .55). Similarly, the random time on task effect for the "Job search" item as estimated in model M1 (Hypothesis 1) was only slightly negative, that is, -.06. As a second step, task success was predicted by the time spent on the search engine results page, the time spent on the two relevant web pages, and the time spent on the three irrelevant web pages. The obtained effect for time spent on the relevant web pages was positive and significant as expected, .96 (z = 2.53, p =. 01), that is, spending more time on the target pages for evaluating the accessed information and monitoring the multiple criteria for constraint satisfaction was associated with a higher probability of achieving a correct response. In contrast, for the time spent on the search engine results page a significant negative effect of -1.78 was revealed, (z = -2.97, p < .01). The time spent on irrelevant web pages was not significantly related to task success (estimated effect of .13, z = .23, p = .82). As a measure of effect size, we computed Nagelkerke's R^2 which was .25, that is, about a quarter of the response variability could be explained by the component time predictors. This result pattern suggests that successful problem solvers quickly discarded the irrelevant search engine results page, whereas relevant pages meeting evaluation criteria were checked carefully. This pattern is fully compatible with the view that positive time on task effects in difficult items are due to a strategic allocation of cognitive resources, as already suggested by the moderation of the time on task effect by domain, item difficulty and ability level.

Discussion

Computer-based assessment provides new possibilities to assess cognitive abilities and underlying processes by measuring not only the outcome of a task but also behavioral process data that might be interpreted in terms of cognitive processes happening throughout task completion. This means that to some degree, data from computer-based assessments may be used to address research questions through means of process analysis that were previously confined to experimental research. This is of interest especially in combination with the rather large sample sizes obtained in educational assessments (compared to lab experiments). Thus, while there used to be a trade-off – either go with small samples and deep process analysis, or have large samples and test result data only – this tradeoff can be remedied to some degree by using process data from large scale assessments.

The goal of this study was to investigate the effect of time on task on task success in reading literacy and problem solving in technology rich environments, and to test potential moderating variables. Our central hypothesis was that the relative degree of strategic versus routine cognitive processing as required by an item as well as the test taker's acquired ability determines the strength and direction of the time on task effect. Accordingly, our results revealed that the time on task effect was moderated by the domain, the item difficulty and the individual ability.

Time on task effects in Reading literacy

For reading literacy, overall a negative time on task effect was found, that is, brief response times were associated with correct responses, and taking more time apparently was not related to greater task success. Very slow respondents seem to lose track and thus fail on the task. This observation especially concerns easy reading items as shown by the negative correlation between item easiness and the item-specific time on task effect, which means that for easy items

the time on task effect was more negative than for difficult ones. To put it simply, in very easy items, the correct solution was either obtained quickly or never. In contrast, for difficult reading items, this association got weaker and in some instances was reversed. Taking individual differences in reading ability into account, these findings were consistently extended, that is, with increasing reading ability the time on task effect got more negative whereas it got weaker or even positive with decreasing reading ability. Thus, for poor readers completing hard reading items, time on task showed a positive effect, whereas for proficient readers working on easy items, a very strong negative effect was found. The latter result means that the few proficient readers who did not master the easy reading items took more time than the majority of proficient readers who were successful. In contrast, in a group of less skilled readers this time difference between correct and incorrect answers in the same items was less pronounced, as shown by the weaker negative time on task effect.

The observed result pattern that incorrect responses are associated with longer response times has consistently been found for other untimed performance measures as well, for instance, general knowledge tasks (Ebel, 1953), matrices tasks (Hornke, 2000), figure series, number series, and verbal analogy tasks (Beckmann, 2000), verbal memory tasks (Hornke, 2005), and discrimination tasks (for a review of reaction time research on this matter see Luce, 1986). Hornke (2005) discusses that correct responses with short latencies are eye-catching. Incorrect responses in contrast may be preceded by an ongoing process of rumination, and ultimately switching to random guessing. This interpretation is consistent with our finding in that especially for easy items there is a strong negative time on task effect, and also explains why in easy reading items, generally skilled readers had a lower chance of getting the item correct when the response took longer. Similar effects were reported by Hornke (2000) and Beckmann (2000). These

authors also observed that especially in highly skilled persons, longer response times were associated with weaker performance.

Across the cognitive operations required in reading items, there was no significant variation of the time on task effect. Thus, differences in the time on task effect across items cannot be ascribed to the presence or absence of specific cognitive operations as outlined in the PIAAC framework. In line with our findings on the dependency of the time on task effect on item difficulty, the clusters of access, integrate and evaluate items are not very well distinguishable by their level of difficulty. Other item features than the cognitive operations are hence responsible for the variation of the time on task effect with item difficulty. The results concerning cognitive operations have implications for further framework development. As the association of time on task with task success covaries with item difficulty but not with cognitive operation, some other item features than the cognitive operations specified by the framework jointly affect item difficulty and the time on task effect within an item. If our cognitive interpretation of time on task effects holds, it might be worthwhile to look for item features that drive item difficulty and differential time on task effects. Identifying these features might further contribute to clarifying the PIAAC reading items' demands in cognitive terms and as such contribute to further advance the assessment framework.

As one future step, we intend to classify the PIAAC items, for instance in terms of their navigational demands, such as the number of different navigation devices that need to be used, and the number of navigation steps that have to be taken to complete a problem solving task. Item features such as these are not yet entirely covered by the aspects detailed by the framework. However, theoretically they might not only drive item difficulty but also account for variation in the time on task effect.

Time on task effects in Problem Solving

For problem solving, overall a significant positive time on task effect was found: Long response times were associated with correct answers and short response times with wrong answers. Similar to reading, the time on task effect varied significantly across items. For easy items it was weaker and around zero, whereas for difficult items it became even more positive. This means that when dealing with challenging problems, spending more time was associated with higher probability to give a correct response. Across individuals, poor problem solvers could benefit more from spending more time on a task than strong problem solvers. Although causal interpretations are not possible, this result suggests that poor problem solvers can compensate for their lack of general ability by putting in more effort when working on a particular task, especially when this task was hard to solve. Thus, the difference in time on task between correct and incorrect solutions was greater for weak problem solvers than for strong problem solvers, which is reverse to the finding for reading.

The results for reading literacy and problem solving nevertheless converge when considering the extreme cases in which a skilled person encounters an easy item or a less skilled person engages in a difficult item. In the first case, the resulting time on task effect is negative (even for problem solving), and in the second case, it is positive (even for reading literacy). Thus, the strength and the direction of the time on task effects seem to be governed by general factors, ability and difficulty. Both high ability levels and easy items presumably are associated with a large proportion of cognitive component processes that are apt to automatization (in easy items) or in fact automatized (in skilled persons), bringing about a negative time on task effect. In contrast, low ability levels and difficult items presumably are associated with the need to engage in controlled and thus time-consuming cognitive activity to a large extent, bringing about a positive time on task effect.

These interpretations are further backed by our in-depth analysis of the time-taking behavior in the sample problem solving item “Job search”. This analysis was based on time data reflecting different steps of task solution and presumably information processing. It revealed that only for time spent on steps that are needed to solve the tasks, that is, to visit and evaluate the target pages for multiple criteria, a positive time on task effect emerged, whereas for spending time on the non-informative search engine results page and the non-target pages, negative or null effects were found. When spending time on the target pages, the problem solver deals with the part of the problem space that enables to move step-by-step to the knowledge state that includes the solution (Simon & Newell, 1971), or to integrate relevant information rather than identifying various other aspects of the problem (Wirth & Leutner, 2008). Thus, this finding supported our hypothesis that the positive time on task effect in problem solving items reflects the need for and the benefit from devoting time to strategic and controlled cognitive processing. This interpretation suggests that task success is a function of the time spent on relevant pages (however, the opposite causal effect could also be true, that is time on task depends on task success). The negative effect of time spent on the search engine results page may indicate the strategy to select web pages based on the limited information provided there. Although this approach could in principal be useful to filter search results, in the given task the results page did not indicate whether search criteria would be met or not. Thus lingering on a page that could not contribute to solving the task was in fact detrimental to succeeding.

Time on task and a dual processing framework

We derived our hypotheses on differential time on task effects both between and within domains by means of applying a dual processing framework to reading and problem solving items used in the PIAAC study. The hypotheses thus derived were confirmed, hence our results are consistent with the notion that positive time on task effects reflect the strategic allocation of

cognitive resources, whereas negative time on task effects reflect the degree of automatization. Although the findings are entirely consistent with the predictions derived from such a framework and further backed by analyses on a within-task level, this interpretation has to remain somewhat speculative for the time being. The information that can be gained from large scale computer-based assessments (although providing much more information than traditional paper-and-pencil based assessments) is still limited. Usually, the information stored in log files is ambiguous as to its interpretation in cognitive terms. In this article, we have assumed that taking more time on more difficult items indicates engaged cognitive processing. Other interpretations of the pattern of results are yet conceivable. For instance, it might be the case that time on task effects also reflect differences in motivation, that is, test takers do not only take *more time* to think about an item but also they think *harder* – resulting in a confounding between depth of processing and time taken. Related to that, Guthrie et al. (2004) consider time on task as an indicator of engagement, which means to read a text attentively, concentrated on the meaning, and with sustained cognitive effort. Issues such as these can only be resolved by combining the analysis of large scale process data with research tools allowing for an even more fine-grained analysis of cognitive processes, such as eye-movements or think-aloud techniques (see Rouet & Passerault, 1999). As a consequence, we aim at corroborating our results through experimental studies that combine actual large scale testing materials and still more fine-grained assessments of cognitive processes in the future.

Limitations

In the present study, test takers were free to adapt their speed-accuracy compromise both within and between items, which has consequences on the interpretation of the obtained results. As the speed level of test takers was not controlled, the obtained variation in the association between time on task and task success across items may be due to different item difficulties as

claimed in Hypothesis 2 or also due to within-person differences in the selected speed level across items. However, the latter explanation does not seem plausible as there is empirical evidence for the assumption of stationarity of speed when completing power tests (cf. e.g., Goldhammer & Klein Entink, 2011; Klein Entink, et al., 2009). Stationarity of speed is also implied by the fixed level of accuracy which is a standard assumption in item response models (cf. van der Linden, 2007).

As we did not manipulate the speed level of test takers experimentally, we cannot conclude that the predictor time on task has any causal effect on task success which, however, is suggested by the positive time on task effect in those items requiring a higher level of controlled processing. In contrast, in items that can be completed more automatically and for which a negative effect was revealed, time on task should rather be conceived as an indicator of competence in addition to the task result.

As another limitation, the sample size of the present study and the number of responses per item, respectively, was quite limited for testing measurement models. Therefore, future research should aim at replicating the findings based on greater samples, for instance from the PIAAC main study. Another important replication goal would be to investigate whether results on the time on task effect are comparable across countries.

In PIAAC the construct of problem solving in technology-rich environments was newly developed as well as the measurement procedure. Thus, future research will have to provide more information about this assessment's validity and its predictive power. Moreover, the relation of problem solving in PIAAC to other problem solving measures and their theoretical underpinnings require further clarification. There are several conceptual commonalities, for example, representing the difference between a current state and a goal state, defining a series of sub-goals and applying related non-routine cognitive and behavioral operations to transform the given state

into the targeted state, including progress monitoring. However, there are also remarkable differences. For instance, the construct of complex problem solving (cf. Funke & Frensch, 2007) assumes systems where complexity is defined by the number of elements and the relations among them. The problem solving process is comprised of the acquisition of knowledge by means of exploration and the application of the obtained knowledge. Although acquiring knowledge or information is also a key aspect of problem solving as defined in PIAAC, acquired knowledge in a complex problem solving task represents the explored system of elements and relations itself. In contrast, in PIAAC problem solving the explored system is just the medium carrying the information that is required to solve the task. However, an unfamiliar computer environment and unknown functionality would turn the problem solving in technology-rich environments task into a complex problem solving task (for technical problem solving see e.g., Baumert, Evans & Geiser, 1998). Regarding our findings on problem solving as proposed by PIAAC, future research needs to show whether the pattern of results holds true also for other conceptions of problem solving that, for instance, are anchored in cognitive theory (see e.g., Fischer, Greiff, & Funke, 2012) or used in other large-scale assessments like PISA (cf. Greiff, Holt & Funke, 2013).

Educational implications

The present study frames the meaning of time in information processing tasks by referring to models of and individual differences in skill acquisition. Therefore although the analyses are based on assessment items, our results allow for some tentative conclusions on educational procedures in reading and problem solving instruction. Our results indicate that for learning and applying higher level cognitive abilities, required component abilities should be well-routinized. If there is no established routine processing, for instance, when a poor reader encounters difficult reading items, information processing needs to rely on strategic processing as indicated by the reversed positive effect of time on task on task success. This means that for poor readers to be

successful, they need to switch to compensatory behaviors, that is, reducing reading rate, looking back in text, reading aloud, and pausing, and/or compensatory strategies, that is, shifting attention to lower level requirements and rereading text, to cope with their deficits (cf. Walczyk's, 2000, Compensatory-Encoding Model: "With enough time, any text can be vanquished!", p. 565).

From an instructional point of view this means that becoming a good reader or problem solver requires the development of self-regulatory and metacognitive skills necessary to know when an effortful, controlled processing mode is to be employed. In the controlled processing mode, appropriate compensatory mechanisms can be initiated that have been learned and incorporated before. This might, for example, mean that in the face of reading comprehension difficulties, a part of a text is re-read or in problem solving, time is taken to focus attention on relevant subgoals.

As the individual time on task effect is assumed to reflect the way of processing information, it may help to further describe the individual performance level and to identify instructional needs. As suggested in Fig. 4 (bottom left panel), average readers show a great variation in the time on task effect suggesting various levels of automaticity of component abilities. Moreover, the in-depth investigation of temporal patterns in highly interactive items can point to deficits in the information processing strategy (cf. Zoanetti, 2010). For instance, if in the "Job search" item log file data would reveal that a problem solver spends much time both on non-target pages and target pages, this pattern would suggest that they cannot process disconfirming information efficiently to quickly discard a non-target page.

From an educational measurement perspective, the present study suggests that the meaning of time on task is not uniform. Thus, when collecting time information across items and individuals that are heterogeneous in difficulty and ability level, respectively, the role of time and its interpretation may differ. Regarding item response models including time as a regressor, van

der Linden (2007) argued that time can only be interpreted uniformly as an indicator of speed if the items do not differ substantially in the amount of labor. In the present study where items differ considerably in the amount of information processing and problem solving, we take the different interpretations of time on task into account by letting its effect vary across items (random effect).

All in all, the analyses and results reported here illustrate the potentials that lie in exploiting time on task, or fractions of it, that become available through computer-based assessments. They do however also clarify that any process measure must be cautiously interpreted, at least by taking a closer look at the particular tasks and their demands. Regarding the two constructs studied here, reading literacy and problem solving in technology-rich environments, our study proves them to be quite different in terms of cognitive processing. Ability, item difficulty, and time on task do interact in different ways. As Wirth and Klieme (2003) have shown based on student assessment in a national extension to PISA, problem solving tests and especially computer-based problem solving tests, add to the traditional set of literacy dimensions. In structural models, problem solving can be clearly distinguished from traditional abilities. These structural analyses and our in-depth analyses of processing time provide evidence that problem solving abilities have to be separated from traditional educational outcomes such as reading literacy. Problem solving is one of the most prominent examples of cross-curricular, non-routine, dynamic "21st century skills" that are currently aimed at as educational goals and covered in large scale surveys. Claims that these new abilities are different from traditional outcomes have mainly been supported by pragmatic or philosophical arguments. Now, we see that even in terms of cognitive processing and time allocation, there is a difference between reading literacy and problem solving abilities.

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Table 1

Overview of main model parameters on the time on task effect and model comparison tests.

Domain	Research question/Hypothesis	Model	Time on task effect random across	χ^2 of model difference test, df in brackets	Fixed effect β_1	Variance of random effect	Correlation of random effects
Reading Literacy	Baseline model	M0	-		-.55***	-	-
	Testing Hypothesis 1 and 2: Time on task effect by domain and item	M1	Items		-.61***	.55	-.39
	Comparison with baseline model	M1 vs. M0		77.65 (2)***			
	Restricted model without random effect correlation	M1r	Items		-.59***	.54	-
	Comparison with unrestricted model	M1 vs. M1r		5.16 (1)*			
	Exploring the time on task effect by cognitive operation	M2	Cognitive operations		-.51***	.003	-1.00
	Restricted model without random time on task effect across cognitive operations	M2r			-.55***	-	-
	Comparison with unrestricted model	M2 vs. M2r		.79 (1) n.s.			
	Testing Hypothesis 3: Time on task effect by person	M3	Persons		-.59***	.14	-.65
	Comparison with baseline model	M3 vs. M0		15.09 (2)**			
	Restricted model without random effect correlation	M3r	Persons		-.57***	.09	-
	Comparison with unrestricted model	M3 vs. M3r		12.85 (1)**			
Problem	Baseline model	M0	-		.49***	-	-

Solving	Testing Hypothesis 1 and 2: Time on task effect by domain and item	M1	Items		.56*	.89	-.61
	Comparison with baseline model	M1 vs. M0		73.99 (2)***			
	Restricted model without random effect correlation	M1r	Items		.54*	.87	-
	Comparison with unrestricted model	M1 vs. M1r		6.50 (1)*			
	Testing Hypothesis 3: Time on task effect by person	M3	Persons		.51***	.22	-.79
	Comparison with baseline model	M3 vs. M0		5.98 (2)$^{+}$			
	Restricted model without random effect correlation	M3r	Persons		.49***	.12	-
	Comparison with unrestricted model	M3 vs. M3r		5.98 (1)*			

Note. *** p<.001 , ** p<.01 , * p<.05, $^{+}$ p<.10, n.s.= not significant.

Figure Captions

Figure 1. Sample items: Reading literacy item “Preschool rules” (upper panel); Problem solving in technology-rich environments item “Job search”, only the start page showing the search engine results is depicted but not the linked pages (lower panel).

Figure 2. Graphical representation of model M1 including as predictors a general intercept, relative item easiness, individual ability, as well as time on task for which the effect varies across items.

Figure 3. Distribution of estimated item easiness parameters for reading literacy (upper panel) and problem solving in technology-rich environments (lower panel). On average, reading literacy items were easier than problem solving items.

Figure 4. Upper row: Time on task effect by item for reading literacy (left panel) and problem solving in technology-rich environments (right panel). The solid line indicates the fixed time on task effect, the dots show how it is adjusted by item. For difficult items the time on task effect gets more positive whereas it gets more negative for easy items. Lower row: Time on task effect by person for reading literacy (left panel) and problem solving in technology-rich environments (right panel). The solid line indicates the fixed time on task effect, the dots show how it is adjusted by person. For less able individuals the time on task effect gets more positive whereas for able persons it gets more negative.

Figure 5. Time on task effect by item and skill level for reading literacy (upper panel) and problem solving in technology-rich environments (lower panel). For combinations of two items (easy vs. hard) with two persons (less able vs. able) the probability to obtain a correct response is plotted as a function of time on task.

Aufgabe 1 - Frage 1/3

Sehen Sie sich die Liste mit den Kindergartenregeln an. Beantworten Sie die folgende Frage durch Markieren der entsprechenden Stelle(n) in der Liste.

Um welche Uhrzeit sollten die Kinder spätestens im Kindergarten eintreffen?

Kindergartenregeln

Willkommen in unserem Kindergarten! Wir freuen uns auf ein großartiges Jahr mit viel Spaß, Lernen und gegenseitigem Kennenlernen. Bitte nehmen Sie sich einen Augenblick Zeit, um unsere Kindergartenregeln durchzusehen.

- Bitte sorgen Sie dafür, dass Ihr Kind bis 10.00 Uhr hier ist.
- Bringen Sie eine kleine Decke oder ein Kissen und/oder ein kleines Stofftier für den Mittagsschlaf mit.
- Ziehen Sie Ihr Kind bequem an und bringen Sie Kleidung zum Wechseln mit.
- Bitte keinen Schmuck oder Süßigkeiten. Wenn Ihr Kind Geburtstag hat, sprechen Sie bitte mit der Erzieherin Ihres Kindes über eine besondere Zwischenmahlzeit für die Kinder.
- Bitte bringen Sie Ihr Kind vollständig angezogen mit, nicht im Schlafanzug.
- Bitte tragen Sie sich mit Vor- und Zunamen ein. Dies ist eine Zulassungsvorschrift. Vielen Dank.
- Frühstück gibt es bis 8.30 Uhr.
- Medikamente müssen sich in beschrifteten Originalverpackungen befinden und in den Medikamentenbogen eingetragen werden, der in jedem Gruppenraum ausliegt.
- Falls Sie irgendwelche Fragen haben, wenden Sie sich bitte an die Erzieherin Ihrer Gruppe oder an Frau Mahler oder Frau Baum.

Aufgabe 1 - Teil 1

Sie suchen einen Job und haben diese fünf Internetseiten gefunden.

Sie möchten eine Seite nutzen, bei der Sie sich nicht anmelden und auch keine Gebühren zahlen müssen.

Speichern Sie alle Seiten als Lesezeichen, die Ihre Anforderungen erfüllen.

Wenn Sie die Seiten als Lesezeichen gespeichert haben, klicken Sie auf den Weiter-Pfeil, um fortzufahren.

Internet

Datei Bearbeiten Lesezeichen Hilfe

URL: www.suchergebnisse.de/jobsuche

Suchergebnisse

Jobsuche

Finden Sie Ihren neuen Job - JobSuche.de
Die beste Internetseite für Jobsuchende. Suchen Sie zuerst bei uns!
www.jobsuche.de

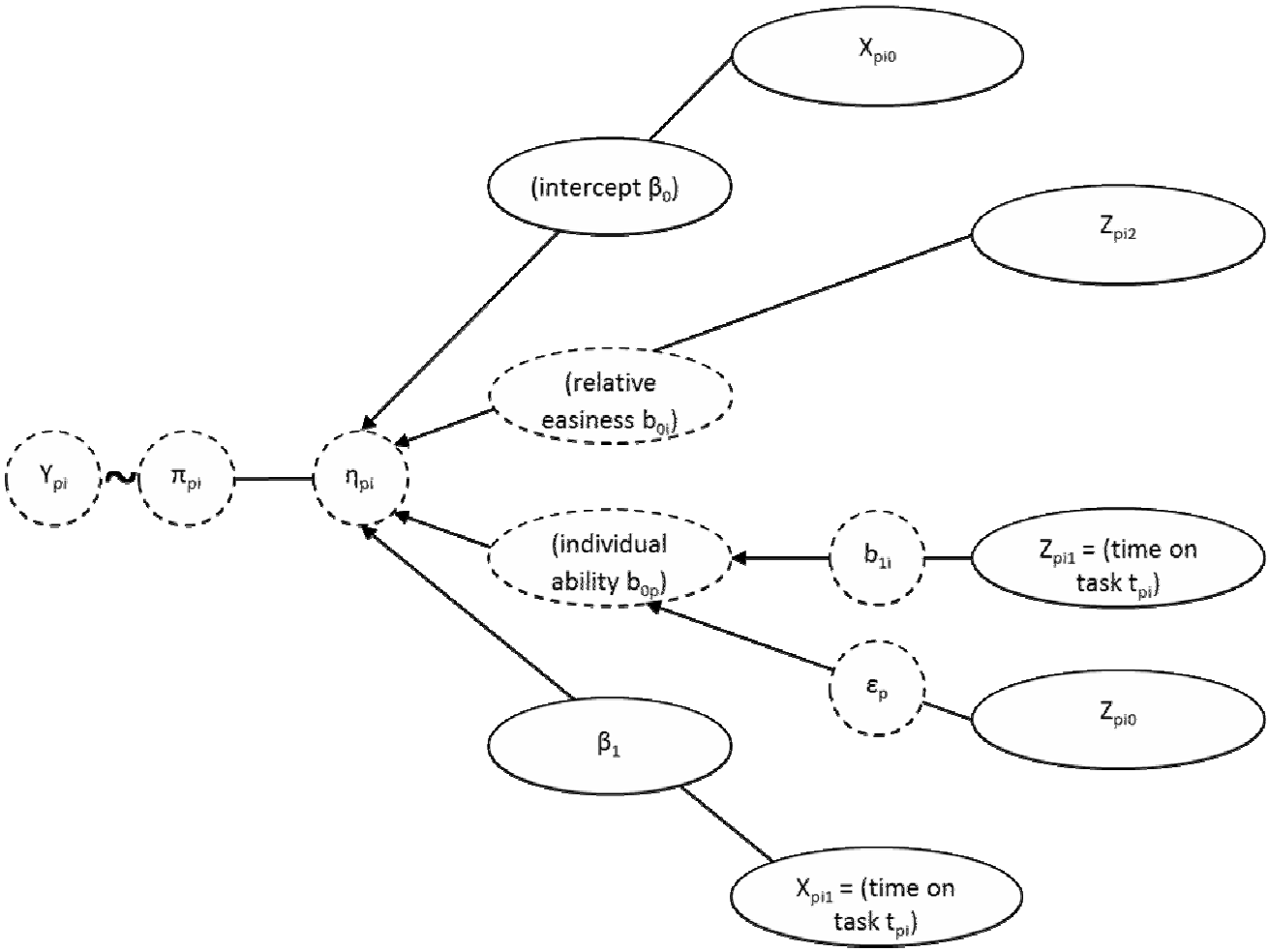
JobAgent
Bei uns finden Sie die besten Jobs im Internet.
www.jobagent.de

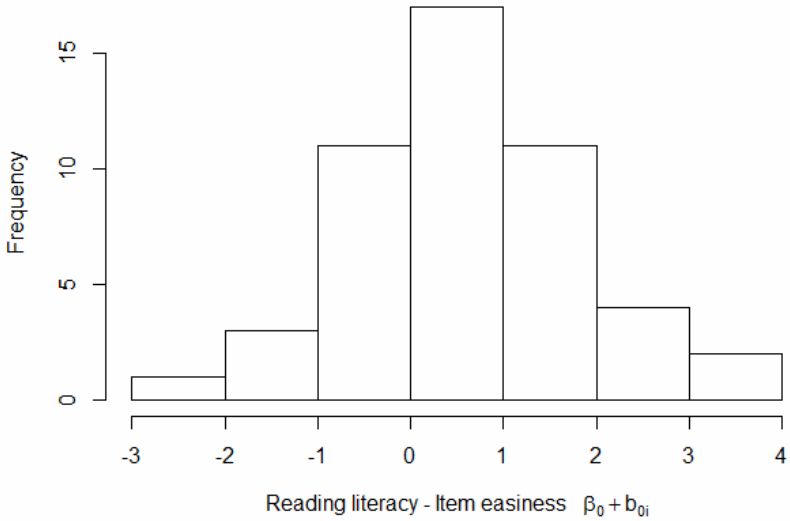
Auf Jobsuche?
Starten Sie Ihre Jobsuche bei uns.
www.jobservice.de

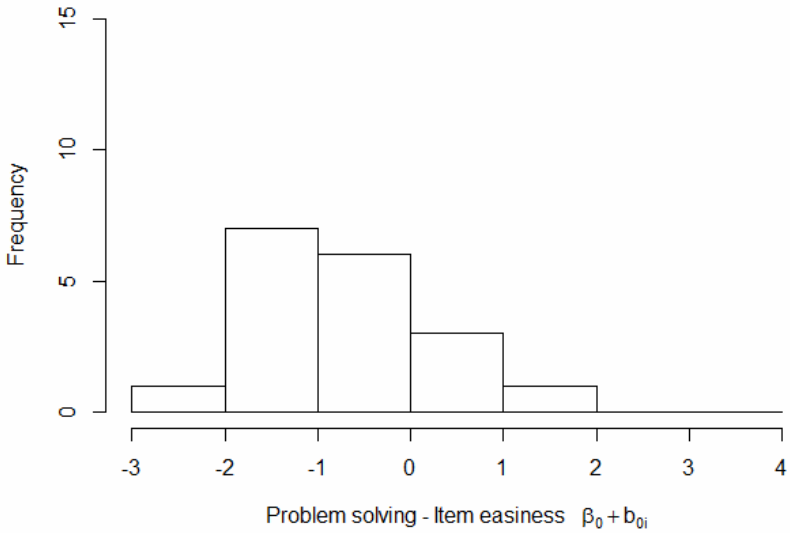
Karrierestart.de
Der Stellenmarkt für die besten Jobs.
www.karrierestart.de

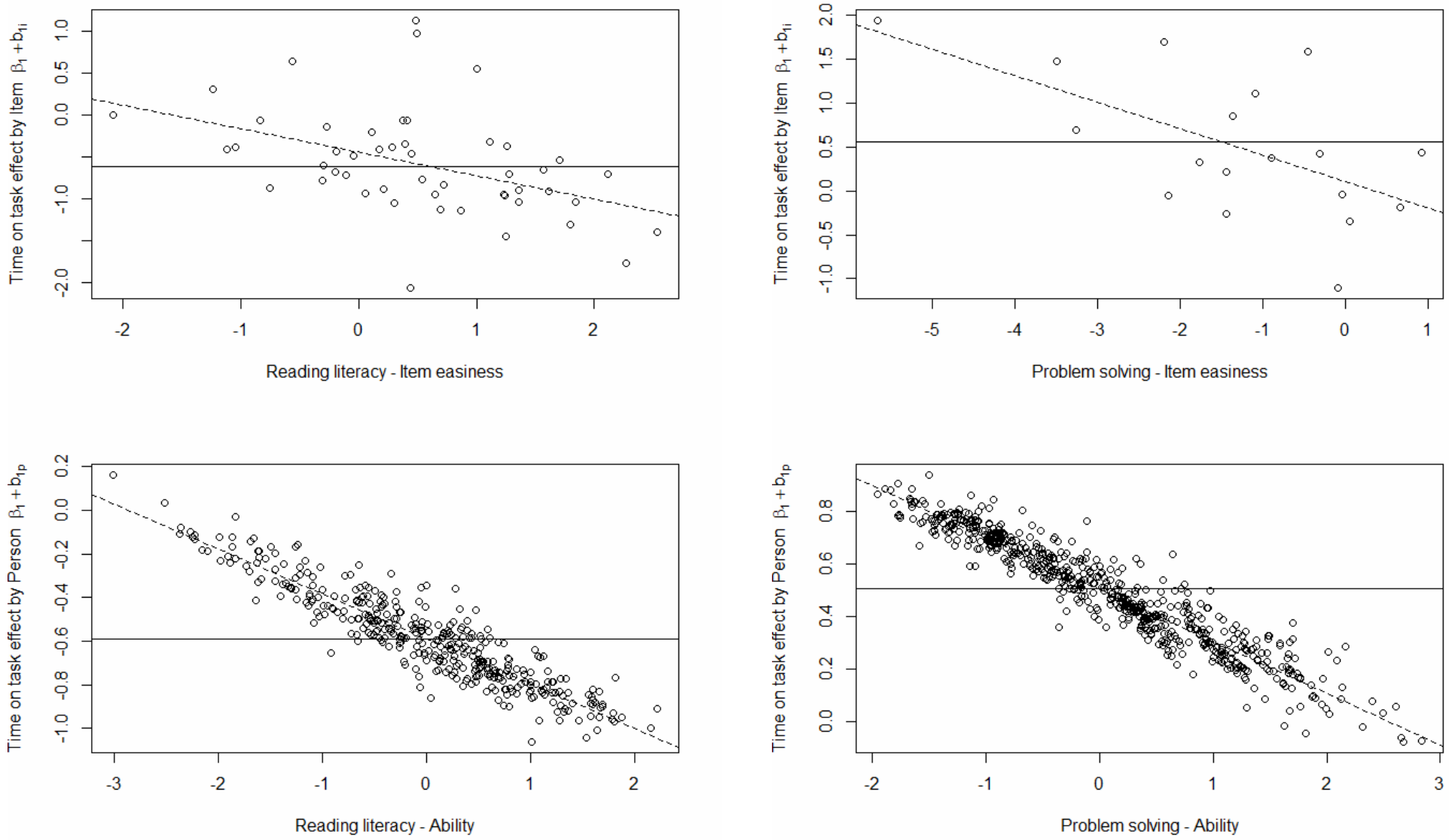
Traumjobs online
Wenn Sie den perfekten Job für sich suchen, sind Sie hier genau richtig.
www.megajobs.de

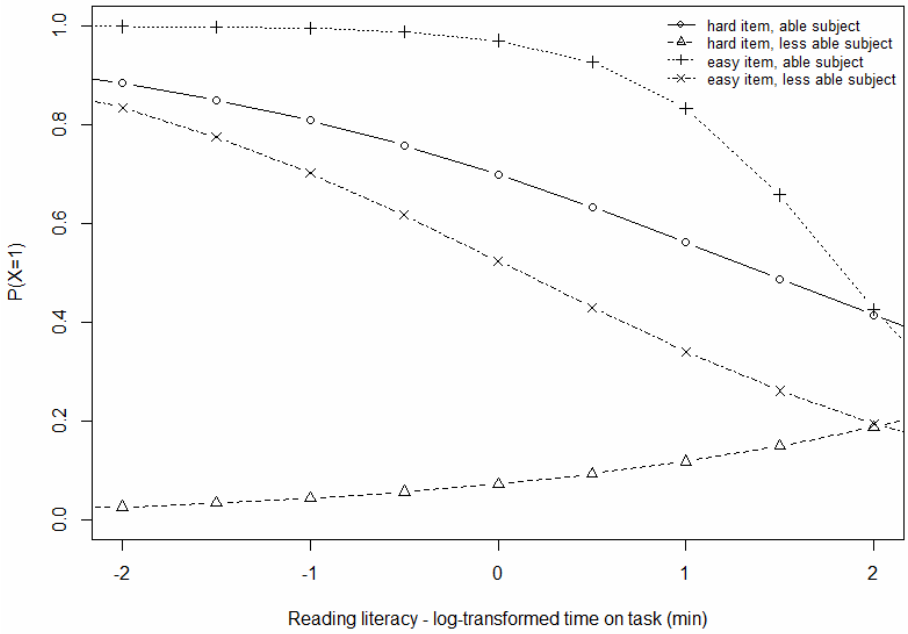
Internet

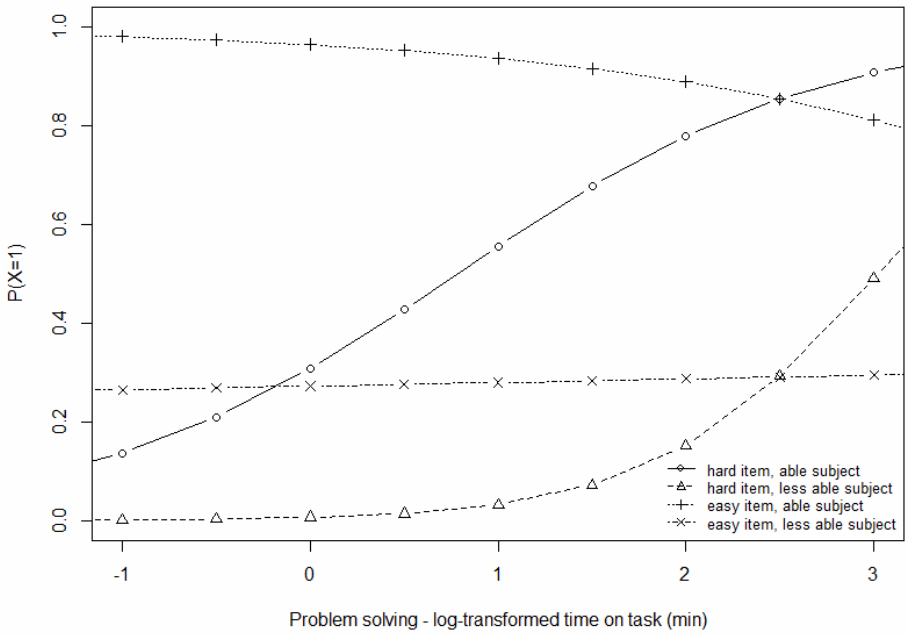

X_{pi0}
(intercept β_0)
Z_{pi2}
(relative easiness b_{0i})
Y_{pi}
π_{pi}
η_{pi}
(individual ability b_{0p})
b_{1i}
Z_{pi1} = (time on task t_{pi})
ε_p
Z_{pi0}
β_1
X_{pi1} = (time on task t_{pi})


Frequency
0
5
10
15
-3
-2
-1
0
1
2
3
4
Reading literacy - Item easiness $\beta_0 + b_{0i}$


Frequency
0
5
10
15
-3
-2
-1
0
1
2
3
4
Problem solving - Item easiness $\beta_0 + b_{0i}$


Time on task effect by Item $\beta_1 + b_{1i}$
Reading literacy - Item easiness
Time on task effect by Item $\beta_1 + b_{1i}$
Problem solving - Item easiness
Time on task effect by Person $\beta_1 + b_{1p}$
Reading literacy - Ability
Time on task effect by Person $\beta_1 + b_{1p}$
Problem solving - Ability


hard item, able subject
hard item, less able subject
easy item, able subject
easy item, less able subject
P(X=1)
0.0
0.2
0.4
0.6
0.8
1.0
-2
-1
0
1
2
Reading literacy - log-transformed time on task (min)


hard item, able subject
hard item, less able subject
easy item, able subject
easy item, less able subject
P(X=1)
0.0
0.2
0.4
0.6
0.8
1.0
-1
0
1
2
3
Problem solving - log-transformed time on task (min)