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Why Knowledge is Relevant in Real-World Settings: Innovative Approaches to Examine the Knowledge-is-Power Hypothesis

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Abstract

Domain-specific knowledge contributes to individual differences in many cognitive tasks. Research suggests that the underlying mechanisms might best be described with the knowledge-is-power hypothesis, claiming that prior knowledge facilitates the acquisition of new knowledge. However, investigations of this effect are often restricted to narrow low-stakes settings. This thesis aims to examine the knowledge-is-power hypothesis in more naturalistic and educational settings.

First, the influence of domain-specific knowledge on comprehension of new information was tested with an innovative assessment capitalizing on the internet. In order to investigate individual differences in digital literacy, test-takers were presented with health-related comprehension problems. Instead of reading a given text, they were instructed to search the internet for the information required to answer the questions. The relationship between this newly developed test and fluid and crystallized intelligence was investigated, while controlling for computer usage. Prior knowledge strongly influenced digital literacy. Together with fluid intelligence digital literacy could be explained exhaustively while computer usage did not add to the variance explained.

A crucial time for learning processes and knowledge acquisition is the transition from school to work. Despite the relevance of this transition period, studies about the prediction of educational performance in vocational schools are scarce. Knowledge acquisition in vocational education and training (VET) was be predicted by cognitive abilities such as knowledge and reasoning as well as the non-cognitive construct of typical intellectual engagement. Differences in domain-specific knowledge were predicted for different stages of VET (1st year, 2nd year and 3rd year) and in distinct vocational domains. Crystallized intelligence emerged as the strongest predictor for all vocational domains and at every stage of VET while reasoning showed moderate to weak effects and typical intellectual engagement did not add to the variance explained at all.

Overall, the knowledge-is-power hypothesis is supported even in broader and more naturalistic settings but seems to depend on several conditions such as the distinction between typical behavior and maximal effort and the constraints on the testing situation.

1. Introduction

Knowledge is an integral factor in contemporary and consensual theories on the structure of intelligence (Horn & Noll, 1997; McGrew, 2009) as crystallized intelligence (*gc*). However, definitions and operationalization of *gc* differ greatly, depending on the theoretical framework. As determined by the respective theory, *gc* has been conceptualized as a broad factor, including skills and knowledge in diverse content domains (Cattell, 1943), or mainly defined by verbal abilities (Carroll, 1993). It has even been argued that *gc* may be identical to verbal abilities (Kan, Kievit, Dolan, & van der Maas, 2011). However, this has been considered to be inadequate and insufficient as an operationalization of *gc* (Schipolowski, Wilhelm, & Schroeders, 2014). Due to the different conceptualizations of *gc* in various studies, it becomes unclear to what extent results are comparable across studies. This would also affect the associations with relevant related constructs such as fluid intelligence. In the following, the conceptualization of fluid and crystallized intelligence in major theories of intelligence will be presented. The subsequent sections focus on the knowledge-is-power hypothesis and contextualized approaches to the prediction of knowledge acquisition.

1.1. The Theoretical Conceptualizations of Fluid and Crystallized Intelligence

The concept of *gc* was first introduced by Cattell (1943) who distinguished two broad factors of intelligence: fluid intelligence (*gf*) which can be defined as decontextualized reasoning ability and “shows itself in successfully educing complex relations among simple fundaments whose properties are known to everyone” (Cattell, 1971, p.98), while crystallized intelligence is understood as a comprehensive knowledge factor, describing the influences of learning, education and acculturation in various domains including language (Cattell, 1971). The *Gf*-*Gc* theory was extended to include more constructs besides *gf* and *gc* (Horn, 1988; Horn & Noll, 1997) but the conceptualization of *gc* remained focused on acculturated knowledge. In the Cattell-Horn framework, measurements of *gc* typically included both knowledge and language tests. However, more specific language skills such as spelling or grammar supposedly captured a separate factor (Horn, 1988). In this framework, *gf* represented the ability to "arrive at understanding relations among stimuli, comprehend implications, and draw inferences" (Horn & Noll, 1997, p.69). While contemporary conceptualizations of gf include inductive and deductive reasoning as well as working memory performances (Horn & Noll, 1997), other conceptualizations claim that non-figural reasoning tasks are instead closely related to *gc* (Horn, 1998). However, more recent studies have concluded that while figural reasoning is generally considered prototypical of *gf*, a broad assessment of this construct should also include verbal and numerical reasoning (Wilhelm, 2004).

Carroll's (1933) Three-stratum theory placed *gf* and *gc* on the second stratum below a general intelligence factor. *Gc* was primarily defined by language-related abilities such as "verbal or printed language comprehension (V)", "lexical knowledge (VL)", "reading comprehension (RC", "listening ability (LS)", and "writing ability (WA)". Still, Carroll (1933) repeatedly remarked on the close association between vocabulary and knowledge tests. This close relation might be due to similarities in their operationalization and the respective acquisition processes of vocabulary and declarative knowledge. However, it was also argued that this relationship might not be a logical necessity since good language comprehension skills can be achieved even without acquiring general knowledge. In the Three-stratum theory, three abilities of the first stratum indicate fluid intelligence: sequential reasoning, inductive reasoning and quantitative reasoning. Compared to the *Gf*-*Gc* theory, a distinction is made between inductive and deductive thinking. Sequential reasoning marks deductive thinking and is almost entirely based on verbal tasks (Carroll, 1994).

The Cattell-Horn-Carroll (CHC) theory is both a synthesis and an extension of the Three-stratum theory and the extended *Gf*-*Gc* theory. It distinguishes between language skills and factual knowledge (McGrew, 2009; Schneider & McGrew, 2012). The *gc* factor is one of four broad constructs representing acquired skills and knowledge and captures "the knowledge of the culture that is incorporated by individuals through a process of acculturation" (McGrew, 2009, p.5). Domain-specific knowledge is captured in a separate factor (*gkn*) and described as deeply specialized knowledge (or 'expertise') acquired on a specific subject matter that does not typically represent the knowledge of the individuals culture (McGrew, 2009). However, this distinction between *gc* and *gkn* is debatable, especially since the definition of 'expertise' is vague and the conceptualization of *gkn* includes factors such as "Knowledge of culture" and "General science information" (Schneider & McGrew, 2012, p.125). Furthermore, there are distinct factors for quantitative knowledge (*gq*) and reading and writing skills (*grw*). All four factors are covered by Cattell's original definition of *gc* and Schneider and McGrew (2012) also believed it reasonable to consider a higher-order knowledge factor that unites *gcm*, *gkn*, *gq*, and *grw*.

1.2. The Knowledge-is-Power Hypothesis

Even though the distinction of domain-specific knowledge from a general knowledge factor is not clear-cut, domain-specific knowledge is often considered to be a main contributor to individual differences in many cognitive tasks. Research suggests that the underlying mechanisms might best be described with the knowledge-is-power hypothesis, claiming that prior knowledge facilitates the acquisition of new knowledge in a specific domain (Hambrick & Engle, 2002). The mechanisms behind this hypothesis will be explained in more detail in Chapter 2. So far, investigations of this effect are often restricted to narrow low-stakes settings such as baseball (Hambrick & Oswald, 2005) or chess (Chase & Simon, 1973). While these settings are certainly useful to clearly distinguish between experts and novices, broader settings would help to investigate the general assumptions of the knowledge-is-power hypothesis in more naturalistic environments. Therefore, the primary aim of this thesis is to examine the knowledge-is-power hypothesis in more naturalistic and educational settings. The first part focuses on the influence of domain-specific knowledge on the acquisition and comprehension of new information, examined with an innovative assessment capitalizing on the internet. The ability to comprehend new information is closely related the successful acquisition of new knowledge (Best, Rowe, Ozuru & McNamara, 2005; Ozuru, Dempsey & McNamara, 2009; Schroeders, Buchholz, Formazin, & Wilhelm, 2013). Online information procurement constitutes a key aspect of accessing new information in school as well as working life and even in our leisure time. In order to investigate individual differences in the ability to search for and process information, a contemporary assessment would require a test that enables the measurement of contextualized comprehension ability in a more realistic and innovative way e.g. by using contemporary technology like the internet. Many paper-pencil assessments have been transferred to the computer without adjustments to the new medium. Furthermore, most tests regarding comprehension ability are reduced to reading comprehension tasks. This restriction to linear texts and the use of fixed stimuli is an unnecessary limitation in the operationalization and might lead to the erroneous assumption that reading is essential or determinant for the processing of comprehension problems. On the contrary, comprehension ability can be understood as the process of developing mental representations, by which prior long-term knowledge is colligated with the available information given through text, audio or video through complex mental processes (van den Broek, 2010; van den Broek & Kendeou, 2008).

With the use of the internet, a more realistic and innovative assessment without fixed stimuli might be possible. Instead of highly artificial simulation environments, participants could be presented with tasks in a specific domain (e.g. medicine/health). Despite the apparent relevance of the aforementioned comprehension ability, there are several research questions that have not been answered yet. Aside from the role of the test medium for the processing of comprehension problems (Higgins, Russel & Hoffmann, 2005; Pomplun, Frey & Becker, 2002; Schroeders & Wilhelm, 2011), this includes particularly the factorial structure of comprehension ability (Schroeders, Buchholz, Formazin, & Wilhelm, 2013; Schroeders, Wilhelm, & Bucholtz, 2010; Senkbeil, Ihme, & Wittwer, 2013). The use of contemporary technology for a momentary and ecological assessment of cognitive abilities seems especially important for an investigation of real-world outcomes in today's information society.

1.3. Knowledge Acquisition in Educational Contexts

As mentioned before, the acquisition of new knowledge is important during all times in our lives. A crucial time for learning processes and knowledge acquisition is the transition from school to work. In many cases, the transition between school and work takes place in form of vocational education and training (VET). Obviously, the success of VET is of importance for both the trainee and the future employer. During three years on average, the students work half-time at an enterprise and go to school during the rest of the time. The classes are geared to specific occupations, providing lessons in general (e.g., Math, English, German) as well as job specific subjects (e.g., Accounting, Software Development). When determining success in vocational education, the job-specific aspects of knowledge acquired in the course of the three years are especially interesting. It should be noted however that acquisition of job-specific knowledge is not all there is to VET. Non-cognitive aspects like affective and motivational facets are further correlates of educational and vocational success (Mount, Barrick, Scullen, & Rounds, 2005). Despite the relevance of this transition period between school and work, studies about the prediction of educational performance in vocational schools are scarce. Therefore, the second part of this thesis aims to add to the literature on VET by investigating vocational knowledge in three distinct professions.

How do people acquire high-level skills in certain domains? What are the predictors of individual differences in scholastic, academic, and occupational success? In order to establish a meaningful predictor model, reliable predictors are necessary. Cognitive abilities belong to the best established predictors of educational and vocational success in social sciences (see Schmidt & Hunter, 1998; Schmidt, 2002). Vocational knowledge acqusition in VET can be explained, for the most part, by fluid and crystallized intelligence. Fluid intelligence is considered to be the ability to reason and often regarded to be essential and prototypical for general cognitive ability (Gustafsson, 1984; Marshalek, Lohman & Snow, 1983). Fluid abilities have proven to be primary predictors of cognitive performances such as mathematical problem solving and verbal comprehension (cf. Jensen, 1998). Cattell's theory of crystallized and fluid intelligence provides a theoretical framework for knowledge as a part of intelligence. In line with this concept, knowledge would be located in the factor of crystallized intelligence. In tradition with this conceptualization of crystallized intelligence as general knowledge, it should be measured as knowledge across several domains (Cattell, 1971; Schipolowski, Wilhelm, & Schroeders, 2014).

The acquisition of new knowledge is the focus of a plethora of research regarding learning processes and closely tied to expertise research. The Cattell-Horn-Carroll (CHC) theory provides context for expertise. According to this framework, expertise can be understood as "specialized knowledge domains developed through intensive systematic practice and training (over an extended period of time) and the maintenance of the knowledge base through regular practice and motivated effort" (McGrew, 2009, p. 6). It has been argued that the specificity of knowledge might be relevant for the prediction of higher-order cognitive performance (Hambrick & Engle, 2002), in the context of the knowledge-is-power hypothesis. Knowledge tests are well validated and established selection criteria for college admission (Camara & Echternacht, 2000) and well established to predict academic performance (Kuncel, Hezlett, & Ones, 2001; Kunina, Wilhelm, Formazin, Jonkmann, & Schroeders, 2007). However, it is still unclear to what extent the assumptions of the knowledge-is-power hypothesis depend on conditions such as the testing environment or the depth of knowledge, especially in broader and more naturalistic settings. Furthermore, knowledge is often excluded from intelligence assessments. A great body of literature claims that general intelligence is more relevant than knowledge for the prediction of academic success. This is mostly due to the assumption that decontextualized reasoning abilities are equivalent with a general intelligence factor. Not only does this result in a tremendous loss of information on relevant outcome variables but also ignores the fact that general intelligence includes rather than excludes knowledge (Carretta & Ree, 1996; Ree, Carretta, & Teachout, 1995, Stauffer, Ree, & Carretta, 1996). To sum up, the aim of this thesis is to investigate the knowledge-is-power hypothesis in ecologically valid settings and emphasize the importance of knowledge in an intelligence framework for real-world outcomes.

1.4. The Thesis' Structure

The present thesis is structured in a theoretical and an empirical part. The first three chapters describe the theoretical background of the thesis. The second chapter summarizes and compares perspectives on comprehension abilities and depicts the role of domain-specific knowledge and reasoning for the prediction of said abilities. This chapter further provides perspectives for contemporary assessments of comprehension abilities and knowledge acquisition and the possible linkage to the concept of digital literacy. A momentary ecological assessment of comprehension tasks capitalizing on modern technology is depicted. The third chapter provides a definition of domain-specific knowledge and expertise in the context of vocational education and training. Previous findings about the prediction of vocational knowledge acquisition by cognitive and non-cognitive constructs are reviewed in the context of the knowledge-is-power hypothesis. Theories of intelligence are discussed as well as the impact of investment traits on knowledge acquisition.

The empirical part of the thesis is divided in two major sections. The first part links domain-specific knowledge to digital literacy by investigating the knowledge-is-power hypothesis. A newly developed test of digital literacy without fixed stimuli is evaluated and the predictive power of intelligence, prior knowledge and computer usage are investigated. The second part of the thesis establishes a prediction model for domain-specific knowledge in VET, with a focus on health-related occupations. Invariance is tested across the three years of education and the predictive power of cognitive abilities and intellectual investment is tested across these groups. Furthermore, the results are compared to findings in the domains of business and technology.

Finally, the results are summarized and discussed in the context of the knowledge-is-power hypothesis and in the framework of contemporary intelligence theories. Implications for knowledge assessments in the “digital era” and consequences for career counseling are taken into account and limitations of the thesis are discussed.

2. Knowledge Acquisition in the Context of Comprehension Abilities and Digital Literacy

Chapter 2 has been published in Möhring, A., Schroeders, U., Leichtmann, B., & Wilhelm, O. (2016). Ecological Momentary Assessment of Digital Literacy: Influence of Fluid and Crystallized Intelligence, Domain-Specific Knowledge, and Computer Usage. *Intelligence, 59*, 170-172. doi:10.1016/j.intell.2016.10.003, with permission from Elsevier.

2.1. Introduction

The internet is a nearly ubiquitous available resource for the procurement of information. It profoundly changes the way people connect and access information (Fisher, Goddu, & Keil, 2015) and serves as an external memory that can easily be accessed if required (Sparrow, Liu, & Wegner, 2011). Given the abundance of online information, and its omnipresence in modern societies, the ability to search online for information has become almost indispensable. To illustrate, healthcare organizations are interested in empowering patients and involving them in treatment decisions (Hack, Degner, & Parker, 2005). This requires comprehension of medical knowledge for shared decision making and patient's compliance in general (Kienhues, Stadtler, & Bromme, 2011). Laypersons will usually have to deal with a large degree of uncertainty regarding alternative treatments. Therefore, they often turn to easily accessible information on the internet to foster their healthcare decisions (DeLenardo, 2004; Eysenbach, 2003). Our ability to represent, manipulate, and combine information indicates the extent to which we understand the information. Due to technological innovations, the way we access and use information to solve real world problems has radically changed. However, it is unclear whether available measurement approaches are able to sufficiently assess this digital literacy (Leu, Kinzer, Coiro, & Cammack, 2004).

The abilities challenged in tests of reading comprehension are arguably the closest relatives to what is required when trying to solve real world problems based on access to information from the internet. Despite the apparent relevance of comprehension abilities for solving these real world problems, there are several specific research questions that have to be answered conclusively before we can infer whether comprehension tasks can be appropriate measures of digital literacy or not. This particularly includes the question as to what extent comprehension abilities can be described by a set of established cognitive ability factors when the required information has to be gathered through the internet. Therefore, with the present study, we aim to investigate, whether or not performance in a computerized comprehension test can be accounted for by fluid intelligence, relevant knowledge, and basic computer skills.

2.2.Comprehension abilities

Comprehension abilities can be understood as the process of developing mental representations, by which prior long-term knowledge is incorporated with the available information given through text, audio, or video through complex mental processes (van den Broek & Kendeou, 2008). Accordingly, comprehension can be considered to be an active and complex cognitive process. Consequently, comprehension shows strong relations with problem solving (Best, Rowe, Ozuru, & McNamara, 2005) and knowledge acquisition (van den Broek, 2010). Despite the fundamental role of comprehension abilities, its assessment is often restricted to reading or listening abilities relying on a fixed presentation of information. That means that participants are required to read a text, sometimes enriched with tables and figures, or listen to audio records, and subsequently answer questions based on that information. To answer these questions, different processing skills are required, such as simple retrieval of information or drawing conclusions from a paragraph (for a review of reading comprehension and its assessment see Pearson & Hamm, 2005). It should be noted that, while both reading and listening abilities are comprehension tasks, they rely on different input modalities (visual vs. auditory). However, under realistic conditions, information processing is not limited to a single modality. Therefore, restricting the assessment of comprehension abilities to this format limits the validity of the construct.

In principle, there are two perspectives, trying to explain the underlying nature of comprehension abilities. The modality-specific perspective assumes that information is processed via different pathways (Paivio, 1986; Mayer, 2005): one for auditory and the other for visual input. This implies that distinguishable latent constructs should be underlying reading and listening comprehension abilities. This distinction has been especially significant for the theory of multimedia learning (CTML, Mayer, 2005), which claims that using input that depends on both visual and auditory stimuli (e.g. videos) would place a heightened cognitive load on participants and therefore diminish the performance. However, studies on the modality-specific perspective are often limited by only taking into account the mean structure. This neglects the fact that enriching stimuli with additional information affects the complexity and therefore the difficulty of the task.

The second perspective on comprehension abilities is the modality-unspecific perspective. It states that comprehension ability is independent from the means of the information input. Thus, reading and listening comprehension would be explained by one general latent construct of comprehension ability. There have been recent investigations on the question of the factorial structure of comprehension abilities (Schroeders, Buchholz, Formazin, & Wilhelm, 2013). Structural equation modeling was used to evaluate the correlations between different comprehension abilities and established cognitive constructs. Not only do the results show almost perfect correlations between reading and listening comprehension but also manage to relate them to a comprehension task called viewing comprehension - also known as video comprehension (Wagner, 2010) or multi-media comprehension tasks (Schnotz, 2005) - that encompasses both visual and auditory input

(Schroeders, Wilhelm, & Bucholtz, 2010). Overall, these results suggest that one factor is sufficient to explain the individual differences in comprehension abilities.

Contemporary comprehension tasks should combine different modalities such as viewing comprehension tasks. In the assessment of viewing comprehension, participants have to gather information from a video, relate the extracted bits of information to each other, and connect them to prior knowledge. Despite their high face-validity and sound psychometric properties, viewing comprehension tasks are rarely used (Schroeders, Bucholtz, Formazin, & Wilhelm, 2013; Schroeders, Wilhelm, & Bucholtz, 2010). Even though in viewing comprehension tasks visual and auditory information comprehension is jointly assessed, the tasks are still restricted to the information provided in the item stimulus without the participant actively searching for suitable information. In real life, however, we often deal with inconsistent (Eysenbach, 2003) or unreliable (Bates, Romina, Ahmed, & Hopson, 2006) sources of information. These and similar aspects of comprehension abilities are not reflected in the design of traditional paper-pencil reading comprehension tests.

2.3.Fluid and crystallized intelligence as predictors of comprehension abilities

Despite the different conceptualizations, comprehension abilities show a strong theoretical and empirical overlap with cognitive abilities. Both fluid intelligence (McKeown, Beck, & Blake, 2009; O'Reilly & McNamara, 2007) and domain-specific knowledge (Kendeou & van den Broek, 2007; Ozuru, Dempsey, & McNamara, 2009; Surber & Schroeder, 2007) have been repeatedly shown to be influential for successful mental representations of text. *Gf*, the ability to reason, is strongly related or synonymous with working memory capacity (Kyllonen & Christal, 1990; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002) and substantially correlated with comprehension abilities (Rost, 1985, p. 55). *Gf* is also often regarded as prototypical for general cognitive ability (Gustafsson, 1984;

Marshalek, Lohman, & Snow, 1983). According to Cattell's investment theory (e.g., Cattell, 1943; Horn & Cattell, 1966, 1967), fluid abilities are invested to acquire knowledge, i.e. they are needed to develop crystallized abilities.

Domain-specific knowledge, a core facet of *gc*, should be seen as an important prerequisite for higher-order cognitive performance (Hambrick & Oswald, 2005). *Gc* can be regarded as acculturated knowledge across a broad range of domains (Cattell, 1971; Schipolowski, Wilhelm, & Schroeders, 2014). Compared to decontextualized cognitive abilities, such as *gf*, domain specific knowledge seems to be more important for the prediction of cognitive achievement (Hambrick, 2003, 2004), which is expressed in the "knowledge-is-power" hypothesis. Hambrick (2003) found prior knowledge exerted a strong influence on knowledge acquisition in the field of basketball. The study suggested that new knowledge was integrated into a framework of prior knowledge. Other studies showed that expert knowledge facilitates information retrieval within a domain, such as chess positions (Chase & Simon, 1973), maps (Gilhooly, Wood, Kinnear, & Green, 1988), and music (Meinz & Salthouse, 1998). Furthermore, domain-specific knowledge seems to promote reading comprehension on the subject matter (Adams, Bell, & Perfetti, 1995).

In summary, both knowledge and fluid intelligence can be expected to contribute to individual differences in comprehension abilities. The predictive power of *gf* and *gc* depend on the specific context, that is, the age and the ability of the sample (Ackerman, 2000; Beier & Ackerman, 2005), the specific comprehension abilities items (Ackerman, 2000), the way *gf* and *gc* are assessed, and the way in which the data are modeled (Brunner, 2008). For instance, Schroeders et al. (2013) found a strong effect of *gf* on video-based comprehension, but the effect of *gc* was somewhat reduced arguably because all participants were given the same information through the item stem. However, in real life settings, exhaustive information required to solve the problem is usually not provided. The way in which we search for and process relevant information is pivotal for learning outcomes in school, at work, and during our spare time (Kuhlemeier & Hemker, 2007). Therefore, contemporary measures of comprehension abilities should comprise the ability to search for and process information. Thus, the measurement of comprehension abilities in a realistic and innovative setting would rely on the use of information technology.

2.4.The role of the new media for the assessment of comprehension abilities

During the last two decades, there has been an increased effort to adjust the traditional concept of reading comprehension to the reading of electronic texts (e.g., Coiro, 2003). In this context, *Information Communication Technology* (ICT) literacy is often mentioned as a key component (Goldhammer, Kröhne, Keßel, Senkbeil, & Ihme, 2014; Katz & Macklin, 2007). ICT Literacy is defined as the ability to understand and work with modern information technology, such as the internet (International ICT Literacy Panel, 2002), and takes into account both declarative and procedural knowledge about hardware and software (Richter, Naumann, & Horz, 2010). ITC Literacy can be divided in the following seven components: define, access, evaluate, manage, integrate, create, and communicate. Each of these single components requires the interaction of both informational and technological competences. Within the context of digital literacy there are several terms to describe similar or overlapping constructs, such as digital competence (Cartelli, 2009), media literacy (Moore, 2013), media competence (Fedorov, 2011), computer competence (Richter, Naumann, & Horz, 2010), technology literacy (Davies, 2011), and others. Digital literacy is understood as an overarching concept encompassing several disciplines, amongst them information literacy, computer literacy, and technology literacy (for an overview see Covello, 2010). Overall, the concept of digital literacy is comprised of the intersecting areas technology (i.e. technological environments), cognition (i.e. access, selection and critical evaluation of information) and ethics (i.e. responsible interaction through ICT) (Calvani, Cartelli, Fini, & Ranieri, 2008). There are similar conceptualizations such as the differentiation between medium-related (formal and operational) and content-related (information and strategic) internet skills (van Deursen & van Dijk, 2009, 2010). Operational internet skills encompass the ability to operate an internet browser, search engines, and similar internet-based forms (i.e. different types of fields and buttons and submitting a form). Formal internet skills include navigation on the internet (such as the use of hyperlinks) and maintaining a sense of location while navigating on the internet. Content-related internet skills would contain the skills to locate required information, including the use of search options and queries as well as selecting necessary information and evaluating information sources (information internet skills). Furthermore, content-related internet skills encompass the ability to take advantage of the internet by means of developing an orientation towards a particular goal, taking adequate action and making the right decision to reach this goal and gaining benefits from this goal (strategic internet skills).

Traditional comprehension abilities can be expanded to the selection of relevant visual and textual information from digital sources, which is relevant for both information literacy and visual literacy. Information literacy describes the ability to find sources, analyze and synthesize the material and evaluate the source credibility. Visual literacy focuses on the ability to interpret and understand information presented in pictorial or graphic images and turn all types of information into visual input (Covello, 2010). In other words, both information and visual literacy include the ability to find and understand necessary information. While information literacy is focused on searching for information, visual literacy also includes communicational aspects. Another subdiscipline of digital literacy that overlaps with these constructs is media literacy which describes the ability to analyze and evaluate information of online as well as print media (Covello, 2010). Thus, the cognitive requirements of digital literacy correspond to the above outlined understanding of comprehension abilities. However, there are also differences between the assessments of comprehension abilities with print media vs. digital media that deserve attention.

In contrast to written texts, digital texts are often nonlinear, which should be more difficult in general and particularly difficult for subjects lacking prior knowledge (Salmeron, Canas, Kintsch, & Fajardo, 2005). Specifically with respect to health-related behavior, as is studied in the present paper, it is more the rule rather than an exception that the information is experienced as complex, fuzzy, and contradicting (Bråten, Strømsø, & Salmerón, 2011). Furthermore, because the almost unlimited information in the internet is also qualitatively diverse, the reader has to gather, evaluate, weight, and integrate information according to its perceived usefulness (Brand-Gruwel, Wopereis, & Walraven, 2009).

Usually, such an informational selection and integration process requires the evaluation of multiple documents. Rouet and Britt (2011) suggested a framework for multiple document comprehension: the MD-TRACE model (for Multiple Document Task-based Relevance Assessment and Content Extraction), which comprises five steps: 1) construction of a task model, 2) assessment of information need, 3) document processing, 4) creation of a task product, and 5) assessment of the task product. The third step is especially important in the multiple-document context, since it includes the integration of acquired information from different sources. Similarly, reading online documents can be seen as a special case of multiple document reading. One important aspect of working with digital documents on the internet is the ability to judge the trustworthiness of sources (Brand-Gruwel, Wopereis, & Vermetten, 2005). Findings from Rouet, Favart, Britt, and Perfetti (1997) supported the notion that high domain-specific knowledge is associated with a more comprehensive and accurate evaluation the credibility of information sources. Differently worded, the ability to evaluate the quality and appropriateness of online texts seems to develop jointly with domain expertise. This may be because readers with high levels of domain-specific knowledge require less effort to comprehend texts and are more capable to evaluate the sources in-depth. They also might comprehend the texts at a level necessary to make accurate judgements of their trustworthiness (Bråten et al., 2011).

Multiple-document comprehension relates to online document comprehension, since an information search on the internet usually entails the evaluation of multiple documents. Several predictors of digital literacy or online document comprehension have been discussed in the literature such as the evaluation of source information (Bråten et al., 2011), navigation behavior through online documents (Hahnel, Goldhammer, Naumann, & Kröhne, 2016), epistemological beliefs (Bråten & Strømsø, 2006), and basic computer skills (Goldhammer, Naumann, & Keßel, 2013). However, whether these factors explain any individual differences in such comprehension abilities over and above *gc* and *gf* is still an open question. A consistent result in the research on multiple document comprehension for both print and online documents is that people with lower levels of domain-specific prior knowledge tend to overlook relevant information or to evaluate the trustworthiness of a source based on superficial characteristics (Metzger, Flanagin, & Zwarun, 2003; Stadtler & Bromme, 2007). Processing of source information is in turn essential for understanding and integrating information from multiple documents (Bråten, Strømsø, & Britt, 2009; Sanchez, Wiley, & Goldman; Strømsø, Bråten, & Britt, 2010). Given that domain-specific knowledge and crystallized intelligence may only differ in their breadth (and are often used interchangeably in different research traditions), the findings provide a link between multiple documents literacy and intelligence research. The influence of *gc* on comprehension abilities is crucial for both traditional and multiple-document comprehension (O'Reilly & McNamara, 2007; Richter, Naumann, Brunner, & Christmann, 2005). In the same vein, *gf* is strongly related to the comprehension of multiple (online) documents (Naumann, Richter, Christmann, &

Groeben, 2008), because relating information of different documents reflects reasoning ability (Salmeron et al., 2005).

With the further spread of (mobile) electronic devices, more and more computer-based performance tests were developed to capture these supposedly new comprehension-related competencies such as multiple-document literacy. However, these measures often use highly artificial simulation environments instead of realistic conditions (Katz & Macklin, 2007; MCEETYA, 2007). For example, in the internet-delivered iSkills™ assessment (Katz, 2013; Katz & Macklin, 2007) different computer-related scenarios have to be solved using artificial e-mail, web-browser, or library databases. There are several disadvantages of such an approach – most importantly the huge effort needed to construct and implement items (Senkbeil, Ihme, & Wittwer, 2013; van Deursen & van Diepen, 2013). Besides these economic issues, ecological validity is threatened since the control of the environment severely limits the similarity of the task and reality. Simulation environments are highly artificial and differ from the internet, where no or very general restrictions concerning the information necessary to solve a certain problem exist (the same applies to information that is useless to solving a specific problem). Instead of using fixed stimuli, an ecological momentary assessment of comprehension abilities in the 21st century could rely on ecologically more valid material. An alternative, ecological and more realistic approach could simply use the internet as a dynamic real-life source of information. Participants could be given the task to solve specific problems with the help of the internet without any restrictions concerning available content.

To sum up, we suggest resigning control over the stimulus by removing the stimulus in comprehension items and instead only focus on administering questions that could be encountered in real life. By simply asking questions without providing materials, the acquisition of relevant and instrumental information becomes part of the task itself.

Furthermore, this should create a more naturalistic testing environment for the test taker instead of providing an enclosed minimum amount of information, limiting the test to a mere variation of a multiple choice testlet design.

3. Declarative Knowledge, Reasoning, and Typical Intellectual Engagement as Predictors of Vocational Knowledge

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3.1.Vocational Education and Training

Research on the knowledge-is-power hypothesis focuses on the facilitating effect of domain-specific knowledge on cognitive performances such as comprehension abilities (Vanderwood, McGrew, Flanagan, & Keith, 2002) or knowledge acquisition (Beier & Ackerman, 2005). However, there are only few studies investigating the question what factors contribute to the individual differences in domain-specific knowledge in contextualized high-stakes settings. The following part of this thesis aims to add to the research on the knowledge-is-power hypothesis in a broader setting. Vocational education and training is a crucial prerequisite for the successful transition from school to work. However, educational research often focuses on either primary or tertiary education. For example, research regarding medical education has mainly focused on medical students in different phases of their education by examining admission to medical schools and universities (Lievens, Patterson, Corstjens, Martin, & Nicholson, 2016; Schripsema, van Trigt, Lucieer, Wouters, Croiset, Themmen, Borleffs, & Cohen-Schotanus, 2017), performance in school (Schauber, Hecht, Nouns, Kuhlmey, & Dettmer, 2015), and the transition from university education to practice (Schmidt & Rikers, 2007).While physicians are undoubtedly of great importance for the health system, other health-related occupations are often neglected in research on medical education. More specifically, medical assistants are an important liaison between patients and physicians. In Germany, medical assistants mostly work in medical practices as assistants of physicians. The specific duties of a medical assistant vary depending on the type and size of the healthcare facility, and its specialization, but typically include the implementation of medical treatments as well as the maintenance and management of administrative work (for a comprehensive overview of tasks see Taché & Chapman, 2006; Taché & Hill-Sakurai, 2010). Successful graduation from vocational training programs, such as the medical assistant training, is a necessary prerequisite to start a professional career. Moreover, the specialized medical and health-related knowledge acquired during medical VET is important for later work performance (Hunter, 1983; Lievens & Patterson, 2011). Early dropouts of VET are both a personal risk for VET students and a cost factor for organizations offering VET. Empirical evidence has shown students with low training satisfaction or a mismatch between vocational interests and work requirements are more likely to leave VET without graduating (Judge, Thoresen, Bono, & Patton, 2001; Volodina, Nagy, & Köller, 2015). A more comprehensive understanding about factors contributing to VET success might improve career counseling and, in the long term, reduce dropout rates.

In Germany, VET is characterized by a combination of traditional education in vocational schools and training of hands-on skills in medical practice. The regular training period for medical assistants is three years with an interim exam after the second year and the final graduation exam at the end of the third year. The curriculum of medical assistants in the German federal state Baden-Wuerttemberg comprises a) medical terminology, b) assistance with diagnostic and therapeutic actions for various diseases, c) attending patients during preventive treatments, d) how to maintain patient confidentiality, e) medical data protection, f) legal regulations relevant for their profession, and g) occupational safety and health (Ministry of Education and Cultural Affairs, Youth and Sports of Baden-Wuerttemberg, 2005).To further these insights, the generalizability of our results will be tested by investigating VET students from two vocational domains, clearly distinct from health-related VET: information technology (IT) and business. VET in the IT domain encompasses a combination of electrical, data processing-related and commercial content. The curriculum focuses on the sections: 1) selection and installation of user software, 2) management of different programming environments and applications development, and 3) procurement and customer-oriented disclosure of information (Ministry of Education and Cultural Affairs, Youth and Sports of Baden-Wuerttemberg, 1999). Business-oriented VET courses appear as very diverse occupations. However the most popular business occupations (industrial managers, retail dealers, management assistants in wholesale and foreign trade) share common core content: 1) knowledge about marketing and sales strategies, 2) keeping records and monitoring predefined rules of action, and 3) conducting extensive calculations (e.g., Ministry of Education and Cultural Affairs, Youth and Sports of Baden-Wuerttemberg, 2008). Adding these distinct vocational domains to this investigation allows for a cross validation of the results from health-oriented VET and for the interpretation of group-specific relationships between cognitive and non-cognitive predictors and vocational knowledge.

3.2. Cognitive Abilities as Predictors of Knowledge Acquisition in Vocational Education and Training

The predictive validity of cognitive abilities for school and vocational success is one of the best established findings in social sciences. Numerous studies suggest that fluid and crystallized intelligence are crucial in various academic and occupational settings (Kuncel & Hezlett, 2007; Ree & Earles, 1991; Schmidt & Hunter, 1998). *Gf* is understood as a domain-general ability to reason and is strongly related with, or even synonymous with, working memory capacity (Kyllonen & Christal, 1990; Wilhelm, Hildebrandt, & Oberauer, 2013). Moreover, *gf* is often regarded as essential and prototypical for general cognitive ability (e.g., Marshalek, Lohman & Snow, 1983), which is a powerful predictor of college and university success as well as job performance (Kuncel & Hezlett, 2007; Ones, Viswesvaran, & Dilchert, 2004; Salgado et al., 2003). Accordingly, several studies found a common general factor - often called *g* - that accounted for about 60% of the variance in cognitive changes (for a comprehensive overview see Tucker-Drob, Briley, Starr, & Deary, 2014). For health-related education, Reeve and Basalik (2014) found a substantial impact of cognitive ability as assessed with traditional *gf* tests for the prediction of several outcomes related to health literacy (i.e. “the ability to obtain, process, and understand basic information and services need to make appropriate health decisions”, p.94), but no significant increment of specific health knowledge over and above *gf*. However, the significance of *gf* has rarely been investigated in VET settings. Furthermore, performance on nonverbal reasoning or working-memory measures is often taken as a proxy and equated with intelligence (Furnham & Monsen, 2009; Laidra, Pullmann, & Allik, 2007), although in the context of medical education and work such a narrow operationalization likely results in a biased assessment of intelligence.

Besides *gf*, *gc* is another prominent factor in consensual theories on the structure of intelligence (Carroll, 1993; Horn & Cattell, 1966; McGrew, 2009). *Gc* is defined as acculturated knowledge across a broad range of domains (Cattell, 1971; Schipolowski, Wilhelm, & Schroeders, 2014). While *gc* is conceived as domain-general, people usually acquire in-depth knowledge or expertise in only a few domains (Kanfer and Ackerman, 2004). This would suggest that individuals develop a specific profile of their declarative knowledge according to their actual learning experiences and interests. Whereas such learning opportunities seem homogeneous in school (Schroeders et al., 2015), after regular school education, individuals attend different educational paths and presumably develop distinct knowledge structures with little overlap (Kanfer and Ackerman, 2004). In the framework of the Cattell-Horn-Carroll (CHC) theory, domain-specific knowledge is captured with a separate factor and described as deeply specialized knowledge acquired on a specific subject (see also McGrew, 2009). If these considerations are accurate, medical assistant students should acquire specialized vocational knowledge, which constantly increases throughout the specialized education and later working life, and diminishes with retirement (Ackerman, 1996). However, this process of vocational knowledge acquisition is unrelated or even negatively related to knowledge acquisition in other fields, independent of the specific vocational domain. Cattell (1963) described the relations among *gf*, *gc*, and academic achievement in the Investment Theory, stating that fluid abilities are invested in the development of crystallized abilities. The coupling between *gf* and *gc* should be especially strong in earlier school years but decreases during late childhood and adolescence. In a comprehensive review, Baumert, Lüdtke, Trautwein, and Brunner (2009) concluded that domain-specific knowledge contributes to the performance in educational settings over and above fluid intelligence and that its influence is becoming more important with ongoing education.

Such findings corroborate with the knowledge-is-power hypothesis stating that cognitive endeavors in a specific domain are best predicted by domain-specific knowledge rather than more general cognitive abilities such as fluid intelligence (Hambrick & Engle, 2002). Accordingly, more knowledgeable students are better at acquiring new knowledge than students with less prior knowledge (i.e., Matthew effect, see Schroeders, Schipolowski, Zettler, Golle, & Wilhelm, 2016). The underlying mechanisms include a more accurate retrieval, deeper integration, and faster processing of new knowledge within a given domain. Although the hypothesis has initially been formulated in a general way, it has been tested solely in highly-specific contexts (e.g., Chase & Simon, 1973; Hambrick & Engle, 2002). For example, Hambrick (2003) showed that prior basketball knowledge facilitated the acquisition of new basketball knowledge, whereas the effect of *gf* on learning was negligible. However, compared to specific sport-related knowledge, vocational knowledge is much more heterogeneous and detailed, including metacognition and social skills (e.g., organizing, empathetic respond to patients' or clients' needs). Thus, it is possible that *gc* and *gf* predict knowledge acquisition differently in broader educational and ecological valid settings as described in the power-is-knowledge hypothesis. This raises the question: To what extent can the knowledge-is-power hypothesis be generalized to a more complex real-life setting?

3.3. Investment Traits as Predictors of Knowledge Acquisition in Vocational Education and Training

Non-cognitive aspects such as affective and motivational factors significantly correlate with relevant criteria of educational and vocational success such as dropout intention, job change, or job satisfaction (Barrick & Mount, 1991; Barrick, Mount, & Judge, 2001; Verquer, Beehr, & Wagner, 2003). One prominent candidate that is often discussed in the educational context is *Typical Intellectual Engagement* (*TIE,* Ackerman & Goff, 1994), which is defined as the desire for intellectual activity and interest in understanding complex issues (Wilhelm, Schulze, Schmiedek, & Süß, 2003). People with higher levels of *TIE* are expected to perform better in academic and occupational settings. This personality trait is supposed to impact knowledge acquisition and academic achievement (Ackerman, 1996). Empirically, *TIE* is moderately associated with academic performance (von Stumm, Hell, & Chamorro-Premuzic, 2011). Furthermore, individuals with high levels of *TIE* receive better grades, score higher on standardized ability tests (Chamorro-Premuzic, Furnham, & Ackermann, 2006a; Wilhelm, Schulze, Schmiedek, & Süß, 2003), and possess better general knowledge (Chamorro-Premuzic, Furnham, & Ackermann, 2006b). However, the overall results on the relation of *TIE* and academic performance have been mixed. *TIE* has mainly been studied in school (Schroeders, Schipolowski, & Böhme, 2015) or academic context (Powell & Nettelbeck, 2014) and has shown low predictive power over and above fluid intelligence. Nevertheless, the compensatory effect of *gf* might have been influenced by the nature of the subject since math and sciences typically are associated with fluid abilities (Rolfhus & Ackerman, 1999). VET courses that are less science oriented might show a closer relation between *TIE* and scholastic achievement. Meta-analytic results have further emphasized the positive association between investment traits and intellect (von Stumm & Ackerman, 2013). This association seems to depend on various conditions such as the investment trait measured and the measures of intellect. Nevertheless, while the association between investment and intellect might differ in strength, it does not differ in direction (von Stumm & Ackerman, 2013). A positive association between investment traits and academic performance would have practical relevance in an educational context. Encouraging intellectual investment could possibly help to develop self-motivated learning in students, instead of exclusively rewarding acquired knowledge and effort (Charlton, 2009). More empirical research is needed to provide further insight into the relationship between investment traits such as *TIE* and academic or scholastic achievement. The current investigation aims to expand the knowledge on the relation between *TIE* and scholastic achievement by investigating its influence in VET.

4. Part 1: Ecological Assessment of Digital Literacy

Chapter 4 has been reprinted from Möhring, A., Schroeders, U., Leichtmann, B., & Wilhelm, O. (2016). Ecological Momentary Assessment of Digital Literacy: Influence of Fluid and Crystallized Intelligence, Domain-Specific Knowledge, and Computer Usage. *Intelligence*, *59*, 172-180. doi:10.1016/j.intell.2016.10.003, with permission from Elsevier.

4.1.Introduction

We developed and evaluated a contextualized and ecologically valid comprehension test as an ecological momentary assessment of digital literacy that requires participants to retrieve and integrate information online rather than reading a static text. In order to focus on a broadly relevant domain, we restricted the questions to health-related and medical content. The problems we developed were characterized by the following attributes: a) they cannot be solved with the information provided in the item stem and b) there are multiple ways to solve the problems by retrieving information from multiple online sources. Participants were instructed to search for information on the internet so we did not constrain access in terms of content. Finding the correct answer depended on the ability of the participant to retrieve, weight, and evaluate pieces of information gathered from multiple documents, and to relate this information to previous knowledge.

In the first of two studies, we examined the relation between fluid intelligence, general knowledge, and the digital literacy tasks. Based on our own research with comprehension measures (Schroeders et al., 2013; Schroeders et al., 2010) and the results of studies we presented in the introduction, we expected the contextualized digital literacy to be a linear function of both facets of intelligence. The relative size of the contribution of each as a predictor is a trickier issue. Findings from (Beier & Ackerman, 2005) suggested that the influence of *gf* and *gc* on learning depended on the restrictiveness of the learning environment, reinforcing the differences between a high constraint maximal effort and a low constraint typical performance situation. More precisely, *gf* becomes more important for learning outcomes in a more restricted environment (i.e., laboratory multimedia presentation), compared to self-directed learning at home. Similar to the conditions of self-regulated knowledge acquisition, information procurement and comprehension was not restricted in the current study. Accordingly, we expected *gc* to be more decisive than *gf* in explaining individual differences in the ability to solve the ecological digital literacy test – but importantly, the collinearity of both predictors needs to be considered and treated appropriately analytically.

In the second study, we replaced the predictor “general knowledge” with a measure of declarative health-related knowledge. Study two also included a measure of fluid intelligence as a further predictor of digital literacy. In line with the knowledge-is-power hypothesis, domain-specific knowledge should exert a strong influence on cognitive performances such as comprehension abilities (e.g., Hambrick, 2003; Recht & Leslie, 1988). Therefore, we expected health-related knowledge to be a more influential predictor of digital literacy than fluid intelligence.

In both studies, we examined computer usage as an additional potential predictor of comprehension abilities that rely on information retrieved from the internet. Although basic computer skills, such as using a keyboard or mouse as input device, can be assumed to be ubiquitous in today’s information society (Goldhammer et al., 2013), some findings suggested that the amount of previous internet use is associated with online information procurement (Hargittai, 2001). However, these basic skills primarily affect the use of internet technology, such as navigating in the hypermedia structure, instead of reading strategies and information-oriented skills that would be necessary for successful information procurement (van Deursen & van Dijk, 2011). Therefore, we assumed no additional influence of computer usage or basic computer skills over and above fluid intelligence and prior knowledge on digital literacy.

4.2. Study 1

4.2.1. Method

Participants. The sample consisted of n_1 = 120 adults (69 females) between 18 to 50 years of age (M = 29.8, SD = 11.1). Participants were recruited via flyers, local newspaper advertisements, and social networks in Ulm, Germany. To ensure an adequate understanding of the instructions, participants with insufficient command of the German language were excluded. Test-takers were compensated with either 15 € or detailed feedback about their performance. One person was excluded due to responses indicating an insufficient understanding of the instructions.

Measures. Table 1 provides an overview of all measures used in Studies 1 and 2, including the total number of items and maximum time for the task.

Table 1. *Overview of the Measures (Study 1 and 2)*

	Study 1		Study 2	
Measure	*# Items*	*Time*	*# Items*	*Time*
Digital literacy	13	60	10	38
Crystallized intelligence, BEFKI 8-10[1]	64	20	12	5
Fluid intelligence, BEFKI 8-10[1]	16	14	16	14
Health-related knowledge	-	-	15	20
Computer usage, CUQ[2]	35	10	35	10

Note. #Items = number of items, Time is given in minutes. [1] Berlin Test of Fluid and Crystallized Intelligence for Grades 8-10 (Wilhelm, Schroeders, & Schipolowski, 2014). [2] Computer Usage Questionnaire (Schroeders & Wilhelm, 2011).

Digital literacy test. The digital literacy test consisted of 13 comprehension questions from the domains of medicine and health. The items differed in complexity with regard to the volume and sophistication required in retrieving and integrating information. For example, some items listed key symptoms of a disease that had to be identified. Other items presented a single picture or table, asking the test takers to name the depicted health problem or method of treatment. A sample item is provided in Figure 1. The following answer formats were used: 1) multiple choice (MC) items with four response alternatives and one correct solution (7 items) with the response alternatives being visible on the same screen as the questions; 2) two lagged multiple choice (LMC) items in which the response alternatives were presented after the retrieval period, and c) three short answer questions. In order to solve the short answer questions, a single word had to be entered. The participants were instructed to use an internet browser of their choice (Firefox, Chrome or internet Explorer) to search for the answer of a question. Thus, participants had to switch between two windows: one with the digital literacy test and the second with the internet browser. Each problem had an individual time restriction, varying between two and eight minutes, that was established through pilot testing. The item-specific countdown of the time remaining was permanently presented in the upper right corner of the browser. During the last 15 seconds an acoustic signal informed participants to stop searching and to provide an answer (for the exact instructions see Supplement 8.1.1.). Participants were forwarded to the next question if time ran out. It was not possible to return to previous questions. All items with their specific time limits are presented in Supplement 8.1.2.

Figure 1. Sample Item of the Digital Literacy test: Osteosynthesis.

Fluid and crystallized intelligence. In addition to the comprehension test, fluid and crystallized intelligence were assessed with the *Berlin Test of Fluid and Crystallized Intelligence for grades 8-10* (Wilhelm et al., 2014). Fluid intelligence was measured with the figural reasoning scale (16 items), a prototypical measure of fluid intelligence (Wilhelm, 2004). Participants had to identify patterns in a sequence of geometric figures (see Figure 2). Crystallized intelligence was assessed with the declarative knowledge items from the extended item pool of the BEFKI 8-10 (Wilhelm et al., 2014). The *gc* scale has three subscales covering knowledge in the sciences (e.g., “What is the function of red blood cells? a) they are involved in the process of wound closure; b) they are primarily responsible for disease resistance (immune response); c) *they transport oxygen in the blood*[1]; d) they transport nutrients in the blood”), the humanities (“Who was Friedrich Nietzsche? a) a historian; b) *a*

[1] Correct answers are italicized.

philosopher; c) a mathematician; d) a chemist"), and social studies ("What is the definition of gross national product (GNP)? GNP is a... a) measure of the tax revenue of the government; b) measure of the states' social expenditure; c) *measure of the income of residents in a national economy*; d) measure of the export volume of a national economy). We used a newly compiled version of that scale with a focus on science. The version had 28 items measuring knowledge in the sciences, 18 in humanities, and 18 in social studies.

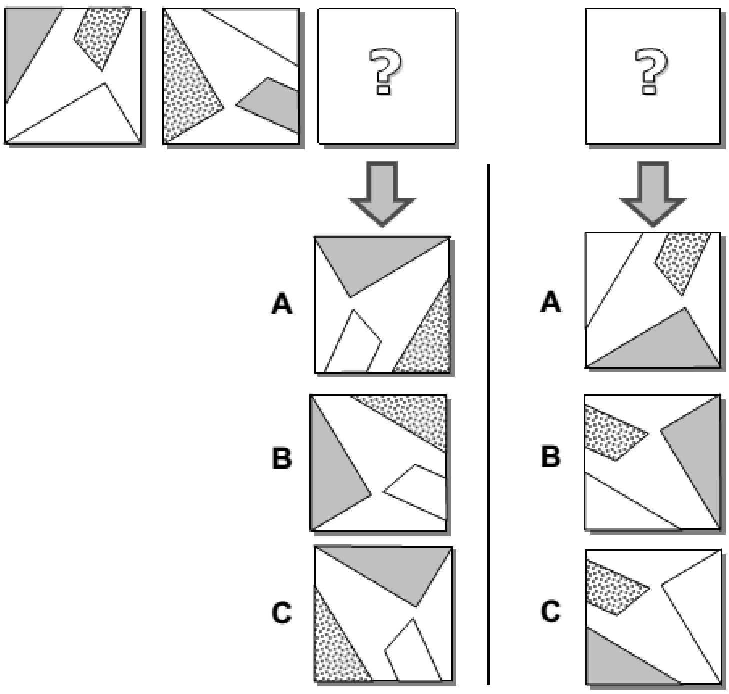

Figure 2. Sample Item of the Figural Fluid Intelligence Scale.

Computer usage. Participants worked on a modified version of the *Computer Usage Questionnaire* (Schroeders & Wilhelm, 2011) to assess the frequency of everyday computer activities and the use of certain programs (e.g., "How often do you use an internet browser?"). All questions were rated on a five-point scale (1 = "never" to 5 = "very often"). The CUQ was extended with 17 additional items covering online shopping behavior, the use of web-enabled mobile phones, search engines, and file sharing utilities.

Data analysis. All analyses were done with *Mplus 7.11* (Muthén & Muthén, 1998-2015). The *weighted least squares mean and variance adjusted* (WLSMV) estimator was used for all measurement models on item level, because simulation studies for models with dichotomous data have shown its superiority to maximum likelihood (ML) estimation (Beauducel & Herzberg, 2009). According to Yu (2002), for categorical data in samples of up to 250 participants the following cut-off values indicate good model fit: *Comparative Fit Index* (CFI) ≥ .96, *Root Mean Square Error of Approximation* (RMSEA) ≤ .05, and *Weighted Root Mean Square Residual* (WRMR) ≤ 1.0. Simple models with small samples (N = 100) and dichotomous outcomes can still be considered to be acceptable with CFI ≥ .93, RMSEA ≤ .07 and WRMR ≤ 1.0 (Yu, 2002). For the structural equation models, indicators were parceled. This approach is viable when the uni-dimensionality for the scale can be assumed and residual correlations are negligible (Little, Cunningham, Shahar, & Widaman, 2002). We used parceling to keep the number of indicators low in order to get robust and reliable parameter estimates (Bagozzi & Edwards, 1998).

4.2.2. Results

Measurement models and item selection. For the digital literacy test item selection was necessary since the new or modified items were not sufficiently tested. We excluded items from the digital literacy test if their difficulty was extreme (excluding items with p > .95 or below guessing probability), if their item-total correlation was low (r_{bis} < .25) or non-significant. This procedure reduced the original 13 items to a final set of 10 for the digital literacy measure. Although r_{bis} of the item "Total Endoprosthesis" was above the cut-off point, the item was deleted because it substantially deteriorated model fit. Item statistics for all comprehension items are displayed in Table 2. The reliability of the scale, McDonald's ω (McDonald, 1999), was .76.

Table 2. *Difficulties and Item-Total-Correlation for the Digital Literacy Items*

	Study 1		Study 2	
Item	*M*	r_{it}	*M*	r_{it}
Nobel Prize	.83	.42	.76	.39
Meningitis	.83	.42	.73	.49
Depression	.22	.39	.08	.49
Hemogram	.58	.53	.60	.46
Mold fungus*	.56	.24	-	-
Grapefruit	.71	.27	-	-
Parkinson’s Disease*	.85	.24	.80	.40
Scoliosis	.91	.36	.91	.40
Viper	.55	.50	.58	.53
Osteosynthesis	.25	.37	.28	.35
Aphasia	.24	.54	.27	.35
Salbutamol	.77	.48	.74	.24
Total Endoprosthesis*	.70	.26	-	-

Note. M = mean difficulty; r_{it} = item-total correlation; Items marked with * were deleted in Study 1 (see item selection).

For all structural equation models, the scales of the predictor variables were aggregated to parcels in order to reduce the number of parameters to be estimated. More precisely, for fluid intelligence three parcels with equal difficulty were calculated, for *gc*, parcels included items of the three subscales: sciences, humanities, and social studies. The content-based parceling was also used for the CUQ where we combined the items of each subscale resulting in four parcels (Games, Office, internet, and Multimedia). Furthermore, computer user profiles from Wittwer and Senkbeil (2008) showed that students who used the computer frequently for information searches on the internet and communicating with other people, also play games more often than others. Therefore, a residual correlation between the internet and Game parcel was allowed. One item of the *gf* scale was deleted due to its non-significant factor loading (λ = .20). All model fit statistics are reported in Table 3. Although some CFIs were slightly below the cut-off values suggested by Yu (2002) for good models, other fit indices suggested good or at least acceptable model fit.

Table 3. *Fit Indices of the Measurement Models (Study 1)*

	χ^2	*df*	*p*	CFI	RMSEA	SRMR	WRMR
Digital literacy	39.8	35	.27	.935	.034	-	0.781
gff	107.5	90	.12	.919	.040		0.862
gc	149.9	104	.00	.943	.061	-	0.821
CUQ	0.02	1	.88	1.0	< .001	.002	-

Note. gff = figural fluid intelligence; *gc* = crystallized intelligence; CUQ = computer usage questionnaire. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; SRMR =Standardized Root Mean Square Residual; WRMR =Weighted Root Mean Square Residual.

Prediction of digital literacy. Next we examined the relation of digital literacy ability with established cognitive constructs, that is, with fluid and crystallized intelligence. We used structural equation modeling to predict participants' performance in the digital literacy test through *gf* and *gc* (model 1). The prediction model provided good fit to the data: $\chi^2(101)$ = 107.2, p = .32, CFI = .975, RMSEA = .023, and WRMR = 0.711. Overall figural fluid intelligence and crystallized intelligence explained 83% of the individual differences in comprehension. However, due the substantial correlation between the predictors (ρ = .47) we disentangled the intelligence factors by estimating a nested factor model with *gc#* nested below an overarching intelligence factor *g* (model 2). This nested factor model (see Figure 3 lower panel) allowed for an examination of the relative contributions of each predictor and also provided good model fit: $\chi^2(99)$ = 105.0, p = .32, CFI = .976, RMSEA = .023, WRMR = 0.703. Even though the contributions of *gc* and *gf* were almost equal in model 1, the nested factor model showed an emphasis on the overarching intelligence factor *g* and a decline in variance accounted for by the nested knowledge factor ($R^2_{gc\#}$ = 21%).

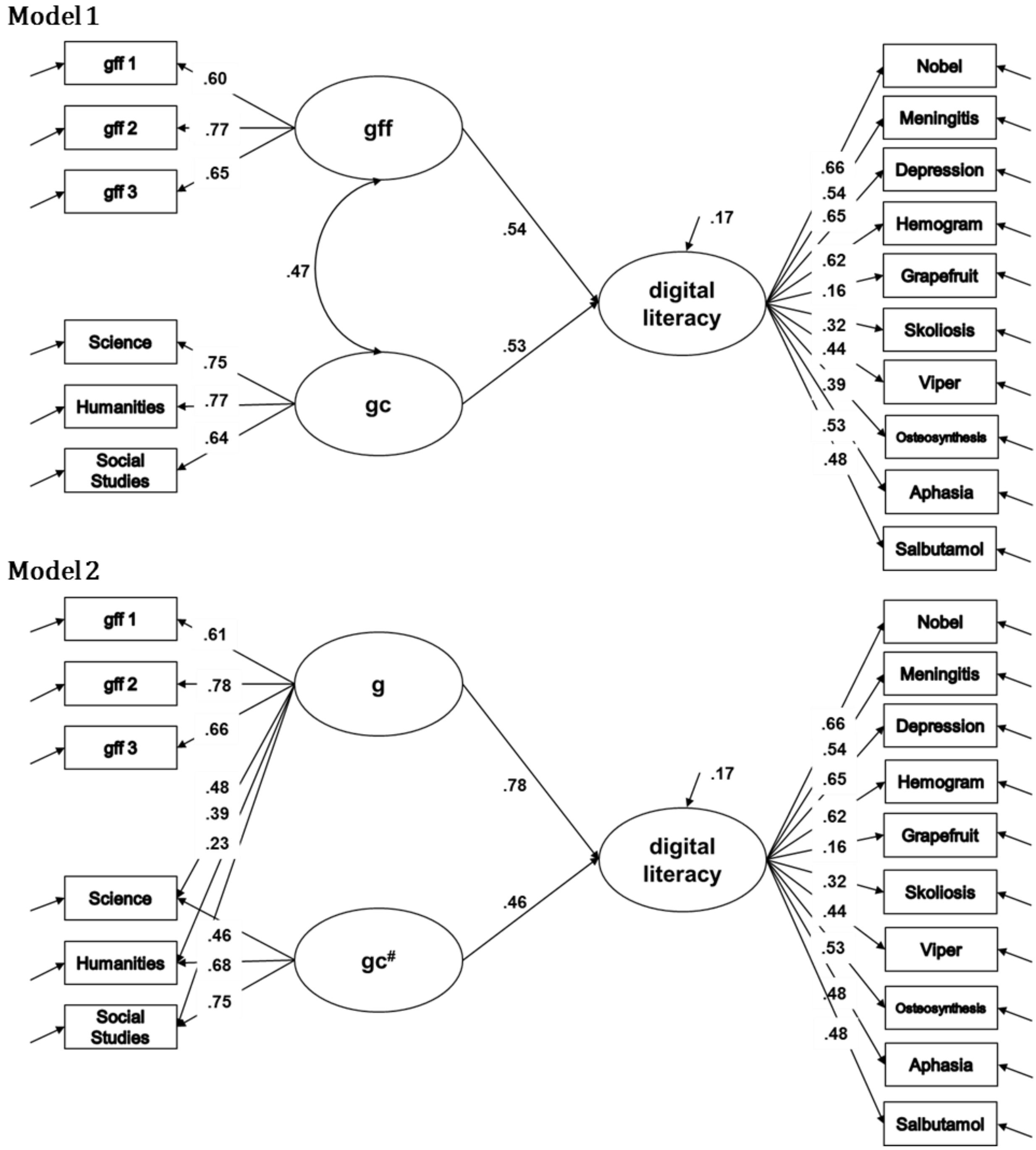

Figure 3. Prediction Models of Digital Literacy through Fluid and Crystallized Intelligence (Study 1).

Note. Model 1: fluid (*gff*) and crystallized (*gc*) intelligence as correlated factors. n_1 = 119, χ^2 (116) = 118.7, *p* = .41, CFI = .989, RMSEA = .014, WRMR = 0.702. Model 2: crystallized intelligence ($gc^{\#}$) nested bellow intelligence (*g*). n_1 = 119, χ^2 (114) = 116.6, *p* = .42, CFI = .990, RMSEA = .014, WRMR = 0.698.

To examine whether computer usage significantly contributed to the prediction of digital literacy, computer usage was added as an additional predictor in model 3 (Figure 4). Computer usage did not significantly increase the amount of variance accounted for in comprehension ability (R^2 = .85 (χ^2 (161) = 166.6, p = .36, CFI = .983, RMSEA = .017, WRMR = 0.699). Since our *gc* scale emphasized medical knowledge, we further tested its contribution after removing all four medicine items from the *gc* factor: $\beta_{gc\#}$ = .46 and β_g = .77 (n_1 = 119, χ^2(161) = 157.8, p = .56, CFI = 1.00, RMSEA < .001, WRMR = 0.669, R^2 = .83).

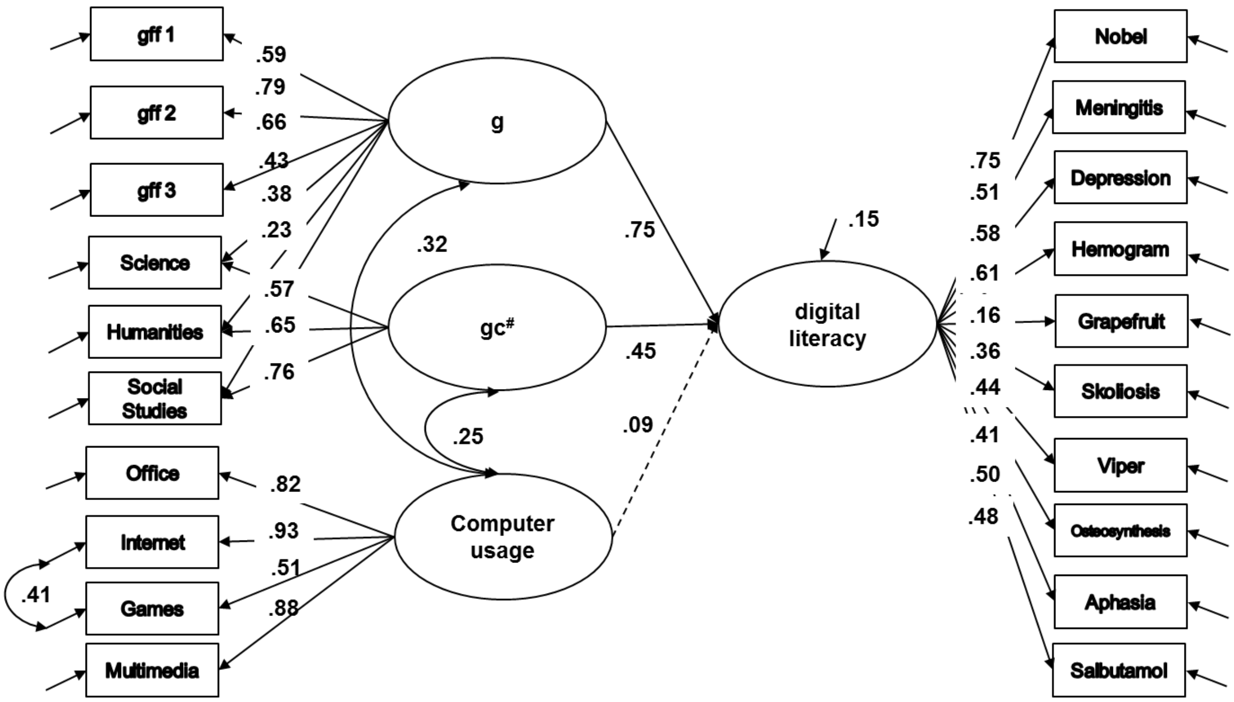

Figure 4. Prediction Model of Digital Literacy through Fluid and Crystallized Intelligence, and Computer Usage (Study 1).

Note. Crystallized intelligence ($gc^{\#}$) nested bellow intelligence (g) (model 3); non-significant relationships between latent variables are indicated with a dashed line. n_1 = 119, χ^2 (162) = 168.6, p = .35, CFI = .981, RMSEA = .018, WRMR = 0.704.

4.2.3. Discussion

The results of Study 1 are encouraging. The new measure had a good range of difficulties, satisfactory item-total correlation, and sufficient factor saturation. As expected, we found a strong influence of both fluid intelligence and declarative knowledge and no further effect of computer usage on digital literacy. Whether or not the *gc*-science predictor includes items that capture medical knowledge is not decisive; deleting all medicine items from the scale did not change our results. We followed up on this result in Study 2 by including a more specialized domain-specific health knowledge test, thus, checking for the specificity of the knowledge factor. The inclusion of domain-specific health knowledge, instead of general knowledge, might result in a stronger influence of knowledge. This was investigated in Study 2.

4.3. Study 2

4.3.1. Method

Participants. In the second study participants were 171 students (138 females) from a vocational high school in the state of Baden-Wuerttemberg. Mean age was 17.9 years (*SD* =.17). Students were recruited from classes specializing in either pedagogy/psychology (n_{2a} = 146) or chemistry/agrobiology (n_{2b} = 25). Taken together, 56.4% of the students were in their first year of school, 33.3% were second year students, and 10.3% were in their third and final year. Students were tested in a 70 minutes session.

Measures. Study 2 used nine items from the final item set of Study 1. One item with a low factor loading (“Grapefruit”) was deleted; the item “Parkinson’s Disease”, that was close to the cut-off in Study 1, was included. Analogous to Study 1, fluid intelligence was assessed with the figural fluid intelligence subscale of the BEFKI 8-10. In order to keep the testing time at a reasonable length, the *gc* short scale of the BEFKI gc was used as a proxy of crystallized intelligence. This scale consisted of 12 items in total from sciences, humanities, and social. In addition, test takers completed a test with 15 multiple choice items covering health-related topics such as the core symptoms of different diseases, hygienic standards, organizational aspects of health-care, and prevention (e.g., “Which of the following diseases requires a vaccination? a) Lyme disease; b) hepatitis C; c) malaria; d) *pertussis*”). Information for the health-related questions was derived from several text books and exams regarding the vocational education and training of medical assistants. We again used the revised version of the CUQ (Schroeders & Wilhelm, 2011) as a measure of computer usage.

4.3.2. Results

Measurement models. The measurement model of the digital literacy test showed good model fit (Table 4). Two items yielded different difficulties and item-total correlation, respectively, in comparison to Study 1 (see in Table 2). More precisely, only 8% of the test takers were able to solve Item 4 (“Depression”), although it had moderate difficulty in the first study. Item 10 (“Salbutamol”) showed a low loading and item-total correlation that is in contrast to the results of the first study. Due to its negative loading, Item 10 was excluded from further analysis.

Table 4. *Fit Indices of the Measurement Models (Study 2)*

	χ^2	*df*	*p*	CFI	RMSEA	SRMR	WRMR
Digital literacy	34.1	35	.51	1.0	< .001	-	0.735
gff	108.0	90	.10	.963	.034	-	0.882
gc	33.8	41	.78	1.0	< .001	-	0.654
Domain-specific knowledge	25.8	27	.53	1.0	< .001	-	0.702
CUQ	2.5	1	.11	.988	.094	.028	-

Note. gff = figural fluid intelligence; *gc* = crystallized intelligence; CUQ = computer usage questionnaire; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of

Approximation; SRMR =Standardized Root Mean Square Residual; WRMR = Weighted Root Mean Square Residual.

The measurement model of the medical knowledge test showed a good fit to the data (Table 4), item-total correlation ranged from r_{bis} = .10 to .45, and item difficulties ranged between *M* = .13 and . 97. Items were deleted if they showed low item-total correlations (r_{bis} < .25) or extreme difficulties (*M* < .25 and *M* > .95). Item selection resulted in a final set of 9 items for the health-related knowledge test.

Prediction of digital literacy. A model with *gf*, *gc,* and computer usage, based on parcels, as predictors of digital literacy (model 4, see Figure 5) showed good fit to the data. CFI was close to the suggested cut-off value for good fit and still above the cut-off for an acceptable fit. The other model fit statistics indicated a good fit, $\chi^2(143) = 151.5$, $p = .30$, CFI = .952, RMSEA = .019, WRMR = 0.795. Overall, the predictors explained R^2 = .84% of the variance in digital literacy. In order to analyze the respective influence of *gc* and to replicate the results of Study 1, we used the nested factor model approach. This model revealed a very strong influence of *gc* on performance in the comprehension measure (β = .73). The effect of the overarching *g*-factor (β = .58) was highly significant, too. Computer usage had a non-significant regression weight – just as in Study 1 and in line with our predictions.

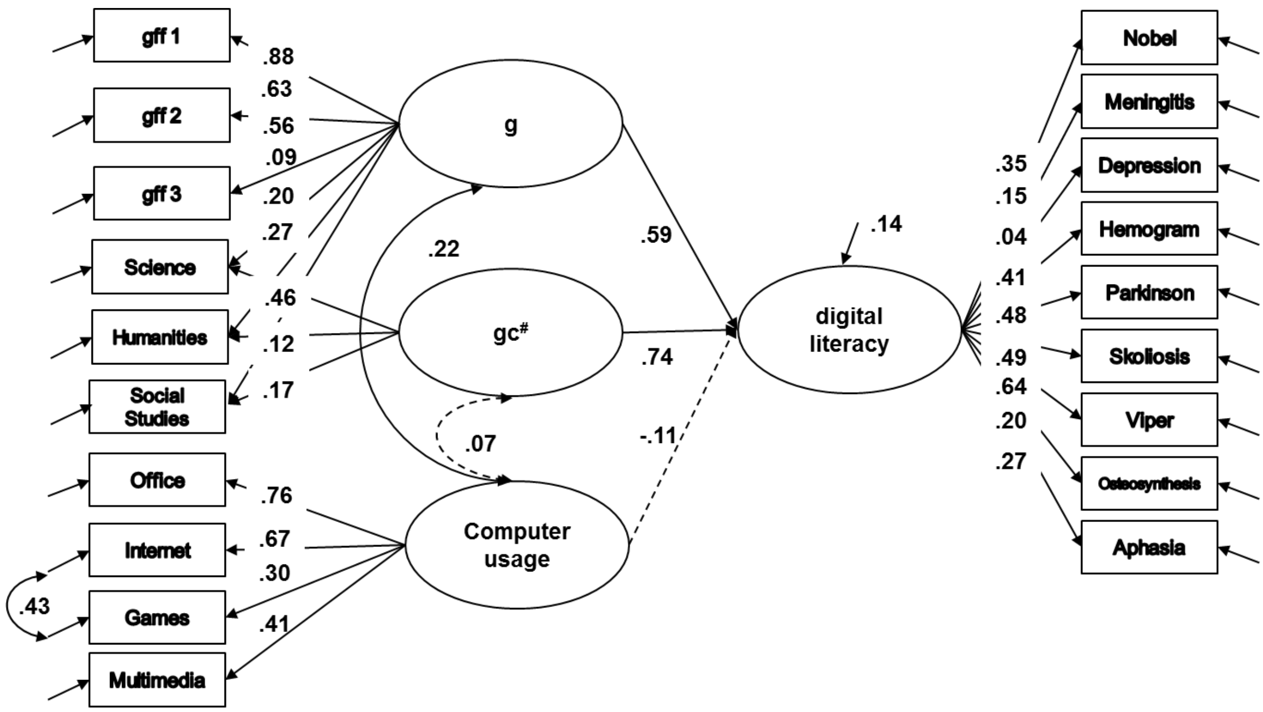

Figure 5. Prediction Model of Digital Literacy through Fluid and Crystallized Intelligence, and Computer Usage (Study 2).

Note. Crystallized intelligence ($gc^{\#}$) nested bellow general intelligence (*g*) (model 4); non-significant relationships between latent variables are indicated with a dashed line. n_2 = 171, χ^2 (143) = 151.5, *p* = .30, CFI = .952, RMSEA = .019, WRMR = 0.795.

In addition to replicating the results of Study 1, the aim of the second study was to use specific health-related knowledge, instead of general knowledge, to probe the knowledge-is-power hypothesis. This model should predict performance on the digital literacy test by domain-specific health-related knowledge and fluid intelligence. Accordingly, the nested domain-specific knowledge factor with nine health-related knowledge items was used to replace the nested general knowledge factor (model 5: χ^2(77) = 509.4, *p* = .20, CFI = .952, RMSEA = .018, WRMR = 0.908). The model showed a good fit to the data with the CFI close to the suggested cut-off value as proposed by Yu (2002) and all other fit indices meeting the respective cut-offs. Modification indices suggested to remove one item of the domain-specific knowledge with a low factor loading (λ = .10). Deleting this item resulted in slightly improved model fit ($\chi^2(74) = 476.5$, $p = .22$, CFI = .957, RMSEA = .017, WRMR = 0.902), without changes in the regression coefficients ($\beta_g = .60$ and $\beta_{gkn} = .80$). The residual variance of the digital literacy factor was close to zero ($\zeta = -.01$), suggesting that both predictors might explain digital literacy exhaustively. Fixing the residual variance to zero did not result in a deterioration of model fit ($\chi^2(73) = 475.8$, $p = .23$, CFI = .959, RMSEA = .017, WRMR = 0.902; $\Delta\chi^2(1, n_2 = 171) = 1.00$, $p = .32$). Health-related knowledge showed a stronger influence on the criterion (β= .81) than the general intelligence factor (β= .59), suggesting that domain specific knowledge accounted for most of the individual differences in digital literacy. Jointly with *gf* it could account completely for digital literacy.

4.3.3. Discussion

Item characteristics of Study 2 were comparable to the ones of Study 1, with the exception of two items (“Depression” and “Salbutamol”). Most likely, the differences in the item characteristics reflect differences in prior knowledge of the samples. With regard to the prediction of digital literacy, fluid intelligence and knowledge accounted for individual differences in comprehension (see model 5). As expected by the knowledge-is-power-hypothesis, specific health-related knowledge showed the strongest influence and explained a significant part of individual difference in comprehension ability ($\beta = .81$). In combination with fluid intelligence, digital literacy could be exhaustively explained. Computer usage did not show an influence over and above fluid intelligence and knowledge.

4.4. General Discussion

In the last few decades, research on web-based ability testing has increased (Kuhlemeier & Hemker, 2007; Senkbeil et al., 2013). In order to cope with the changes in information technology, the use of contemporary technologies in the assessment of traditional constructs, such as comprehension abilities, was necessary. In contrast to paper-pencil-based comprehension tasks, the relations to established cognitive abilities, such as fluid and crystallized intelligence, have not been sufficiently investigated for ecologically valid digital literacy tasks. Previously, most research regarding information procurement and knowledge acquisition via the internet was based on self-assessments (Markauskaite, 2007), paper-pencil knowledge tests (see Goldhammer et al., 2014), or simulation studies in a highly artificial settings (International ICT Literacy Panel, 2002; see also Katz & Macklin, 2007; OECD, 2011). To overcome the shortcomings of these approaches, we examined comprehension abilities with an ecological momentary test of digital literacy in a more realistic setting by requesting that participants browse the internet to find relevant information to solve health-related comprehension problems. The aim was to analyze the psychometric properties of the newly developed test and to describe its association with fluid and crystallized intelligence and domain-specific knowledge as the primary predictors. Furthermore, the relationship between computer usage and digital literacy was investigated.

In Study 1, we addressed the prediction of digital literacy through *gf* and *gc*. Both facets of intelligence are considered to be closely related to the ability to process new information (see Hambrick, 2003), which is supported by the present results. The findings indicated that performance in the digital literacy test was strongly associated with fluid intelligence. Crystallized intelligence accounted for about 20 % of the overall variance, if nested beneath an overarching intelligence factor. In the model with correlated *gf* and *gc* factors, the influence of crystallized intelligence was stronger but still smaller than the effect of fluid intelligence. This is similar to previous findings regarding comprehension abilities in the natural sciences (Schroeders et al., 2013). The findings of Beier and Ackerman (2005), regarding learning outcomes in typical behavior and maximal effort assessments, suggested that both *gf* and *gc* played important roles in learning and the relative weights of the predictors were dependent on the learning environments. Similarly, our results from Study 1 showed strong influences from both *gf* and *gc*. The stronger impact of *gf* relative to *gc* in

Study 1 emphasized the differences between typical and maximal performance situations, rather than high and low constraints as indicated by the strong influence of *gf* (DuBois, Sackett, Zedeck, & Fogli, 1993). In regard to more practice-oriented learning environments, this could suggest that situations with missing information, with time pressure, and with the necessity to evaluate different sources of information, have a stronger imposition on fluid intelligence. However, the way of modeling intelligence strongly influences the relative contributions of fluid intelligence and crystallized knowledge, which should be taken into consideration. Most studies reporting a strong influence of knowledge used correlated factor models (Hambrick, 2004; Sirin, 2005) to predict cognitive performance.

In our study, *gc* is a relevant predictor of digital literacy, regardless of the content domain. However, the findings might also point to an intellectual investment trait, that is, a disposition to acquire new knowledge, such as Typical Intellectual Engagement (*TIE*, Ackerman & Goff, 1994). *TIE* is characterized as the desire for intellectual activity and interest in a profound understanding of complex issues (Wilhelm, Schulze, Schmiedek, & Süß, 2003). This personality trait is associated with crystallized intelligence (von Stumm & Ackerman, 2013) and academic performance (von Stumm, Hell, & Chamorro-Premuzic, 2011), but its influence on academic achievement over and above reasoning seems to be small to negligible (Powell & Nettelbeck, 2014; Schroeders, Schipolowski, & Böhme, 2015). Furthermore, knowledge in the humanities has been reported to relate stronger to *TIE* than scientific knowledge (Rolfhus & Ackerman, 1999), rendering it unlikely that *TIE* accounts for individual differences in digital literacy in the health domain in our study. Nevertheless, future research could investigate motivational and personality variables besides the predominant cognitive variables (Ackerman, 2009).

The relative weight of fluid and crystalized intelligence in explaining digital literacy is also determined by the depth of the content of the domain-specific knowledge test, similar to traditional comprehension tests (Hambrick & Engle, 2003). Several studies suggests that *gc* is a stronger determinant of cognitive performances when it is measured as domain-specific knowledge instead of as general knowledge of several domains (Chase & Simon, 1973; Hambrick, 2003; Kellogg, 2001). In line with the knowledge-is-power hypothesis (Hambrick & Meinz, 2011), we showed that prior health-related knowledge was a better predictor than g. In model 5, which specifies both health-related knowledge and fluid intelligence as predictors, digital literacy could be explained exhaustively. Knowledge, which is located on the *gkn*-*gc*-continuum nearer to the domain-specific pole, presumably facilitates the use of efficient keywords, evaluation of the credibility of different sources, and the detection of relevant information. Nevertheless, *gc* was still strongly correlated with digital literacy, supporting results from prior research (Adams et al., 1995; O'Reilly & McNamara, 2007) as well as the conceptualization of *gc* as an intelligence factor.

In summary, the findings of both studies suggest that the knowledge-is-power hypothesis depends on several relevant conditions, such as the distinction between typical behavior and maximal effort (Ackerman, 1994) and the constraints on the testing situation (Beier & Ackerman, 2005). It should also be noted that our assessment of *gf* was restricted to the figural facet of fluid intelligence. While figural fluid intelligence is generally considered prototypical for fluid intelligence and general intelligence, a broad assessment of this construct should also include verbal and numerical reasoning (Wilhelm, 2004).Including all *gf* facets would shift the predictive power further in favor of fluid intelligence.

A limitation of our studies might be statistical power of the confirmatory models. To determine the required sample size to achieve stable parameter estimates, several factors have to be taken into account such as the complexity of the model, the distribution of variables, and the model estimator (Muthén & Muthén, 2002). In order to reduce the number of freely estimated parameters, we parceled the predictor variables. Thus, in Study 1 the most complex model with all predictors (model 3) had 162 degrees of freedom. Calculating the required sample size for a test of close fit according to Kim (2005) results in n = 125 for a desired power of .80 ($n_{study\ 1}$ = 119). In Study 2, we replicated the results of Study 1 with a larger sample. For the most complex model (model 4), the required sample size for a desired power of .80 is n = 134 (Kim, 2005). Therefore, the sample of Study 2 with n = 171 was sufficient. Power in less complex models is better of course. Nevertheless, studies with larger samples are important to replicate results.

We were also interested in the potential influence of computer usage. Adding computer usage as an additional covariate expectedly did not show a significant influence on digital literacy over and above intelligence. Previous studies might have overestimated the relationship between computer usage and school performance because they did not assess important predictors of performance. In line with the present results, Wittwer and Senkbeil (2008) found no relation between cognitive performance and the frequency of computer usage. This was supported by our results showing that digital literacy could be explained by domain-specific knowledge and fluid intelligence, whereas computer usage did not show an incremental influence, even when different content factors (Office, internet, Games, Multimedia) were taken into account. It should be noted that concepts similar to digital literacy such as hypertext reading abilities have been associated with the ability to use computers in general (Greiff, Kretzschmar, Müller, Spinath, & Martin, 2014). Such computer skills would include basic activities such as using the mouse, sending e-mails, and editing text. Basic computer skills have been reported to be related to reading comprehension of digital texts (Goldhammer et al., 2013). Other potential predictors of digital literacy are generic evaluation skills and procedural meta-cognition. However, for the present studies, we created a realistic and ecologically valid testing environment. The unrestricted internet search without control over the information retrieved differs fundamentally from the stimulus material used in previous implementations of digital literacy and traditional comprehension tests. Accordingly, our results emphasize the role of intelligence in real-world outcomes.

Arguably the most relevant real-world outcome is death and intelligence has been established as a key predictor of mortality (Deary & Batty, 2007). Baker, Wolf, Feinglass, and Thompson (2008) conducted a prospective cohort study and found independent effects of health literacy and cognitive abilities on mortality for elderly individuals. Intelligence might enhance individual health care behavior and therefore reduce mortality (Gottfredson & Deary, 2004). Most likely other factors such as socio-economic status (e.g., lower occupational class and income) might moderate the IQ-mortality link (Batty, Deary, & Gottfredson, 2007).

The ecological momentary digital literacy test was psychometrically sound in terms of reliability and discriminatory power as well as the distribution of difficulties. The internet has become a vital source for any kind of information. Therefore, searching the internet for additional information fosters the authenticity of the comprehension tasks. A potential threat to validity, however, is the “seductive-details effect” which might attenuate the desired increase in ecological validity. The effect occurs when participants are distracted from instruction by interesting but irrelevant details (Mayer, Heiser, & Lonn, 2001). While the inclusion of seductive details increases the ecological validity, which is essential for studies with naturalistic learning environments, this could also decrease the performance. Theoretical explanations for this effect relate to working memory overload, attention distraction, schema interference, and coherence disruption. However, adding details that are only tangentially related to the instructional objective of a task can also further the interest of the test-taker for the subject investigated and consequently help to focus their attention on the material. Results thus far supported the seductive-details effect with small and moderate effects, moderated by several factors. A time limit might lead to lower performance because larger amounts of information have to be processed (Rey, 2012). However, in case of self-directed learning with no fixed amount of informational material, a time restriction might help to focus the participants’ attention on the relevant information, thus decreasing the seductive-details effect. In the present study, information procurement was time restricted and self-directed, rendering the risk of a seductive-details effect to be small.

5. Part2: Knowledge-is-Power in Vocational Education and Training

The contents from Chapter 5.1. and 5.4. concerning medical assistants as well as the description of the measurement instruments in Chapter 5.2.3. and the results in Chapter 5.3.1. and Chapter 5.3.2. on medical assistants have been published in Möhring, A., Schroeders, U., & Wilhelm, O. (2018). Knowledge is Power for Medical Assistants: Crystallized and Fluid Intelligence as Predictors of Vocational Knowledge. *Frontiers in psychology*, *9*, 28. doi: 10.3389/fpsyg.2018.00028. CC BY 4.0, https://creativecommons.org/licenses/by/4.0/.

5.1.Introduction

The successful graduation from vocational training programs such as the medical assistant courses is a necessary prerequisite to start a professional career. Considering the relevance of VET success from the perspective of educational and labor market policy, empirical findings on individual differences in vocational education are surprisingly scarce in contrast to findings on success in primary, secondary, and university education. The second part of this thesis adds to the research literature by analyzing the joint and unique effects of *gf*, *gc* and *TIE* in explaining individual differences in vocational knowledge for VET students. Instead of focusing on a single occupation, differences in domain-specific vocational knowledge were predicted in three distinct vocational domains (health, business, and information technology). Furthermore, most previous studies focused on only one group of predictor variables, thereby possibly missing a large portion of variance (Volodina, Nagy, & Köller, 2014). Considering cognitive and non-cognitive predictor variables simultaneously would allow for a more realistic assessment of the predictive utility of each set of variables. The implemented research design allows to estimate these effects at different phases of VET and to elaborate on the question to what extent the knowledge-is-power hypothesis holds true in a realistic educational high-stakes setting. High-stakes assessment refers to settings with a crucial role in gaining access to education, employment, or credential opportunities (Sackett, Schmitt, Ellingson, & Kabin, 2001). This includes admission testing for VET entry as well as final exams for the professional qualification.

Several studies showed that a common g factor is pivotal for educational success (Reeve & Basalik, 2014; Tucker-Drop, Briley, Starr, & Deary, 2014). For example, Carretta and Doub (1998) found that general ability was a better predictor of training outcomes than prior vocational knowledge, for participants in technical training for various career fields. Therefore, we can assume that a general intelligence factor would show the strongest influence for VET students from the technology domain as compared to the business and medical domains. These results are in stark contrast to the predictions of the knowledge-is-power hypothesis, claiming that domain-specific knowledge mainly contributes to knowledge acquisition (Hambrick & Engle, 2002). Inconsistent findings reported in the research literature can be linked to several factors. First, the specificity of the *learning situation*, that is to say, *gf* is more important for learning outcomes in restricted environments (i.e., laboratory multimedia presentation), whereas it is less important for self-directed learning at home (Beier & Ackerman, 2005). In the context of VET, students usually attend lessons at school and apply the knowledge in the practical part of their education. Thus, knowledge is imparted in well-structured classes as well as in unregulated learning environments. Second, the relative contribution of *gf* and *gc* also depends on the *learning outcome*. Since the current study focuses on the scholastic aspects of VET, we expect a stronger influence of *gc*. Vocational knowledge is defined as “the accumulation of facts, principles, concepts, and other pieces of information that are considered important in the performance of one’s job” (Dye, Reck, &McDaniel, 1993, p. 153). This definition emphasizes the relevance of *gc* compared to *gf* as a predictor of vocational knowledge acquisition.

The concept of *TIE* ties closer into the motivational aspect of abilities. As mentioned in Chapter 3.3., the influence of *TIE* has rarely been studied in non-academic samples. Since entering a VET course is not restricted to a specific school leaving certificate in Germany, a sample of VET students is less ability-restricted than university students. This might further enhance the impact of *TIE* on educational performance. Furthermore, the focus on social science related knowledge in the curriculum in the business domain might result in a more pronounced effect of *TIE* compared to studies focusing on math and science achievement (Schroeders, Schipolowski, & Böhme, 2015). In contrast, we would expect negligible effects of *TIE* for the IT domain and the medical domain.

Third, the *subject of learning*, that is, the specific knowledge domain might be important for the influence of *gf* and *gc* on knowledge acquisition. *Gf* has been shown to have a stronger impact on learning in the physical sciences, such as physics and chemistry, whereas *gc* was a better predictor for knowledge in arts, humanities, and civics (Ackerman, 2000). With respect to health-related knowledge, such as nutrition, mental health, and illness, there is also a substantial predominance of *gc* compared to *gf* (Beier & Ackerman, 2003), which also points to a stronger effect of *gc* in the education of medical assistants. Similar effects would be expected for the group of technology students due to the focus on natural science in their education while business-related occupations should be closer related to *gc* through their strong association with the domain of civics (Ackerman, 2000). Finally, sample characteristics, such as age and sex, might have a large impact on the results (Beier & Ackerman, 2003; Kubeck, Delp, Haslett, & McDaniel, 1996). For instance, empirical evidence points towards a stronger influence of *gc* in older adults, as compared to younger adults, with less occupational experience (Beier & Ackerman, 2005). This would imply a weaker influence of *gc* on vocational knowledge of VET students.

In summary, the respective contribution of *gf*, *gc* and *TIE* to vocational knowledge acquisition depend on several factors. For the present study, we expect a positive influence of both *gc* and *gf* on vocational knowledge for all VET students, but a stronger impact of *gf* for IT students as compared to health and business students due to their close relation to natural sciences. In accordance with the knowledge-is-power hypothesis, we expect *gc* to show a greater impact on vocational knowledge than *gf*. We expect no or only a small effect of *TIE* over and above *gc* and *gf*. In comparison to previous research, the learning situation, outcome, and content domain describe a realistic and ecologically valid scenario. As an alternative way of modeling, individual differences in vocational knowledge acquisition during VET might also be explained by an overarching *g*-factor (Chamorro-Premuzic et al., 2008; Furnham and Monsen, 2009). Thus, we will present an additional model with a *g*-factor and a nested $gc^{\#}$ factor (i.e., residual knowledge factor) as predictor variables and compare the results to the ones of the *gf*-*gc*-model. If the knowledge-is-power hypothesis holds, $gc^{\#}$ should still have a stronger impact on vocational knowledge than *g*. Even though the study was cross-sectional, the research design allowed for an evaluation of educational success at the different stages of VET, thus, providing a rough estimation of learning trajectories. We would expect a substantial increase in vocational knowledge with ascending years of VET while *gc*, *gf* and *TIE* should not change significantly. With ongoing training, the influence of *gc* on VET knowledge acquisition should increase or remain stable.

5.2. Method

5.2.1. Sample.

A sample of n = 1854 students was recruited from 20 vocational schools in the German federal state of Baden-Wuerttemberg. VET students were recruited from all three years of education to participate in a computerized group testing. The main sample of 1690 students was recruited from February to March 2015. Due to the relatively small sample size of students from IT-related occupations at the end of March 2015 (n = 208), a second data collection took place at the end of November to the beginning of December 2015 in order to add to the statistical power in this sample. Detailed information on the demographic variables is given in Table 5. Participation in this study was voluntary; individual feedback on their results was offered to all participants.

Business VET. Overall, 1034 students pursued an economical and business related education (60.3 % females), with an average age of 20.24 (*SD* = 3.16), ranging from 15 to 47 years. The specific occupations encompassed industrial managers (*n* = 258), retail dealers (*n* = 358), management assistants in wholesale and foreign trade (*n* = 231), and office administrators (*n* = 155). Since all demographic information was provided voluntarily, the information on the specific training course is missing for 32 students who did not want to enclose this information. Therefore, the overall sample includes 441 students in their first year of vocational education, another 356 students in their second year, and finally, a group of third-year students consisting of 237 students. Due to technical problems, four participants had missing values on more than one fourth of the items in one scale, at least. They were excluded from further analysis. This resulted in a final sample of 1030 business trainees.

Health VET. A sample of *n* = 448 medical assistant students (97.8% female) was recruited from five vocational schools. Age of the participants ranged from 15 to 44 years (*M* = 20.02, *SD* = 3.45). VET students were recruited from all three years of education to participate in a computerized group testing. Detailed information on the demographics is provided in Table 1. The group of second year students was the smallest with *n* = 127 participants but still reached our goal of 120 to 150 participants per group (see Möhring, Schroeders, & Wilhelm, 2018).

Technology VET. Of the 372 students of the information technology group only 6.5 % were females. They belonged to occupational fields with a focus on information technology, including IT specialists from the branches of application development (*n* = 63) and system integration (*n* = 272), management assistants in IT-systems (*n* = 25) as well as IT systems technicians (*n* = 12). In the state of Baden-Wurttemberg, the VET for these occupations is based on the same curriculum with only slightly varying emphasis, depending on the training course. The average age was 20.86 (*SD* = 4.12), ranging from 16 to 45 years. Overall, 159 students belonged to the first year of VET, 133 students were in their second year, and 80 students were in their third year of education.

Table 5. *Sample Characteristics*

	technology	health	business
Sample size	372	448	1034
1st year	159	172	441
2nd year	133	127	356
3rd year	80	149	237
Age *M* (*SD*)	20.86 (4.12)	20.02 (3.45)	20.24 (3.16)
Female [%]	6.5	97.8	60.3
School graduation [%]			
vocational track (*Hauptschule*)	1.9	14.5	10.6
intermediate track (*Realschule*)	45.4	73.8	56.2
academic track (*Gymnasium*)	50.0	8.8	28.1
Others (e.g., mixed track schools)	2.7	2.8	5.1

5.2.2. Procedure.

All students participated in a one-time-assessment in the respective class. All of the tests were computerized and presented with the program Inquisit 4.0. Depending on the accommodations, either the school's computers were used to access a web-version of Inquisit or the examiners provided laptops for the students to work on a local version of the program. After answering a few demographical questions, including their highest school graduation (i.e. educational attainment), they were presented with 30 questions of domain-specific knowledge on the subject matter of their training course. This was followed by 15 tasks of domain-specific knowledge from the other two domains, respectively. After answering all domain-specific knowledge questions, the students were presented with the scale of typical intellectual engagement. Lastly, they were tested on their crystallized and figural fluid intelligence. Overall, the testing time amounted to about 100 minutes.

5.2.3. Measurement Instruments.

In the following sections, the measures will be presented, starting with the description of the development of the domain-specific knowledge tests. Afterwards, the measures for crystallized and fluid intelligence will be described as well as the *TIE* scale.

Domain-specific knowledge tests. Vocational knowledge was assessed with a domain-specific knowledge test covering the different relevant topics of the VET course (see also, Möhring, Schroeders, & Wilhelm, 2018). The following sources were used for item development: 1) the curriculum of medical assistants, business students, and IT-specialists (e.g., Ministry of Education and Cultural Affairs, Youth and Sports of Baden-Wuerttemberg, 1999, 2005, 2008), 2) standardized final and interim exams that were provided by the *Chamber of Industry and Commerce* (Industrie- und Handelskammer, IHK) from the years 2010–2014, and official test questions for exam preparation (e.g., Zimmermann, 2014), and 3) text books used in VET courses (e.g., Fox, Greiner, Groger, Hibbeler, Mosler, & Wecke, 2008). Items had a multiple choice format with three distractors and one correct answer.

A total of 118 items for health knowledge, 114 items for business knowledge, and 115 items for technology knowledge were tested in a pilot study in March and April 2014, with a sample of 292 medical assistant students, 431 business students, and 98 IT-specialist students (for more details on the pilot study see Supplement 8.2.1). Items covered the content of all three years of VET as described in the respective framework curricula. In more detail, for medical assistants this includes: 1) medical knowledge that is relevant in patient care before, during, and after medical treatment. For example, this includes emergency treatment as well as health-related and medical knowledge; 2) laboratory knowledge, such as knowledge about hygienic standards or medical instruments as well as hands-on skills to analyze laboratory samples; and 3) knowledge about organizational aspects of a medical workplace and social interaction with patients which comprises the procurement and management of materials, accounting, documentation, and scheduling. The data from the pilot study was used for a comparison between a three-dimensional factor model, based on the content domains, and a one-dimensional factor model. χ^2 difference testing revealed a significant advantage of the three-dimensional model, $\Delta\chi^2(292) = 8.17$, $p = .04$. Therefore, medical knowledge, laboratory knowledge, and organizational knowledge were used as subtests for the domain-specific knowledge test (Möhring, Schroeders, & Wilhelm, 2018).

The business knowledge test covered the following contents: 1) Strategic and operational management, includes abilities in organizational aspects and planning as well as procurement, production planning and control. Furthermore, knowledge about profit and loss accounting and the audit of the annual financial statements was required. 2) Knowledge about marketing and sales concerned aspects of market investigation. This includes questions about product, price, communications and distribution policy. Another facet relates to capital budgeting as well as internal and external financing. 3) General economic knowledge, contained knowledge about economic policy, market types and human resources. This three-dimensional structure was also supported by the difference testing between a one-dimensional and a three-dimensional measurement model, $\Delta\chi^2(431) = 24.85$, $p < .01$

Finally, the technology knowledge test was composed of the following contests: 1) Knowledge regarding basic IT-Systems, which encompassed aspects about hardware and electronics. 2) Application development included knowledge about programming, data bases, and software. 3) Network knowledge tested knowledge of configuration, information processing, and aspects of maintenance. Again, the three-dimensional model was tested against a one-dimensional model and the χ^2 difference test revealed a significant advantage of the three-dimensional model, $\Delta\chi^2(98) = 13.4$, $p < .01$

From the item pool of the pilot study, 50 items were selected for each knowledge test, based on their difficulty (≥.25 and ≤.95) and part-whole corrected item-total correlation for each subscale ($r_{bis} \geq .25$). To keep the individual workload to a minimum, a multiple matrix design with three training-year specific booklets was used (see Möhring, Schroeders, &

Wilhelm, 2018). It is often reasonable for performance tests in the academic context to target different school grades. Those tests are intended to differ in difficulty, meaning that the test versions for lower grades are easier than those for higher grades. In order to compare the results between grades it is often desired to put scores from such tests onto a common scale (Kolen & Brennan, 2004). While tests from different grades might differ slightly in content and difficulty, they usually share a similar reliability. With vertical scaling, the tests of neighboring grades may share some common material but each test is, to some degree, inadequate for all but one grade. The common material can be used as an anchor test that connects the tests for different grades. More specifically, each test consisted of 30 items with 10 items being equal in all booklets, and another 10 items shared between adjacent test forms. We used a vertical linking design (see Table 6) in order to connect the different training-year specific test forms and to estimate students' abilities on a common scale (Kolen & Brennan, 2004).

Table 6. *Vertical Linking Design Across Three Years of Vocational Education and Training*

First year					
Second year					
Third year					

Note. Every cell represents 10 items. Items in the same column are identical.

Fluid and crystallized intelligence: Both *gf* and *gc* were assessed with the *Berlin Test of Fluid and Crystallized Intelligence for Grades 8-10* (Wilhelm, Schroeders, & Schipolowski, 2014). Figural reasoning is considered prototypical for reasoning and was accordingly measured with the figural reasoning scale (Wilhelm, 2004). A sequence of geometric figures was presented and participants had to identify which were the next two figures in the sequence out of three alternatives for each missing figure. Participants worked on 16 items for a maximum of 14 minutes.

Gc was assessed in three broad domains: 1) natural sciences (e.g., Which of the following is the formula for hydrochloric acid? [1] a) HF, b) HBR, c) *HCI*, d) HI), 2) humanities (e.g., Who was Friedrich Nietzsche? a) a historian, b) *a philosopher,* c) a mathematician, d) a chemist), and 3) social studies (e.g., What is the definition of gross national product (GNP)? GNP is a... a) measure of the tax revenue of the government, b) measure of the states' social expenditure, c) *measure of the income of residents in a national economy*, d) measure of the export volume of a national economy). The *gc* test consists of 64 items covering the "breadth and depth" of the declarative knowledge (Horn & Noll, 1997, p.69). Test time was 20 minutes.

Typical intellectual engagement. The typical intellectual engagement (*TIE*) of the students was measured with the short form of the Typical Intellectual Engagement Scale (*TIE*; Wilhelm, Schulze, Schmiedek, & Süß, 2003). The questionnaire contains the three subscales reading, contemplation, and intellectual curiosity (e.g., "There are very few subjects that bore me."). Students rated their agreement with 18 statements on a 6-point scale (1 = *"do not agree at all"*, 2 = *"do not agree"*, 3 = *"somewhat disagree"*, 4 = *"somewhat agree"*, 5 = *"agree"*, 6 = *"strongly agree"*). Negatively pooled items were reversed for all analyses.

5.2.4. Data analysis.

Item Response Models. The *Item Response Theory* (IRT) provides a statistical framework for the analysis of manifest variables as indicators of latent constructs. In this respect it can be considered to be similar to *Factor Analysis* (FA). Unlike FA however, IRT does not aim to find the fewest possible number of latent factors to be explained by the manifest variables. Instead, IRT analysis models the relationship between person and item characteristics, i.e. the ability of a person and the difficulty of a test item (Reckase, 2009). The simplest model is the one parameter logistic (1PL) IRT model also known as Rasch model. As

[1] Correct answer in italics.

the name suggest, it is based on a single parameter, the *difficulty* of the item. This parameter provides information about the likely probability of the correct answer. Empirical results however indicate that the discriminating power of items varies as well. This is accounted for in the two parameter logistic (2PL) IRT model by adding the *discrimination parameter* to the model. The difficulty parameter can be interpreted in the same way as in the 1PL model. That is to say, items can differ in regard to their capability to differentiate between examinees with high and low levels of the construct assessed. An advantage of the 2PL models is their capability to weigh highly discriminative items higher than items with less discriminatory power when estimating theta.

Linking is an IRT procedure to put both item and person parameters into the same coordinate system. Equating is a special case of linking, requiring a number of properties (Dorans, Pommerich, & Holland, 2007, p.23). Most notably, the test forms for equating are considered to be equivalent and to be used by the same population. Since this is naturally not a given in competence tests designed for different school years, equating procedures will not be the focus of this thesis. A commonly used design is the common-item design which uses a subset of common items that are identical across the test forms. Due to the vertical linking design (Kolen & Brennan, 2004) of the domain-specific knowledge tests, two-parameter logistic (2PL) models, which are equivalent to CFA models with the WLSMV estimator (Asparouhov & Muthén, 2015), were estimated for each year. The resulting *Weighted Likelihood Estimates* (WLEs; Warm, 1989) for the three domains (e.g., medical knowledge, laboratory knowledge, and organizational knowledge) represent students' domain-specific knowledge after linking items on a common scale according to Haberman (2009). Scaling and linking within in an IRT (item response theory) framework were conducted with the R packages *TAM* (Kiefer, Robitzsch, & Wu, 2016) and *sirt* (Robitzsch, 2016).

Structural Equation Modelling. First, we established measurement models for gf and gc in the framework of *Confirmatory Factor Analysis* (CFA) with the *Weighted Least Squares Mean and Variance adjusted* (WLSMV) estimator which is appropriate for dichotomous variables (Beauducel & Herzberg, 2006). According to Yu (2002, pp.94-95) the following cut-off values indicate good model fit: *Comparative Fit Index* (CFI) ≥ .95, *Root Mean Square Error of Approximation* (RMSEA) ≤ .06, and *Weighted Root Mean Square Residual* (WRMR) ≤ 1.0. In subsequent analysis, items of the intelligence measures were parceled to keep the number of indicators within a reasonable range and to get reliable and robust parameter estimates. The parceling approach is viable in the case that the construct is unidimensional and the residual correlations are negligible (Little, Cunningham, Shahar, & Widaman, 2002). For figural *gf*, five parcels with almost similar average difficulty were compiled. For *gc*, the items were parceled according to the three broad content domains of science, humanities, and social studies.

In order to make valid comparisons of students' performance across years of VET, it is necessary to ensure measurement invariance for *gf*, *gc* and *TIE*. Invariance testing with *Multiple Group Confirmatory Factor Analysis* (MGCFA; Cheung & Rensvold, 2002) is a sequential and straightforward procedure of constraining more and more measurement parameters (factor loadings, intercepts, and residual variances) to be equal across groups (i.e., years of VET education). Different levels of invariance are assessed by comparing measurement models, from the least to the most restrictive model (see Table 7). First, *configural invariance* is tested by freely estimating all measurement parameters while all factor means are fixed to zero for identification purpose. For *metric invariance*, factor loadings are additionally fixed to equality between groups. In the next step, *scalar invariance,* the intercepts are also fixed to equality, but means were freely estimated in all except one group. Finally, to test *strict invariance*, residual variances were fixed to equality between groups. While metric invariance is sufficient to compare the bivariate relations (i.e., regressions and correlations) between latent variables across groups, scalar invariance is necessary for the comparison of the mean structure. The assumption of strict invariance is often considered to be too restrictive and inappropriate for practical scenarios. However, aside from "random noise", Deshon (2004) suggested unintentionally measured variables as another possible source of differences in residual variances.

Table 7. *Procedure for Testing Measurement Invariance for Continuous Variables*

	Factor loadings	Intercepts / Thresholds	Residual variances	Factor means
Configural invariance	*	*	*	Fixed at 0
Weak invariance	Fixed	*	*	Fixed at 0
Strong invariance	Fixed	Fixed	*	Fixed at 0/*
Strict invariance	Fixed	Fixed	Fixed	Fixed at 0/*

Note. * = parameter freely estimated; Fixed = parameter fixed to equity across groups; Fixed at 0 = factor means are fixed at 0 in all groups; Fixed at 0/* = factor means are fixed at 0 in one group and freed in the other. Parameters in parentheses are varied in tandem.

Nested data structure. Data from educational environments has typically a nested structure: the vocational students are nested within their classes. This violates the assumption of independent observations, since subjects within the same group (i.e. the same class) tend to be more similar than subjects from different groups. Since most statistical analyses are based on the assumption of independence of observations the nested data structure results in problems for the use and interpretation of the data analysis. For structural equation modeling, neglecting the nested structure of the data would result in biases for the evaluation of the model fit and for the standard errors in the parameter estimation. The intraclass correlations, that is to say the clustering of single variables, lead to a systematic underestimation of model parameters. Furthermore, significance tests of single parameter tend to be more liberal (Muthén, 1994). However, the single parameter estimations are not biased in a nested data structure. To correct for potential biases in the standard errors and model fit statistics, all structural equation modeling was conducted using the *complex* option of the Mplus 7.13 software (Muthén & Muthen, 1998-2015). Instead of using the usual *maximum likelihood* (ML) estimation the parameters are estimated based on the *robust maximum likelihood* (MLR) estimation (Muthén & Satorry, 1995), providing robust goodness-of-fit tests and standard errors of model parameters.

Missing data. Missing data is a common problem in observational studies. The major problems stemming from missing data are 1) a loss of statistical power due to the diminished sample size, 2) a more complicated handling of data since most statistical analyses are based on complete data matrices, and 3) possible differences between available data and missing values may lead to biased parameter estimates. Fortunately, our computerized test design allowed us to prevent participants from skipping questions. While the domain-specific knowledge tests were characterized by including missings into the design, the problems of missing data could still apply to the predictor variables. We have few missing values for the predictor variables in the present data set due to technical problems (ranging from 0.5% to 2.5% per variable). Thus, a single imputation strategy was chosen to estimate missing values by utilizing the maximum likelihood based expectation maximization algorithm.

5.3.Results

5.3.1. Measurement Models.

In a first step, one-dimensional models were conducted for all predictors with individual items as indicators; model fit statistics for the measurement models are reported in Table 8. *Gf* and *gc* were estimated as one-dimensional models and *TIE* as a three-dimensional model with the factors reading, contemplation, and intellectual curiosity. One item had to be deleted from the *gf*-scale due to a data loss caused by a technical problem. The measurement model with 15 *gf*-items as well as the measurement model for *TIE* showed a good fit to the data in all groups. The four medicine items of the *gc* scale were deleted in all further analysis due to substantial overlaps with the curriculum of medical assistants. Although the CFI for the *gc* model was slightly below the cut-off value suggested by Yu (2002) for students of the business and health domains, other fit indices suggested good model fit. For subsequent analysis indicators were parceled in order to reduce the number of estimated parameters and to allow for robust parameter estimation with moderate sample size. *Gc* items were aggregated to parcels according to three broad content areas. *Gf* items were aggregated to parcels with equal difficulty and *TIE* items were aggregated according to the domains reading, contemplation, and intellectual curiosity.

Table 8. *Fit Indices of the Measurement Models*

	χ^2/df	p	RMSEA	CFI	WRMR
health					
gc	1725.8/1539	< .01	.02	.942	0.993
gff	93.5/77	.09	.02	.982	0.854
TIE	200.2/99	< .001	.04	.968	1.0
business					
gc	1689.2/1539	.004	.01	.943	1.061
gff	146.3/90	< .001	.03	.993	0.966
TIE	262.8/99	< .001	.04	.984	1.141
technology					
gc	1993.6/1539	< .001	.03	.974	1.055
gff	127.7/90	.01	.03	.953	1.392
TIE	237.5/99	< .001	.06	.967	1.030

Note. gff = Figural Fluid Intelligence; *gc* = Crystallized Intelligence; TIE = Typical Intellectual Engagement. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; WRMR =Weighted Root Mean Square Residual.

To ensure the comparability of the intelligence scales across the three years of VET, the measurement models were tested for measurement invariance. The models were compared based on the deterioration in the CFI between consecutive models with ΔCFI ≤ .01 indicating invariance (Cheung & Rensvold, 2002). For all measurement models, strict measurement invariance was given (see Table 9), which allows us to examine the relative contribution of *gf* and *gc* on domain-specific knowledge acquisition across years of education. Though the RMSEA values for the measurement invariance testing for *gc* are above the cut-off point, as Kenney, Kaniskan, & McCoach (2014) pointed out, RMSEA for models with few *df*s can often falsely indicate a poor model fit. Considering the CFI for *gc*, we can assume a good fit for the invariance testing.

Table 9. *Fit Indices for the Measurement Invariance*

	χ^2/df	p	RMSEA	CFI	ΔRMSEA	ΔCFI
Health knowledge						
gff						
Configural	14.2/15	.51	< .001	1.0	-	-
Metric	26.4/23	.28	.03	.990	-.02	.010
Scalar	35.5/33	.35	.02	.992	.01	-.002
Strict	40.7/43	.56	< .001	1.0	.02	-.008
gc						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	8.7/4	.07	.08	.992	-.08	.008
Scalar	16.9/8	.03	.08	.985	.00	.007
Strict	20.7/14	.11	.06	.988	.02	-.003
TIE						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	1.4/6	.97	< .001	1.0	.00	.000
Scalar	2.4/10	.99	< .001	1.0	.00	.000
Strict	3.9/16	.99	< .001	1.0	.00	.000
Business knowledge						
gff						
Configural	16.4/15	.35	.01	.999	-	-
Metric	26.5/25	.37	.01	.999	.00	.000
Scalar	30.0/33	.61	< .001	1.0	-.01	-.001
Strict	32.7/43	.87	< .001	1.0	.00	.000
gc						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	10.6/6	.10	.04	.996	.04	.004
Scalar	20.9/10	.02	.05	.992	-.01	.004
Strict	24.8/16	.07	.04	.993	.01	-.001

TIE						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	9.2/6	.16	.03	.996	-.03	.004
Scalar	18.7/10	.04	.05	.988	-.02	.008
Strict	28.5/16	.03	.04	.983	.01	.005
Technology knowledge						
gff						
Configural	16.1/15	.37	.02	.998	-	-
Metric	21.3/25	.67	< .001	1.0	.02	-.002
Scalar	26.7/33	.71	< .001	1.0	.00	.000
Strict	42.6/43	.48	< .001	1.0	.00	.000
gc						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	1.7/6	.95	< .001	1.0	.00	.000
Scalar	7.6/10	.66	< .001	1.0	.00	.000
Strict	15.6/16	.48	< .001	1.0	.00	.000
TIE						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	5.0/6	.54	< .001	1.0	.00	.000
Scalar	7.4/10	.68	< .001	1.0	.00	.000
Strict	13.9/16	.60	< .001	1.0	.00	.000

Note. *gff* = Figural Fluid Intelligence; *gc* = Crystallized Intelligence; TIE = Typical Intellectual Engagement. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation.

For the vocational knowledge test, three-dimensional 2PL models were estimated separately for each year of VET and subsequently linked on a common scale (Habermann, 2009). Five of the original 50 items (1 item from medical knowledge, 2 items from laboratory knowledge, and 2 items from organizational knowledge) had to be excluded from the vocational knowledge test due to negative discrimination parameters, resulting in booklets of 27 items for the first and second year each, and 29 items for the third year (Möhring, Schroeders, & Wilhelm, 2018). For the same reason, eight items were deleted from the business test (4 items from strategic and operational management, 1 item from marketing and sales knowledge, and 3 items from general economic knowledge) and eight items from the technology test (1 item from basic IT systems, 5 items from application development, and 2 items from network knowledge). Person parameters for each content domain of the vocational knowledge test were used as indicators in subsequent SEM. There were significant increases in vocational knowledge, which indicates the successful acquisition of job-relevant knowledge over the course of VET (see Table 10). The standardized mean differences, according to Cohen (1988), ranged from moderate to large effects.

Table 10. *Changes in vocational knowledge per year expressed as effect sizes*

Knowledge domain	Effect size		
	d(1/2)	*d*(2/3)	*d*(1/3)
health knowledge	0.45	0.99	2.29
business knowledge	0.24	1.29	2.06
technology knowledge	1.78	.28	2.11

Note. Effect sizes are given as standardized mean differences between consecutive years (e.g., *d*(1/2) indicates the mean difference between students from the first and the second year of VET); higher values indicate better mean performance of students from the higher year; all changes were significant at $\alpha = .01$.

In contrast, the means of *gf* and *gc* remained stable across the three years of education (see Figure 6), since domain-general knowledge and reasoning ability are not specifically addressed in VET. The almost identical means of the intelligence scales across VET in this cross-sectional data, also advocate for the comparability of the subsamples.

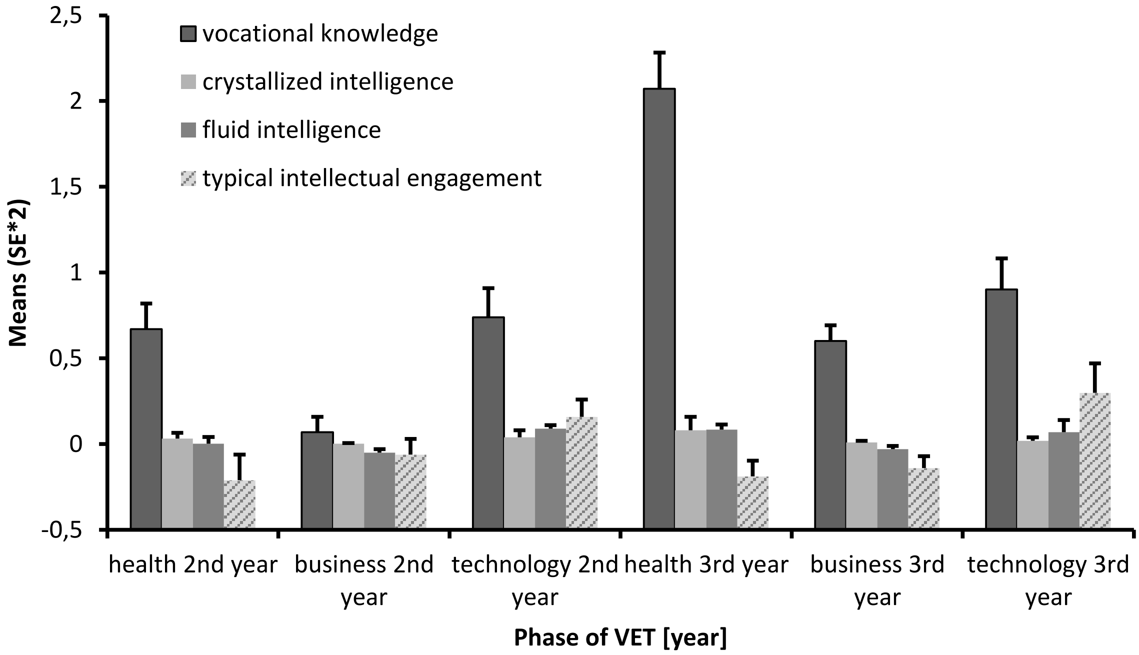

Figure 6. Changes in the means of vocational knowledge, *gc*, *gf*, and *TIE* across the three years of Vocational Education and Training.

Note. Parameters are means of the latent variables from the measurement models of vocational knowledge, *gc*, *gf*, and *TIE* on the level of strict invariance. The means for first year students are fixed at 0.

5.3.2. Prediction of domain knowledge within domains

Structural equation modeling was used to predict individual differences in health knowledge of medical assistants with *gc*, *gf* and *TIE* (Figure 7). After constraining the factor loadings and intercepts to equality across years of education (i.e., strong measurement invariance), the model still provided good model fit ($\chi^2(253) = 330.4$, $p = .001$, CFI = .961, RMSEA = .04, SRMR = .07) as compared to a model constrained to metric measurement invariance, (ΔRMSEA = .00, ΔCFI = .001). *Gc* turned out to be the strongest predictor of vocational knowledge in all three years of VET. Interestingly, *gf* showed no impact on vocational knowledge for the first two years of education and only a small influence in the last year of VET (Möhring, Schroeders, & Wilhelm, 2018). *TIE* shows significant but small effects for the first and second year that drops to zero for third year students.

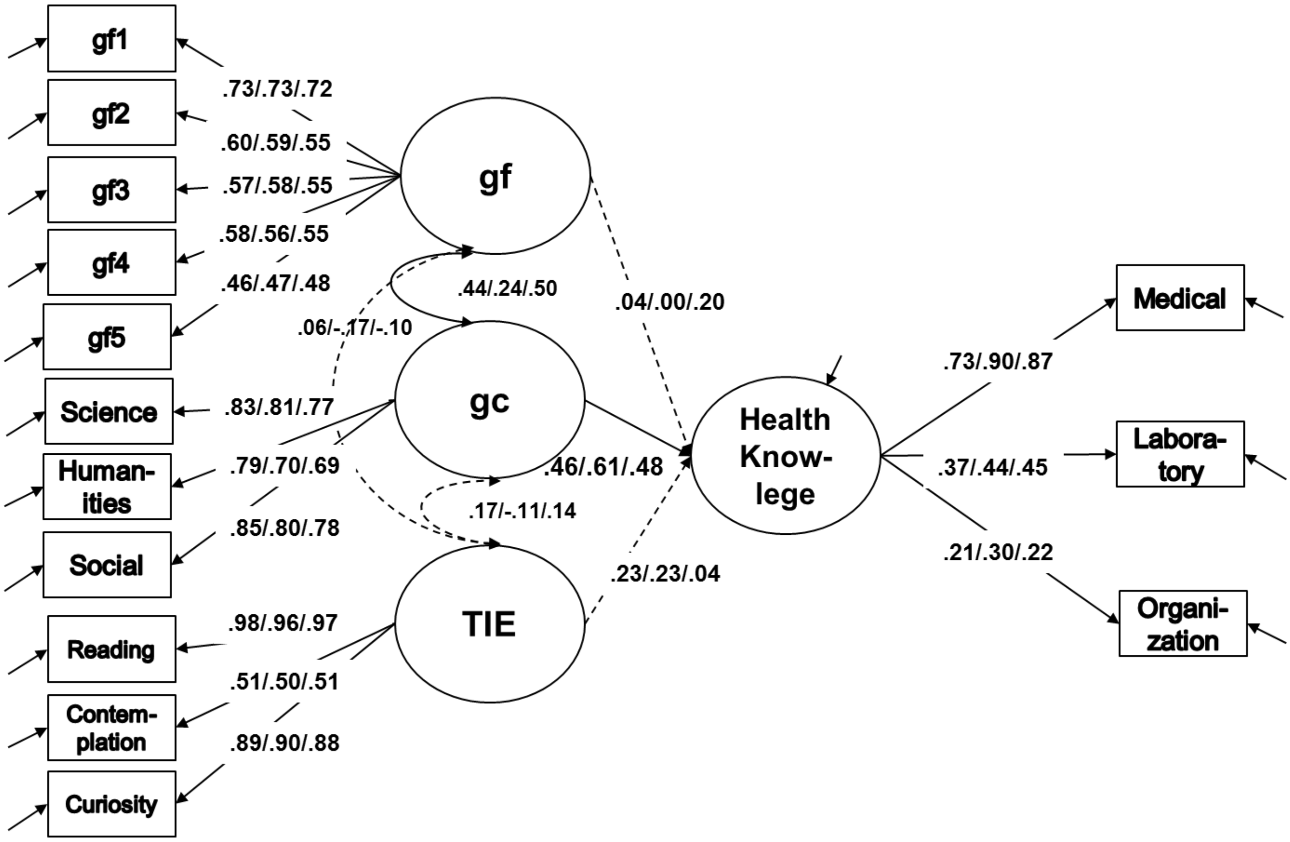

Figure 7. Prediction Model of Vocational Health Knowledge Through *gf*, *gc* and *TIE* (model 1).

Note. Fluid (*gf*) and crystallized (*gc*) intelligence as correlated factors; non-significant relationships between latent variables are indicated with a dashed line. $n = 448$, $\chi^2(253) = 330.4$, $p < .01$, CFI = .961, RMSEA = .04, SRMR = .07.

To further examine the unique effects of *gf* and *gc* on vocational knowledge acquisition, we modeled *gc* as a nested factor (labeled $gc^{\#}$) below an overarching *g* factor (see Figure 8). This allows us to estimate the effect of a general cognitive ability factor and an independent (residual) knowledge factor. Model fit of the nested factor model was good: $\chi^2(253) = 315.0$, $p = .01$, CFI = .963, RMSEA = .04, SRMR = .07. As expected, the overarching *g* factor showed a significant influence on health knowledge with a slight increase for the third year students. However, the predictive power for $gc^{\#}$ was higher than the impact of *g*, with the exception of the third year. And even for third year students, the influence of an overarching *g* factor did not exceed that of $g^{\#}$. In other words, even though *g* had a significant influence on health knowledge for all three years of VET, $gc^{\#}$ remained highly important (Möhring, Schroeders, & Wilhelm, 2018).

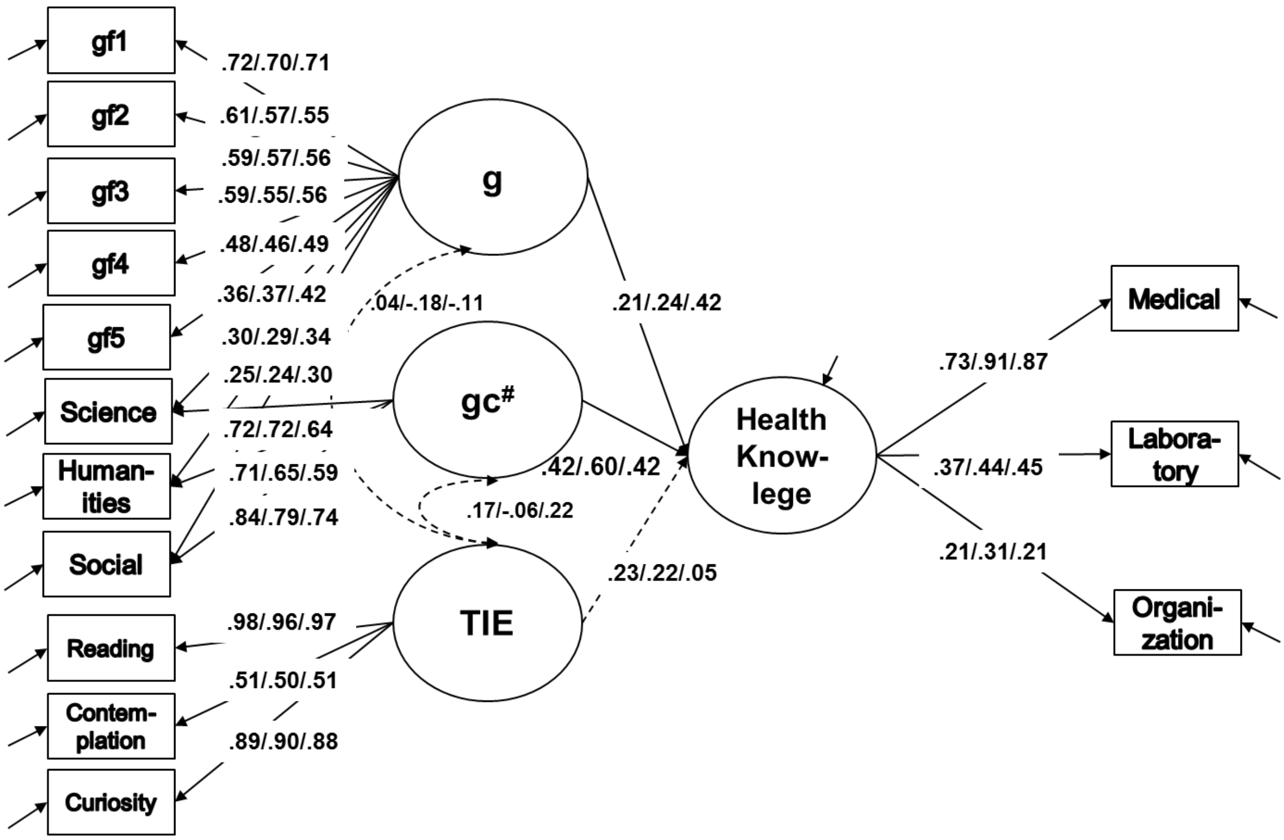

Figure 8. Prediction Model of Vocational Health Knowledge Through *g*, $gc^{\#}$ and *TIE* (model 2).

Note. Crystallized intelligence ($gc^{\#}$) nested below intelligence (*g*); non-significant relationships between latent variables are indicated with a dashed line. $n = 448$, χ^2 (253) = 324.6, $p < .01$, CFI = .964, RMSEA = .04, SRMR = .07.

Figure 9 presents both the correlated (model 3) and the nested (model 4) prediction models for VET students in the business domain. Similar to the results of the medical assistants, these models showed a good fit to the data even after constraining factor loadings and intercepts to equality and did not differ substantially from a model on the level of metric invariance (ΔRMSEA = .00, ΔCFI = .001). Again, *gc* had the strongest impact on vocational knowledge for the three years of VET. The impact of gf was considerably lower than that of *gc* but increased notably for g in the nested model. Nevertheless, the effect of g never exceeded that of $gc^{\#}$. TIE remained non-significant for both models and across all groups.

In a last step, we analyzed the predictive power of *gf*, *gc* and *TIE* for vocational knowledge in technology-oriented VET students. As before, the factor loadings and intercepts were constrained to equality across groups in order to test the model on the level of scalar invariance for both the correlated factor model (model 5) and the nested factor model (model 6). Again, this model did not differ substantially from a model on the level of metric invariance (ΔRMSEA = .01, ΔCFI = .009). Both models showed a good fit to the data, meeting all cut-off criteria (see Figure 10). The respective contributions of *gf* and *gc* are especially apparent in this domain: even after accounting for the shared variance between the intelligence factors with the nested model, the influence of the general intelligence factor remained non-significant. Overall, the results in the IT domain are able to replicate the main findings from the other two domains, i.e. *gc* had the strongest impact on the acquired domain-specific knowledge during all phases of VET. However, for third year students, a change in the respective impact of *gf* and *gc* is notable. Unlike the effect in the health domain, for IT students, the impact of *gc* increased slightly in their last year of VET while the regression coefficient of *gf* dropped to zero. Possible reasons for these small changes will be discussed in Chapter 6.

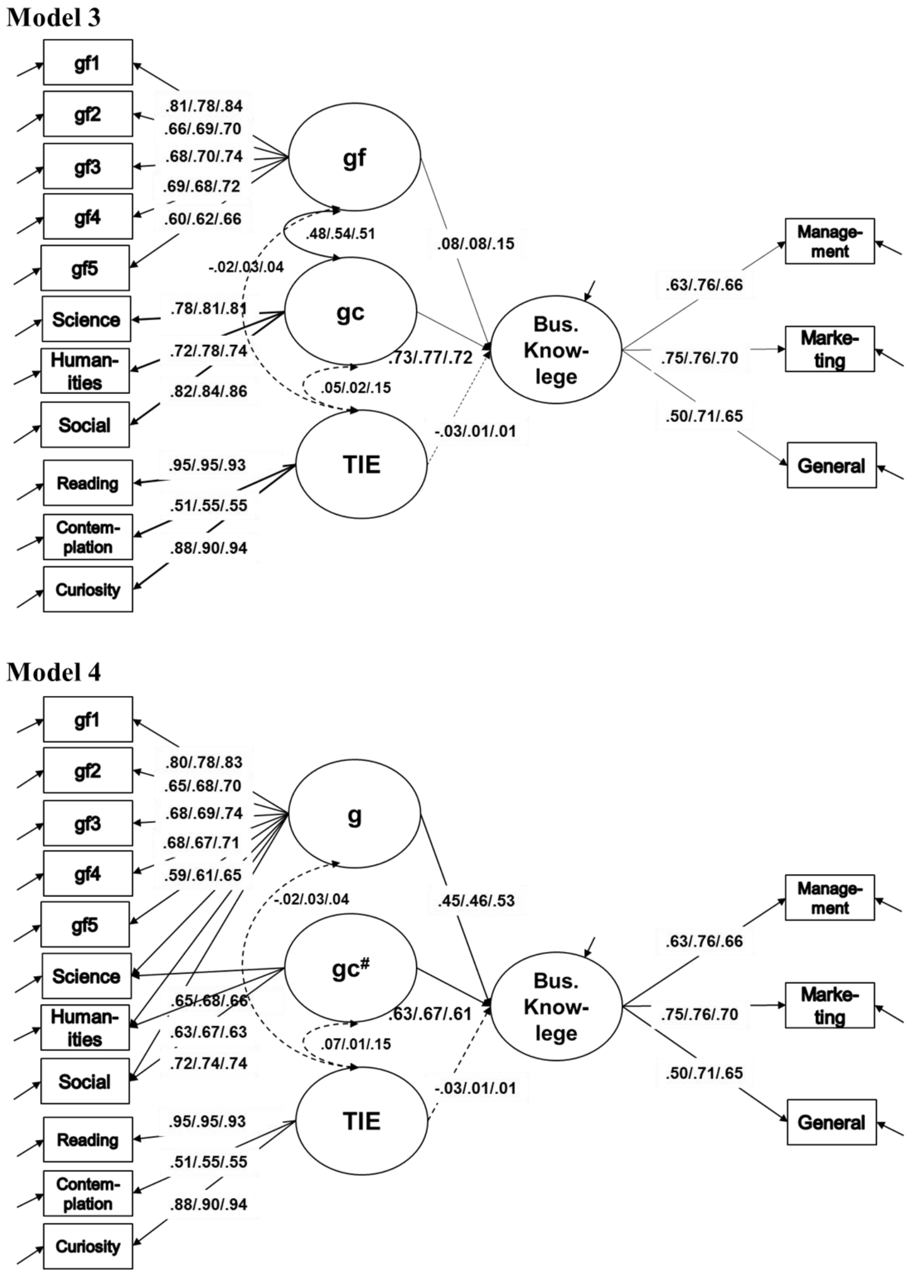

Figure 9. Prediction Model of Vocational Business Knowledge (Bus. Knowledge) Through *gf*, *gc*, *g*, *gc*$^{\#}$ and *TIE*.

Note. Model 3: Fluid (*gf*) and crystallized (*gc*) intelligence as correlated factors; non-significant relationships between latent variables are indicated with a dashed line. $n = 1034$, $\chi^2(253) = 359.5$, $p < .001$, CFI = .982, RMSEA = .03, SRMR = .05.

Model 4: Crystallized intelligence (*gc*$^{\#}$) nested below intelligence (*g*); non-significant relationships between latent variables are indicated with a dashed line. $n = 1034$, χ^2 (253) = 357.9, $p = .01$, CFI = .982, RMSEA = .03, SRMR = .05.

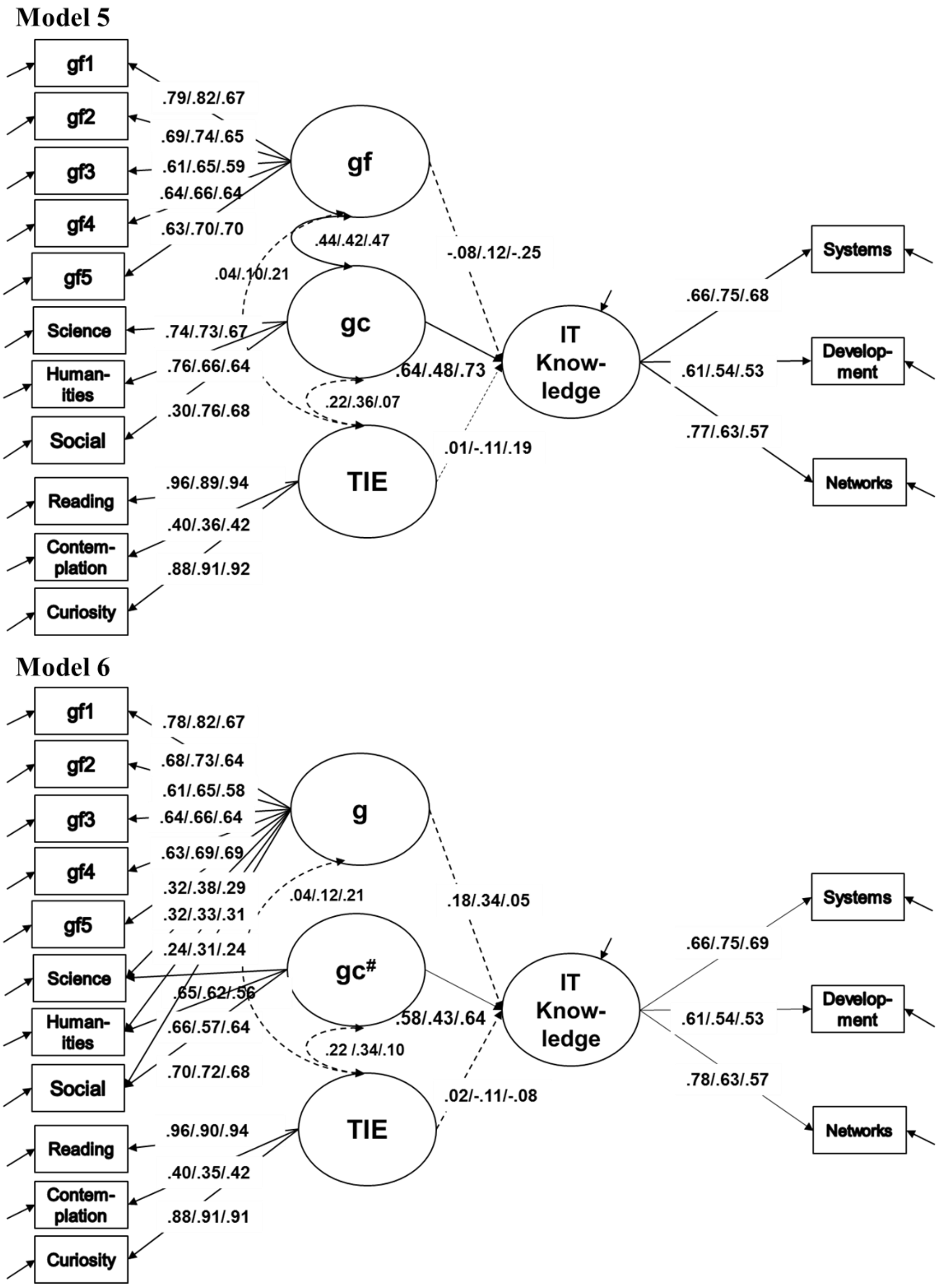

Figure 10. Prediction Model of Vocational IT Knowledge Through *gf*, *gc*, *g*, $gc^{\#}$ and *TIE*.

Note. Model 5: Fluid (*gf*) and crystallized (*gc*) intelligence as correlated factors; non-significant relationships between latent variables are indicated with a dashed line. n = 372, $\chi^2(253) = 344.7$, $p < .001$, CFI = .955, RMSEA = .05, SRMR = .07

Model 6: Crystallized intelligence ($gc^{\#}$) nested below intelligence (*g*); non-significant relationships between latent variables are indicated with a dashed line. n = 372, χ^2 (253) = 344.2, p = .01, CFI = .956, RMSEA = .05, SRMR = .07.

5.3.3. Prediction of domain knowledge between domains

After examining the prediction of domain-specific knowledge in each domain separately, the predictive power of *gf*, *gc*, and *TIE* was further investigated between domains with all students in a single model. A comparison between the domains was possible because students from each domain were presented with two short tests consisting of 15 items each, from the other two domains.

Table 11. *Fit Indices for the Measurement Invariance*

	χ^2/df	*p*	RMSEA	CFI	ΔRMSEA	ΔCFI
gff						
Configural	19.5/12	.08	.03	.997	-	-
Metric	35.3/23	.05	.03	.996	.00	.001
Scalar	70.1/31	< .001	.04	.987	.01	.009
Strict	86.9/41	< .001	.04	.984	.00	.003
gc						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	10.0/4	.04	.04	.998	.04	.002
Scalar	41.7/8	< .001	.08	.988	.04	.010
Strict	63.7/14	< .001	.07	.982	-.01	.006
TIE						
Configural	0.0/0	< .001	< .001	1.0	-	-
Metric	7.2/4	.13	.03	.997	.03	.003
Scalar	37.1/8	< .001	.07	.988	.04	.009
Strict	44.2/14	< .001	.05	.987	-.02	.001

Note. *gff* = Figural Fluid Intelligence; *gc* = Crystallized Intelligence; TIE = Typical Intellectual Engagement. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation.

To illustrate, students from medical assistant classes would work on 30 items of health-related knowledge and additionally on 15 items of business knowledge as well as 15 items of technology knowledge. Therefore, a common scale across all phases and domains of VET could be used to link the domain-specific knowledge tests. The measurement models of the predictor variables were indeed invariant across groups (see Table11), thus allowing for a comparison of regression coefficients across groups in using MGCFA.

The multiple-group model (model 7) for the prediction of domain-specific knowledge across the three domains showed good values, χ^2 (253) = 737.9, p < .001, CFI = .969, RMSEA = .06, SRMR = .06. Just as for the prediction models within each domain, factor loadings and intercepts were constrained to be equal across groups, while the residual variance was estimated freely. Interestingly, while the influence of *TIE* on domain-specific knowledge remained negligible for knowledge in all domains, *gf* showed a significant influence and had a stronger impact than *gc* for knowledge in the technology domain ($\beta_{IT/gf}$ = .30; $\beta_{IT/gc}$ = .12). For both the health and the business domain, *gc* showed the strongest predictive power ($\beta_{health/gf}$ = .44; $\beta_{health/gc}$ = .51; $\beta_{bus./gf}$ = .50; $\beta_{bus./gc}$ = .60). Overall, the parameter estimates for the domains of health and business are comparable to the analyses within each domain. The results emphasize the significance of *gc* for the domain-specific knowledge factor. While this model allows for a comparison across domains, it still neglects the differences across the years of VET. Since the overall sample can be split in 9 groups (3 domains x 3 years of VET), all groups were included simultaneously into a model using MGCFA (model 8).

Only *gc* and *gf* were included as predictor variables for this model, since *TIE* did not add substantially to the variance explained in any of the previous prediction models. Again, factor loadings and intercepts were constrained to equality, in terms of scalar invariance. The model fit was overall acceptable, χ^2 (497) = 1129.0, p < .001, CFI = .965, RMSEA = .07, SRMR = .06. All regression coefficients are displayed in Table 12.

Table 12. *Regression Coefficients for Model 10*

	Gc			Gf		
	β	(*SE*)	*CI*	β	(*SE*)	*CI*
business						
1st year	**.64**	(.06)	.55 - .73	**.14**	(.04)	.08 - .21
2nd year	**.71**	(.06)	.61 - .80	**.13**	(.04)	.07 - .20
3rd year	**.70**	(.06)	.61 - .79	**.16**	(.04)	.10 - .23
health						
1st year	**.76**	(.04)	.70 - .83	**.12**	(.03)	.07 - .16
2nd year	**.73**	(.05)	.65 - .80	**.12**	(.04)	.06 - .19
3rd year	**.68**	(.06)	.59 - .78	**.14**	(.04)	.07 - .20
technology						
1st year	-.26	(.19)	-.57 - .06	**.43**	(.04)	.36 - .49
2nd year	**.53**	(.04)	.46 - .60	**.15**	(.04)	.09 - .21
3rd year	**.53**	(.06)	.43 - .63	**.15**	(.05)	.08 - .22

Note. β = standardized regression coefficient of crystallized and fluid intelligence on domain-specific knowledge; CI = 95% confidence interval of the regression coefficient for crystallized and fluid intelligence; (SE) = standard error of the regression coefficients for crystallized and fluid intelligence; bold print indicates significance at $\alpha = .05$.

Including all 9 groups into the analysis allows us to examine the regression coefficients under the influence of both the specific domain and the year of VET. These results explain the weak influence of *gc* for the IT domain in model 7. Crystallized intelligence has a negative but non-significant regression coefficient in the first year, while fluid intelligence shows a significant influence during this phase of VET. The relationship between both predictors reverses in the course of the three years of education. This can also be seen in the increasing influence of *gc* and the decrease in *gf* in model 5 and model 6. The regression coefficients for health and business are considerably stable with *gc* as the main predictor and no or a negligible influence of *gf*.

Since the three VET domains have different distributions of prior school graduation, the educational attainment was controlled for in a final model and introduced as a background variable (model 11). The model fit was slightly worse than model 10 and only marginally acceptable, χ^2 (591) = 1428.4, p < .001, CFI = .952, RMSEA = .08, SRMR = .07. The resulting regression coefficients did not differ from model 10 and educational attainment showed no substantial influence on the vocational knowledge. The results are summarized in Table 13. Thus, the present results can be interpreted as independent from the students' prior educational attainment.

Table 13. *Regression Coefficients for Model 11*

	Gc			Gf			Educational attainment		
	β	(*SE*)	*CI*	β	(*SE*)	*CI*	β	(*SE*)	*CI*
business									
1st year	**.64**	(.06)	.55 - .73	**.14**	(.04)	.08 - .21	.07	.05	-.01 - .14
2nd year	**.71**	(.06)	.61 - .80	**.13**	(.04)	.07 - .20	.06	.05	-.01 - .14
3rd year	**.70**	(.06)	.61 - .79	**.16**	(.04)	.10 - .23	.07	.06	-.02 - .16
health									
1st year	**.76**	(.04)	.70 - .83	**.12**	(.03)	.07 - .16	.05	.04	-.02 - .12
2nd year	**.73**	(.05)	.65 - .80	**.12**	(.04)	.06 - .19	.06	.05	-.02 - .14
3rd year	**.68**	(.06)	.59 - .78	**.14**	(.04)	.07 - .20	.06	.05	-.01 - .14
technology									
1st year	-.26	(.19)	-.57 - .06	**.43**	(.04)	.36 - .49	.08	.06	-.02 - .17
2nd year	**.53**	(.04)	.46 - .60	**.15**	(.04)	.09 - .21	.07	.05	-.02 - .15
3rd year	**.53**	(.06)	.43 - .63	**.15**	(.05)	.08 - .22	.06	.05	-.02 - .14

Note. β = standardized regression coefficient of crystallized and fluid intelligence and educational attainment on domain-specific knowledge; CI = 95% confidence interval of the regression coefficient for crystallized and fluid intelligence and educational attainment; (SE) = standard error of the regression coefficients for crystallized and fluid intelligence and educational attainment; bold print indicates significance at α = .05.

5.4. Discussion

The current study focused on the prediction of individual differences in domain-specific knowledge, acquired through the course of VET for medical assistants, business students, and IT-specialists. While most studies in educational settings are limited to a single set of predictors (i.e. indicators of maximal vs. typical performance) and limited in regard of the sample (i.e. observing only one year of VET or one specific occupation), the current study predicted knowledge acquisition in VET by cognitive abilities such as *gc* and *gf* as well as the investment trait *TIE*. Differences in domain-specific knowledge were predicted for different stages of VET (1st year, 2nd year and 3rd year) and in distinct vocational domains (health, business, and IT). One of the main finding is that *gc* turned out to be the strongest predictor of domain-specific knowledge throughout the course of education in three distinct vocational domains, emphasizing the importance of general knowledge for educational achievements. It is important to keep in mind that the implemented *gc* test covered knowledge in various domains, such as technology, music, and law, rather than health-related or medical knowledge.

This result is in line with previous findings emphasizing the importance of prior knowledge in learning. For example, Hambrick and colleagues showed that prior baseball knowledge was the most important predictor for baseball-related memory performance (Hambrick & Engle, 2002), current events knowledge (Hambrick, Meinz, & Oswald, 2007), and knowledge acquisition (Hambrick, 2003). Compared to previous investigations of the knowledge-is-power hypothesis, the present study offers an ecologically valid assessment of knowledge acquisition in VET. Thus, the breadth and depth of the learning subject differs from laboratory studies about narrow domains such as baseball knowledge. Second, instead of limiting the investigation to one domain, three distinct domains were examined, namely health, business and information technology. Furthermore, we assessed general knowledge instead of prior domain-specific knowledge as a predictor of knowledge acquisition, which allows for an assessment of *gc* that is in line with Cattell's (1963) definition.

The respective contributions of *gf* and *gc* are influenced by several factors: First, a stronger influence of *gf* has been reported on knowledge acquisition in classroom settings as compared to self-study sessions (Beier & Ackerman, 2005). In the context of knowledge acquisition in VET, the classroom setting represents a formalized learning environment, which is accompanied by additional learning settings in company or medical practice. The education in school and hands-on training outside of school is approximately split in a ratio of 40% to 60%, respectively, which illustrates the importance of vocational knowledge in settings with a practical orientation in VET. Since these settings are less regulated than secondary education with full-time class attendance, prior knowledge is crucial for the VET students' knowledge acquisition. Thus, higher levels of *gc* allow students to more easily integrate new knowledge into a framework of prior knowledge in new and less regulated situations. This unique learning environment might explain the small influence of *gf* on knowledge acquisition of VET students.

Considering the dominance of the assessment of reasoning ability in explaining and predicting learning outcomes (e.g., Kuncel, Hezlett, & Ones, 2004; van der Maas, Dolan, Grasman, Wicherts, Huizenga, & Raijmakers, 2006; Ones, Viswesvaran, & Dilchert, 2004; Salgado et al., 2003) this result is remarkable. The way reasoning was measured in the current study might have biased the results. More specifically, although figural reasoning is the best proxy for the assessment of *gf*, it does not replace a comprehensive assessment of *gf* (Wilhelm, 2004). A broader assessment of *gf*, taking into account verbal and numerical reasoning, might enhance the effect of *gf*. Alternatively, working memory could be used as a predictor of domain-specific knowledge acquisition (Hambrick & Engle, 2002).

The differential contributions of *gf* and *gc* should also be interpreted in light of the high construct overlap between both factors, which some researchers interpret as an indication of a general cognitive ability factor (e.g., Carroll, 1993). However, in the present study, the predictive power of a general *g* factor accounting for reasoning as well as the shared variance between *gf* and *gc* did not exceed the impact of the residual knowledge factor $gc^{\#}$, which was nested below an overarching *g* factor. Thus, even under the assumption that a general cognitive ability factor accounts for the high construct overlap between gf and *gc*, the importance of the knowledge factor for the prediction of cognitive abilities is clearly visible.

The predictive power for fluid intelligence slightly increased for third-year medical assistant students, which might be due to the specific curricular in the third year. Students in the final VET year have to focus on independent planning of practice-oriented tasks (e.g., organizing and assisting in surgical treatments) and complex problem solving (e.g., recognizing suspicious laboratory values), rather than the focus on declarative knowledge in first and second year of VET (Ministry of Education and Cultural Affairs, Youth and Sports of Baden-Wuerttemberg, 2005). However, it seems more likely that these changes in the power of *gf* towards the third year are artefacts of random fluctuations between samples. In comparison, the effect of *gc* increased for students in the technology domain. This might be due to the highly specialized content of the technology-specific test. Unlike the first-year questions of the health and business domains, the technology test contained almost no items that could be answered with general knowledge from higher education alone. Thus, first year technology students might have less specific prior knowledge and accordingly would need to rely on their reasoning abilities more strongly than students from health and business domains. Surprisingly, while the nested model showed a substantial influence of the *g*-factor on domain-specific knowledge for VET students from the domains of business and health, there was no significant effect for the IT students, overall. This is not in line with the a priori hypothesis that the typical association of the technology domain with natural sciences would result in the strongest relation to fluid abilities for IT students. While the effect of the *g*-factor in the health domain was in line with the expectations, the weakest influence was expected for the business domain. Contrary to this hypothesis, a substantial effect of the *g*-factor could be observed for the business domain which might be due to the mathematical focus of the curriculum. Since we did not want to measure the students' mathematical abilities, the use of calculators was permitted for the domain-specific knowledge test. The students needed to apply the adequate formula for the respective problem but did not have to rely on mental arithmetic in order to solve them. Nevertheless, these mathematical knowledge items might have contributed to the higher relation with the reasoning tasks. On the other hand, the low impact of *gf* and the general *g*-factor can hardly be explained by the type of knowledge. Although IT courses in VET focus less on scientific and more on hands-on knowledge than university courses, overall there was still a considerable amount of items requiring reasoning abilities (e.g., structure charts). Unfortunately the third year of the IT domain was an especially small sample with $n < 100$. This lowers the reliability of the respective estimates in this sample. Nevertheless, the groups of first- and second-year students were approximately comparable in size to the groups of medical assistants and while the effect of *gf* is slightly stronger in these groups of IT students, they still can not compare to *gc*. This leads to the overall conclusion that reasoning did not impact the domain-specific knowledge acquisition for IT students in VET. However, these results should still be treated with caution and replicated with a larger sample.

As expected, we found a substantial increase of vocational knowledge between adjacent years of VET and no changes in *gf* and *gc*. The effect sizes of the increase in vocational knowledge in the present study are slightly higher than the typically moderate effects in secondary school education (Beaton, Martin, Mullis, Gonzalez, Smith, & Kelly, 1996; Schroeders, Schipolowski, & Wilhelm, 2015). This supports the assumption that in-depth knowledge especially develops after regular school education, when students are able to choose more specific paths of education. This vocational, in-depth knowledge is primarily acquired in a few domains, resulting in distinct knowledge profiles (Kanfer & Ackerman, 2004). The current findings provide support for the notion that a comprehensive knowledge base is a crucial prerequisite for knowledge acquisition in educational environments (Baumert, Lüdtke, Trautwein, & Brunner, 2009; Baumert, Nagy, & Lehmann, 2012). The results of Baumert et al. (2009) show an increasing influence of *gc* and a decrease of *gf* from the end of elementary schooling to the upper secondary level. This is in line with the current findings, showing a strong impact of *gc* and a negligible effect of gf. This cumulative process of knowledge acquisition is favored by the hierarchically structured VET curriculum. Students with higher levels of *gc* may generally be able to acquire new knowledge more quickly and efficiently. Thus, newly acquired knowledge is integrated in a framework of prior knowledge. According to Cattell's theory of fluid and crystallized intelligence (1943; 1963); besides *gf*, factors such as motivation and teaching are essential for learning. These additional factors are taken into account within *gc*, a compound of complex perceptual, discriminatory, and executive cognitive skills, acquired through practice and experience. It seems likely that students who are more interested and therefore more motivated for achieving success in VET perform better in vocational knowledge tests. In this respect, Cattell (1963) rephrased knowledge as "invested intelligence", that means, while fluid intelligence is necessary for learning, it is not sufficient. Academic achievement is typically stronger associated with investment traits such as Typical Intellectual Engagement or Need for cognition than abstract reasoning ability (Cacioppo, Petty, Feinstein, & Jarvis, 1996; von Stumm, Hell, & Chamorro-Premuzic, 2011). Possibly, the motivation to invest effort and time into the acquisition of vocational knowledge is especially important for VET students with overall lower cognitive performance. Students must also be willing to invest their intelligence constantly over a long period of time to study relevant material. Therefore, knowledge tests can also be understood as indirect measures of motivation. This has been pointed out by studies, investigating the performance of trainees in other domains, for example, for the prediction of vocational knowledge of pilot applicants at the end of their training (Zierke, 2014). In accordance with

King, Carretta, Retzlaff, Barto, Ree, and Teachout (2013), Zierke (2014) interpreted these results as indication that the educational success includes both ability in a sense of what the student “can do” as well as motivation as the “will do” portion of educational achievement, which can effectively been assessed with knowledge tests.

The influence of the investment trait *TIE* on domain-specific knowledge in VET has been negligible for all domains as well as for students from all years of VET, in this study. There have been several findings, emphasizing the effect of *TIE* on academic achievement. However these reports may have overestimated the effect because they mostly relied on regression analysis with manifest indicators and were based on selective samples (e.g., university students). Furthermore, Schroeders, Schipolowski, and Böhme (2015) have shown that most of the influence of *TIE* on achievement tests for students in Grade 9 was accounted for by *gf*. The present findings add to these results, showing none or weak influence of *TIE* over and above intelligence for cognitive performances in academic and school settings.

6. General Discussion

6.1. Summary of the results

The presented thesis investigates the assumptions of the knowledge-is-power hypothesis in more naturalistic and educational settings. For this investigation, two approaches have been taken. First, the influence of domain-specific knowledge on comprehension of new information was tested with an innovative assessment capitalizing on the internet. In order to investigate individual differences in digital literacy, test-takers were presented with health-related comprehension problems. Instead of reading a given text, they were instructed to search the internet for the information required to answer the questions. Second, knowledge acquisition in vocational education and training was be predicted by cognitive abilities such as knowledge, reasoning and by the investment trait typical intellectual engagement. Differences in domain-specific knowledge were predicted in different stages of the VET (1st year, 2nd year and 3rd year) and in distinct vocational domains. The focus for all studies was to examine the predictive validity of knowledge for cognitive performances in broad real-life contexts and to investigate whether the assumptions.

For the first part, two studies were conducted, focusing on health knowledge and its role for the prediction of digital literacy. A new test was developed to assess digital literacy in a more naturalistic setting. In order to develop a contemporary assessment of individual differences in digital literacy, we decided to resign control over the stimulus material by allowing for an unrestricted search for information on the internet. The relationship between this newly developed test and fluid and crystallized intelligence was investigated, while controlling for computer usage, in two studies with adults (n_1 = 120) and vocational high school students (n_2 = 171). Structural equation modeling was used to investigate the amount of unique variance explained by each predictor. In both studies, about 85% of the variance in the digital literacy factor could be explained by reasoning and knowledge while computer usage did not add to the variance explained. In Study 2, prior health-related knowledge was included as a predictor instead of general knowledge. While the influence of fluid intelligence remained significant, prior knowledge strongly influenced digital literacy ($\beta = .81$). Together both predictor variables explained digital literacy exhaustively. These findings are in line with the view that knowledge is a major determinant of higher-level cognition.

For the second part, the focus was on the prediction of domain-specific knowledge in VET, which is a crucial transition period between school and work. Knowledge acquisition in VET was be predicted by general knowledge, reasoning ability, and intellectual investment. Domain-specific knowledge tests were developed for the assessment of the domain-specific knowledge acquired in each VET domain (health, business, technology). In order to account for differences in the curriculum and an increasing difficulty of items with advancing grades, a vertical linking design was used for the development of the domain-specific knowledge tests. Furthermore, the tests were linked across the VET courses by including items from the knowledge tests outside the students' subject area. This allowed for analyses across domains. First, the individual differences within every domain were examined in three independent analyses with medical assistants ($n_1 = 447$), business trainees ($n_2 = 1034$), and IT-oriented VET students ($n_3 = 372$). MGCFA was used to compare the impact of the predictor variables on student performance across the three years of VET. Similar results could be observed for each domain: a) *gc* had the strongest impact on domain-specific knowledge, b) the predictive power of *gf* was distinctly below that of *gc*, c) even in a nested model, the impact of *g* did not exceed $gc^{\#}$, and d) the investment trait *TIE* did not add to the variance explained.

Overall these effects hold up across the three groups in each domain. Slight changes were observed for students in the third year of VET for medical assistants and IT students. For third year students in the medical domain, there is a small increase in the predictive power of *gf*. This could be due to the increased focus on hands-on knowledge and more complex diagnostic and therapeutic problems in the curriculum but is most likely due to random fluctuation within the sample, as indicated by the overlapping confidence intervals (1^{st} year:

CI_g = .03 - .39; 2nd year: CI_g = .12 - .49; 3rd year: CI_g = .33 - .70). In the IT domain, we find contrary results, showing an increase of *gc* and a small decrease in the power of *gf* in the third year of VET. These changes are more notably than those in the health domain and they emphasize the relevance of *gc* for the prediction of domain-specific knowledge. However, the confidence intervals between the three years of VET were still overlapping (1st year: CI_g = .02 - .35; CI_{gc} = .39 - .77; 2nd year: CI_g = .27 - .42; CI_{gc} = .28 - .58; 3rd year: CI_g = -.21 - .32; CI_{gc} = .53 - .76). To further examine the differences across domains, MGCFAs were used including students from the three domains in a single prediction model. This model further helped to establish *gc* as the strongest predictor of student performance in VET. Except for first year students in the technology domain, domain-specific knowledge was influenced most strongly by *gc* for all groups (3 domains x 3 years of VET). The regression coefficients for the business and health domain were comparable and showed a neglectable increase for *gf* in the third year of education. All in all, the predictive power of *gf* and *gc* was stable across time and domains for these groups. In contrast, students in the technology domain showed notable changes in the prediction of vocational knowledge. While *gf* was the strongest predictor in the first year, the relation between *gf* and *gc* changed over time and *gc* was clearly the main predictor of the domain-specific knowledge during the third year of VET. These differences between domains could be influenced by different factors which are discussed below. The results for the prediction of vocational knowledge support the general assumptions of the knowledge-is-power hypothesis and further emphasize the importance of *gc* as a comprehensive knowledge factor for the prediction of cognitive performances in real-world environments.

6.2. Domain-specific knowledge, general knowledge and ecological validity

To reiterate, the knowledge-is-power hypothesis postulates that prior knowledge has a strong facilitating effect on several cognitive performances (Hambrick & Engle, 2002). That is to say, people with higher levels of prior knowledge show the most gain of cognitive abilities in their area of expertise. This can include knowledge acquisition (Beier & Ackerman, 2005), comprehension abilities (Vanderwood, McGrew, Flanagan, & Keith, 2002), or memory performance (Hambrick & Engle, 2002). In the present thesis, cognitive abilities were examined in innovative and naturalistic assessments to extend these findings into real-life settings.

Using naturalistic tests and testing environments is useful to enhance the ecological validity and accordingly the generalizability of the results. Ecological validity often helps to enhance external validity (Schmuckler, 2001). An ecologically valid study should be an approximate representation of the real-world setting that is being investigated. This in turn can provide generalizability of the results. However, it would be wrong to assume that these terms can be used interchangeably. An experiment can have high external validity but low ecological validity (Shadish, Cook, & Campbell, 2002). For example, digital literacy is often investigated with traditional multiple choice items. Results from these tests may well be generalizable but they are not a good representation of contemporary information technology – the real-world setting in question. In turn, an ecologically valid test is not necessary externally valid. Even a very naturalistic testing environment can be so specialized that it is impossible to generalize the results across different populations. The debate about ecological validity actually often revolves around theoretical issues. The focus lies on the question whether a parameter X influences the relationship between the parameter Y and behavior Z. Therefore, it would appear to be critical for an ecologically valid assessment that the design adequately accounts for the theoretical constructs in question (Schmuckler, 2001). Ecological validity has a long history of discussions about experimental designs (e.g. Campbell, 1957; Campbell & Stanley, 1967). However, there is no research that is independent of theory nor are there research procedures that are truly theory neutral. All theoretical assumptions endorse particular methods. The relation between the theory, methodological aspects and theoretical interpretation should be acknowledged when discussing ecological validity.

In the case of this thesis, ecological validity becomes relevant in regards to the investigation of the knowledge-is-power hypothesis. For both parts of the current thesis the consequences of implementing ecological validity mostly apply to the assessment of the criterion variable. Developing a momentary ecological assessment of digital literacy was the main focus of the first part. The relevance and consequences of the momentary ecological assessment of the construct in question has been discussed in Chapter 4.1., as have been the consequences for the investigation of the knowledge-is-power hypothesis (see Chapter 5.1.). Overall, the underlying mechanisms also apply to the second part. Specific and narrow knowledge domains such as baseball allow for a very clear distinction between experts and novices in the respective domain. People with little to no interest in baseball will hardly be able to follow the specific vocabulary. A similarly highly specific domain would apparently be the IT domain. VET students from business and medical assistant courses had considerably more problems to choose correct answers on the IT test as compared to the respective other knowledge test outside their subject area. The IT students in turn did not show these problems for their own test and their results on the other two knowledge tests were comparable to those of business and medical assistant students. This leads to the conclusion that technical knowledge is still a very narrow domain for a comparison across domains as compared to business and health knowledge. However, the current results further differentiate between experts and novices in the same domain, that is to say students in different phases of VET. Another difference is the focus on vocational knowledge instead of expertise from hobbies. The key difference in this case is the apparent relevance of the knowledge for novices and experts alike. High-stakes settings typically include admission testing and final exams. The domain-specific knowledge tests were developed and administered to reflect contents from VET examinations.

This contextualized approach can be helpful to investigate the general assumptions of the knowledge-is-power hypothesis. In this regard, one question is whether prior knowledge as the primary predictor needs to be highly domain-specific or if *gc* as a comprehensive knowledge factor has comparable predictive power. Hambrick (2003) examined the influence of prior knowledge on newly acquired basketball knowledge about people and events. Even though both knowledge tests were about basketball knowledge, only prior knowledge about people and events was a relevant predictor rather than knowledge about rules and regulations. However, this study did not include *gc* as a comprehensive prior knowledge factor. The results for the influence of *gc* in the context of the knowledge-is-power hypothesis are mixed. Ackerman, Bowen, Beier and Kanfer (2001) found direct effects of *gc* on knowledge acquisition in several broad domains (e.g. physical sciences, psychology, biology). Similar results have been observed for the prediction of current events knowledge (Ackerman & Kanfer, 2004; Beier & Ackerman, 2001; Hambrick, Meinz, & Oswald, 2007). This supports the idea that a comprehensive knowledge base creates a framework in which new knowledge is integrated. When new information is encountered, existing knowledge is activated. The activation is stronger if the knowledge is associatively related (e.g., Anderson, 1983; McClelland & Rumelhart, 1981).

There have been studies, focusing on closely related prior knowledge instead of a broader *gc*-factor as a predictor of higher cognitive abilities. For example, Hambrick and Engle (2002) found that prior baseball knowledge facilitated the memory performance on radio broadcasts about baseball games while general knowledge had no substantial effect on memory performance. Furthermore, the effect of *gc* in the aforementioned study of Beier and Ackerman (2005) was mediated through prior domain-specific knowledge (see also Ackerman & Beier, 2006). These results point towards differentiated effects, depending on the depth and specificity of prior knowledge and might be supportive of the theoretical distinction between a general and a domain-specific knowledge factor (McGrew, 2009).

The results in the current thesis emphasize the importance of *gc* as a broad knowledge factor. While domain-specific knowledge was a very powerful predictor of digital literacy in Study 2, the *gc*-scale was consistently able to explain a large portion of variance across all studies. In other words, higher levels of knowledge make it easier to acquire new knowledge (see also, Beier & Ackerman, 2005; Hambrick, 2003). This shows a general predictive validity of knowledge that is relatively independent of the knowledge domain of the criterion variable. These results are important because they point out that it is not necessary to develop knowledge tests for every single narrow domain, if we want to predict cognitive abilities or knowledge acquisition. However, for the prediction of domain-specific knowledge acquisition of VET students, subtle differences between the domains were observed and will be discussed in the next section.

6.3.The predictive power of fluid and crystallized intelligence

Among contemporary theories of intelligence, the most prominent factors are *gf* and *gc* (Carroll, 1993; Horn & Noll, 1997; McGrew, 2009). The present research questions were focused on the differential contributions of *gf* and *gc* as predictors of cognitive abilities (contemporary digital literacy tasks and domain-specific vocational knowledge acquisition). It has been the center of a long controversy, whether specific cognitive abilities are able to “move beyond *g*” in the prediction of education and occupational outcomes (e.g., pro: Flanagan, 2000; Gustafsson & Balke, 1993; Zierke, 2014; contra: Jensen, 1998; Ree & Earles, 1991; Schmidt & Hunter, 2004). Though academic achievement has been successfully predicted by general cognitive ability (Binet & Simon, 1916) and is still a powerful predictor (Kuncel, Hezlett, & Ones, 2004), recent studies have provided empirical support for the predictive power of specific cognitive abilities beyond the robust influence of *g* (e.g., Hambrick, Pink, Meinz, Pettibone, & Oswald, 2008; Schipolowski, Wilhelm, & Schroeders, 2014).

As with all empirical research, methodological aspects should be taken into consideration for the interpretation of results. One of the most prominent methods to compare the predictive validity of specific and general cognitive abilities is the use of regression analysis with manifest indicators. Unlike multiple regression structural equation modeling (SEM) allows for a simultaneous analysis of all variables. Furthermore, the measurement error is not aggregated into a residual error term. SEM is an adequate tool to specify and evaluate complex theories and models, such as hierarchical structural intelligence models. This is especially crucial for the nested factor modeling approach (Brunner, 2008; Schmiedek & Li, 2004). In a correlated factor model, the shared variance between all indicators contributes to the correlations between constructs and subsequently complicates the interpretation of the associations. A nested factor model accounts for the shared variance (i.e. *g*-related variance) while at the same time estimating latent variables by capturing variance that is independent of all other factors in the model. Therefore, the relationship between a specific knowledge factor representing unique variance in *gc* to covariates and the criterion variable could be investigated, independently of individual differences in *g*.

As mentioned before, the present results emphasize the importance of *gc* for cognitive performances. In all studies, *gc* was a powerful predictor over and above decontextualized reasoning ability. For the prediction of vocational knowledge acquisition, the findings indicate comparable effect sizes across three very distinct occupational domains: health, business and technology. This is in line with the work of Vanderwood, McGrew, Flanagan, and Keith (2002) demonstrating the importance of *gc* in reading achievement. *Gc* predicted the acquisition of new knowledge over and above a general *g* factor. For the first two studies, both reasoning and knowledge had substantial influence on the newly developed digital literacy test. In line with the knowledge-is-power hypothesis, prior knowledge was an especially powerful predictor and showed a stronger impact than decontextualized reasoning ability. This complements findings of research regarding the prediction of current events knowledge (Beier & Ackerman, 2001; Hambrick, Pink, Meinz, Pettibone, & Oswald, 2008). Similarly, the results of Study 3 confirm the strong influence of knowledge in broader educational settings as compared to the substantially weaker influence of *gf*. However, regarding the current results, there are differences between the VET domains. These differences concern the estimated regression coefficients in the technology domain. The impact of *gc* increases substantially towards the third year while the regression coefficient of *gf* decreases in predictive power. While the influence of *gf* remained comparably low for students from the business and health domain, for first year IT students, *gf* showed a moderate impact on domain-specific knowledge. This group was ultimately the only one that did not support the assumptions of the knowledge-is-power hypothesis. A higher influence of fluid abilities may have been due to the specific knowledge domain. Technology-related knowledge is part of the natural sciences – a domain that is typically closely associated with fluid intelligence (Ackerman, 2000). But why is this only the case for first year students? One explanation might be the cumulative process of knowledge acquisition that would emphasize the effect of *gc* especially in later phases of VET (Baumert, Nagy, & Lehmann, 2012). It can be argued that individual differences of domain-specific knowledge for first year students, who have not yet benefitted much from the school education in VET, were differentiated by the knowledge domain. For occupations in the science domain, *gf* seems to hold considerable explanatory power at this phase while it has a diminished role in other areas. Surprisingly, it seems that the prediction of knowledge acquisition for medical assistant students had more similarities to business than to IT specialist students, despite medical knowledge usually being associated with the domain of natural sciences. This might be due to the curriculum of medical assistants which contains a substantial amount of organizational aspects as well as business and social studies. Even though medical assistants need basic medical knowledge to be able to assist in diagnostic, therapeutic, and preventive practices, they are also responsible for organizational processes in medical practices, including accounting, data protection, and materials management.

Another explanation for the discrepancy between first year IT students and students from business and medical assistant courses might be the difference in educational attainment. Although VET courses in the three domains are ultimately open to students with all types of school leaving certificates, VET for IT-specialists are explicitly recommended for students of academic school tracks (*Gymnasium*). As a result the IT sample has a considerably higher amount of students from the academic track than students from the other two domains. The higher educational attainment level might result in differences in the respective contributions of *gf* and *gc* at the start of VET. However, if that were the case, then these differences would disappear with advancing education, according to the present results. In other words, if we assume that the differences in the first year of VET for IT-specialists are caused by differences in preceding education, we had to consequently assume that this effect disappears with ongoing education in favor of intelligence. However, accounting for preceding education did not change the power of *gf* and *gc* for the prediction of domain-specific knowledge and educational attainment did not show a substantial influence in the prediction model.

A third and more straight-forward interpretation of the results would be that less familiarity with the content and less prior knowledge in a domain result in higher predictive value of *gf* and the predictive power of *gc* relative to *gf* increases systematically with competence. This would be in line with the interpretation of longitudinal data of students from elementary to upper secondary school education by Baumert, Lüdtke, Trautwein, and Brunner (2009). They found decreasing effects of *gf* on learning over time, relative to the effects of prior domain-specific knowledge. While the domain-specific knowledge tests of the business and health domain contain a certain amount of items that could be considered general knowledge (as indicated by low to average difficulties in samples of the general public or other occupational domains as well as overlaps with the *gc*-scale), it is possible that first year students of the technology domain had far less specific prior knowledge to rely on and therefore had to depend on their reasoning abilities. However, these differences between VET domains should be interpreted with caution, since the samples of medical assistants and especially IT specialists are small, which reduces the statistical power of multiple group analyses. Larger samples are required to replicate the results and achieve stable parameter estimates.

6.4.The influence of non-ability constructs

Instead of limiting the present studies to one set of predictor variables (i.e. tests of cognitive abilities), non-cognitive tests were included for a more realistic understanding of knowledge acquisition. Non-cognitive traits have been studied as possible predictors of cognitive abilities with mixed results (e.g., see Ackerman, Bowen, Beier, & Kanfer, 2001; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Powell & Nettelbeck, 2014). However, a majority of studies have investigated the effects of cognitive and non-cognitive variables separately. Yet it seems relevant to account for the shared amount of variance between these constructs (e.g., Ackerman & Heggestad, 1997).

None of the non-cognitive predictors introduced in the present studies showed a substantial influence on the respective criterion. This is especially surprising for the first two studies regarding the prediction of digital literacy. The importance of basic computer skills and computer usage has repeatedly been emphasized in the literature. As pointed out in Chapter 4.4., the impact of computer usage as a predictor variable in foregoing research might have been overestimated because these studies did not assess cognitive variables such as reasoning and knowledge as covariates. Furthermore, there is no clear definition of digital literacy (see Chapter 4.1.). Therefore, the assessments of digital literacy often differ greatly from one another. The focus of Study 1 and Study 2 of this thesis was the implementation of a momentary ecological assessment of digital literacy taking into account relevant covariates aside from computer usage. While it could be argued that there are other potential predictors of digital literacy that were not considered, the present studies primarily emphasize the relevance of intelligence in real-world outcomes. *Gf* and *gc* were able to exhaustively explain digital literacy. This emphasizes the relevance of intelligence for real-world outcomes. There is no substantial amount of variance left to be explained by non-cognitive constructs.

In the educational setting of VET, other constructs were considered for the prediction of knowledge acquisition during VET. Compared to cognitive and motivational constructs, non-cognitive variables such as personality and affective factors are rarely regarded as relevant predictors in educational research. However, investment traits such as *TIE* have shown potential to predict individual differences in academic performance (Chamorro-Permuzic, Furnham, & Ackerman, 2006; von Stumm & Ackerman, 2014; Wilhelm, Schulze, Schmiedek, & Süß, 2003). In comparison, the present findings do not support a substantial influence of *TIE* on knowledge acquisition in VET over and above intelligence. Consistent with previous research (e.g., Schroeders, Schipolowski, & Böhme, 2015), intelligence already explained a large amount of variance in domain-specific knowledge. The investment trait was invariant across the nine groups of VET students and did not account for a substantial amount of variance in any of the groups. Thus, the weak influence of *TIE* was independent of both the duration of VET and the occupational domain. The overall power of *TIE* was in line with previous studies on the prediction of academic performance of university students (e.g., Powell & Nettlebeck, 2014). The associations to the cognitive predictor variables were comparably low, further emphasizing the weak relation between cognitive and non-cognitive constructs in the present studies. There was no indication that the influence of *TIE* differed in non-academic samples or other contentual domains than mathematical and natural sciences.

Nevertheless, this does not mean that non-cognitive predictors are irrelevant in educational settings. The relevance of non-cognitive variables has been shown repeatedly for the prediction of non-cognitive outcomes of educational or vocational success. For example, in a comprehensive study, Volodina, Nagy, and Köller (2015) reported substantial effects of vocational interests on dropout intention of first year VET students. Similarly, investment traits such as *TIE* might be more strongly associated with career choice decisions or job satisfaction. It seems conclusive to assume that people with higher levels of *TIE* would be less satisfied with less intellectually demanding occupations, in a similar way as interest congruence is associated with job satisfaction (Tsabari, Tziner, & Meir, 2005). On the other hand, lower level of *TIE* in a working or learning environment with high intellectual demands might lead to career changes or early dropouts during education due to the excessive demands.

6.5.Implications for career counseling and education in the "digital era"

The successful graduation from training programs such as VET is essential for the transition into work and the acquisition of professional expertise. Dual education is one of the most popular training programs in Germany with about 1.3 million trainees in the year 2015. While approximately 500 000 new training were signed, almost 28% of them were terminated prematurely (Federal Statistical Office, 2016). The successful graduation is important, not only for the trainee but also from the view of employees and politics. Considering the importance of VET from the perspective of educational and labor market policy, empirical findings on individual differences in VET success are surprisingly scarce in contrast to findings on university samples or primary and secondary education. Understanding relevant predictors of VET success is essential for an improvement of career counseling and the subsequent reduction of the number of premature dropouts.

In order to find general effects, we need to take distinct occupational domains as well as different phases of VET into consideration. According to the present results, knowledge tests might be useful in career counseling. Similar to the prediction of academic success of university students (e.g., Donnon, Paolucci, & Violato, 2007), standardized knowledge tests have high predictive validity for the prediction of academic performance during VET. The strong focus of career counseling on motivational aspects leads to a huge loss of information. The development of expertise during VET is essential for a successful final examination and graduation as well as later work performance. Therefore, focusing only on a non-cognitive set of predictors would result in underprediction of VET performance. Furthermore, non-cognitive traits are typically operationalized with measures of typical behavior. As such, they are prone to faking good and social desirability effects (Ones & Viswesvaran, 1998; van de Mortel, 2008). This is especially problematic in high-stakes settings such as college or training admission since the motivation for faking good would be especially high. In contrast, tests of maximum performance such as knowledge tests are more resistant to faking. Though comparable research for VET students is still rare, cognitive abilities are widely recognized as powerful predictors of academic achievement in other areas of education (e.g., Furnham, Monsen, & Ahmetoglu, 2009).

In order to adequately evaluate and improve learning contexts it is necessary to understand the processes of knowledge and skill acquisition. For an ecological assessment of these processes, tests are required that are adjusted to contemporary learning opportunities. Thus, it is essential to take account of the role the so called new media plays in today’s knowledge acquisition. The internet is crucial for information procurement and learning processes (Fisher, Goddu, & Keil, 2015; Sparrow, Liu, & Wegner, 2011), not only in educational but also working environments. The results from Study 1 and 2 have shown that a reliable and ecologically valid power test can be constructed by capitalizing on the internet as a vital source of information. Even in a more realistic and unrestrained assessment, fluid and crystallized intelligence are the most powerful predictors, similar to traditional comprehension tests (Hambrick & Engle, 2003). What does this imply for research on contemporary learning processes and knowledge acquisition? With modern technology, it is considerably easy to develop and implement power tests that assess these processes. There was no valid reason to assume a lack of validity due to a seductive-details effect (see Mayer, Heiser, & Lonn, 2001) and was especially well received by the student sample of Study 2. This might provide a valid and reliable alternative to self-reports or simulation environments which are used frequently in this field of research (see Goldhammer, Kröhne, Keßel, Senkbeil, & Ihme, 2015). Though the present studies did not administer a qualitative analysis of participants feedback on the test, it seems likely that a power test reflecting real-world information procurement would be well-received by participants due to its face validity. Especially for younger populations such as student samples, it is important to keep up with the technological development. The constant access to information due to the mobile internet is a natural part of today's everyday life for these students.

It should be noted the internet apparently functions as a transactive memory partner (Sparrow, Liu, & Wegner, 2011). Transactive memories are systems that distribute information across a group of individuals (Wegner, 1987). Accordingly, these systems consist of two key elements: internal and external memory. However, in the case of searching for information online, people seem to be unable to accurately monitor the proportion of internal and external memory, and subsequently mistaking external knowledge for internal knowledge. Thus, people tend to neglect the extent to which they rely on external sources such as the internet to access explanatory knowledge (Fisher, Goddu, & Keil, 2015). This creates an illusion of knowledge which should be taken into account by future work in this direction. Through the constant access to a vast amount of information, the boundary between personal and interpersonal knowledge is becoming increasingly blurred (Clark & Chalmers, 1998). This illusion of knowledge can create an over-confidence and lead to erroneous assumptions about what a person can do in situations without external memory sources.

6.6.Limitations and summary

Some critical issues should be kept in mind when interpreting the present results. The main focus of the present thesis was to investigate the knowledge-is-power hypothesis in broader, more naturalistic settings. Due to the complexity of the object of investigation, some limitations were bound to occur. Some of these limitations are the result of the underlying data set, while others had to be accepted in order to keep the study design in manageable limits. Hereafter, the most relevant limitations of this thesis will be summarized. On this basis, possible expansions of the presented findings will be discussed.

6.6.1. Limitations.

First, there are some limitations that are directly related to the observed samples. For one, the current results only consider German samples. Hence, the generalizability of our findings to other settings might be questioned. However, since the results presented here are in line with several other studies (e.g., Beier & Ackerman, 2005; Hambrick, Meinz, & Oswald, 2007; Schroeders, Schipolowski, & Böhme, 2015) they should be generalizable to other situations. Since the concept of dual education is rather specific for Germany and educational and training concepts vary in other countries, it would be especially interesting to see the design of part two of this thesis applied to other societies. Furthermore, it could be argued that the sample sizes might be another limitation. Although the total sample size of VET students was n = 1854, the sample was divided into 9 groups of unequal sizes. This disparity is due to the unequal distribution of VET students across domains. The business domain is by far the most popular VET domain. In comparison, IT courses are not only considerably scarce in comparison, but also consist of fewer students per class. Even with the second wave of recruiting, the group of IT students remained the smallest sample which was especially noticeable for the last year of VET.

As pointed out in Chapter 4.4., several factors are relevant to determine the adequate sample size for a model (Muthén & Muthén, 2002). In order to reduce the number of freely estimated parameter, the indicators of the predictor variables were parceled for all prediction models. This helped to keep the power adequate even in the more complex models, leaving only the sample of third year IT students to be problematic. Therefore, results in the IT domain still have to be considered with caution. It would be desirable to replicate the results reported here with larger samples. Another limitation that applies especially to the second part of the thesis is that this study design was cross-sectional. This limits the interpretation of results, especially since the acquisition of professional knowledge is a complex process that occurs over a long period of time – an average of three years, in case of VET in Germany. Although the examination of the three years of VET in a single model is more informative of these processes than the fixation on a single phase of education, to adequately comment on questions regarding a cumulative effect of knowledge acquisition, longitudinal data would be necessary. Longitudinal studies would be especially interesting in regard to the transitions between school, VET and work, because non-cognitive constructs could be relevant as predictors of career choices. Furthermore, longitudinal data would allow for an examination of the specificity and stability of vocational interests or investment traits which is relevant for interest-based counseling. In this context, future studies might also profit from a longitudinal design when investigating skill and knowledge profiles acquired during VET.

The to the focus on domain-specific vocational knowledge in Study 3 as the outcome variable restricts our results to a solely cognitive perspective of academic success during VET. Although domain-specific knowledge is crucial for the development of professional expertise, VET success is a much more complex construct that can not simply be reduced to individual differences in vocational knowledge. For the purposes of the study presented here (i.e., investigating the knowledge-is-power hypothesis) it was acceptable to limit the criterion variable to domain-specific knowledge tests, since the prediction of higher-level cognitive abilities was the focus. However, to investigate the concept of VET success as the complex and multilayered concept that it is conative and affective factors should be taken into account besides cognitive abilities (Mount, Barrick, Scullen, & Rounds, 2005).

Similarly, it could be argued that the digital literacy test might have been influenced by other non-cognitive constructs besides computer usage. Since digital literacy itself is not a clearly defined concept and mostly used as an umbrella construct, numerous predictors have been introduced in the literature without much consistency. Potential predictors might basic computer skills (Goldhammer et al., 2013) or procedural meta-cognition. Nevertheless, the presented momentary and ecological assessment of digital literacy differs fundamentally from previous implementations of digital literacy as well as traditional comprehension tests due to its unrestricted design that resigns control over the information retrieved from the internet.

For all studies presented in this thesis, the assessment of *gf* was restricted to the figural facet of fluid intelligence, to keep the assessment battery to a manageable extent. Although figural reasoning is generally assumed to be prototypical for the assessment of *gf*, a broader and more reliable assessment should include verbal and numerical reasoning (Wilhelm, 2004). The influence of *gf* might be stronger in an assessment that includes all *gf* facets.

6.6.2. Summary

The aim of the present thesis was to examine the knowledge-is-power hypothesis in more naturalistic and educational settings. Accordingly, the prediction of higher-level cognitive abilities by reasoning, knowledge and broad non-cognitive concepts was the focus of this work. With digital literacy and vocational knowledge acquisition as criterion variables, the lines between experts and novices were more blurred than with most research on the knowledge-is-power hypothesis.

The current findings emphasize the role of intelligence on real-world outcomes and high-stakes situations. Overall, the knowledge-is-power hypothesis can be transferred to broader and more naturalistic settings. Prior knowledge is crucial for the prediction of individual differences in both online information procurement and adequate comprehension of these information as well as knowledge acquisition during all phases of VET. This can be assumed to be generally independent of the contentual domain. In other words, knowledge is a main predictor of scholastic and academic success across distinct occupational domains.

The results imply that cognitive abilities and investment traits play different roles in the successful completion of and graduation from VET. General knowledge was a powerful predictor of domain-specific vocational knowledge acquisition during all phases VET and in different domains. However, the influence of *TIE* was negligible. Considering the results of foregoing studies, it seems likely that *TIE* is more influential on the decision to aim for a specific occupation, similar to vocational interests (Volodina & Nagy, 2016). This could be further analyzed in an integrative framework taking into account the career choices and subsequent transition into VET or work as well as the progress of expertise development during VET.

Taken together, the findings of this thesis indicate that the knowledge-is-power hypothesis, while generally applicable, depends on several relevant conditions, such as the constraints on the testing situation and high-stakes versus low-stakes settings. The relative weight of fluid and crystallized intelligence is also determined by the depth of the content of the knowledge test. However, even a broad assessment of prior knowledge has proven to be a reliable and powerful predictor. This should be noted especially for educational contexts, since students in primary and secondary education are typically required to learn new information from a broad variety of domains, only specializing for a specific domain during tertiary education or later work life. More research is needed to understand the extent to which knowledge assessments should focus on a specific domain in the prediction of real-world outcomes. Overall, it can be concluded that knowledge is a relevant and strong predictor of cognitive abilities and should not be underestimated in the prediction of real-world outcomes.

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8. Supplement

8.1. Supplementary Material of the Digital Literacy Test

8.1.1. Translated Instructions Used for the new Comprehension Test in Studies 1 and 2

In the course of the following test you will be presented with different questions and tasks regarding the subject of "medicine and health". Please search the Internet for a solution for each problem. You will be able to work the tasks in an allotted time range that differs for each task. The time provided to you should be sufficient to solve the task. You may use every source available on the Internet.

Please note:

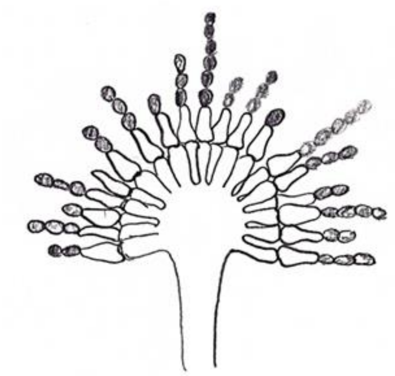
Never close the window with the test, under any circumstances, since you have to return to this page to answer the question. Please use a different browser or a new tab (in a new window) for your online search.

In the upper left corner you can see a countdown showing the remaining working time. During the last 15 seconds an acoustic signal will sound, counting down the seconds. Please return to the test immediately when you hear the signal. Answer the question and click on "next" (in the lower right corner). If you do not click on the "next" button, you will be forwarded to the next question automatically.

You will not be able to return to previous questions. Only click on the "next" button when you are sure that you want to continue with the next question.

8.1.2. Items Used as the Dependent Measure in Studies 1 and 2

1. Nobel Prize: In a medical magazine you find a quiz providing a prize for the correct answer. Solve the following question: Which country did the Nobel Prize winner of physiology or medicine from the year 1919 come from? (*2 minutes*)
    a. Sweden
    b. Belgium
    c. Germany
    d. Denmark
2. Parkinson's Disease: During a walk, you notice an elderly man at a red light. You recognize a slight shudder in his right hand. As the light turns green, the man keeps standing still at first, then moves with delay in jerky, stiff steps. What disorder is typically associated with these symptoms? (*2 minutes and 30 seconds*)
3. Mold Fungus: On the bus, you overhear a conversation between students about a schematic drawing from their biology lessons. You hear the word "mold fungus" and wonder what kind of mold fungus this is. (*4 minutes*)



4. Meningitis: You pay a visit to a sick friend who stayed at home due to his fever. Besides the fever, your friend complains about headaches and a stiff neck. When moving his head, he experiences pain and claims: "It always tenses up when I turn my head." Moreover, your friend appears to be confused. What could he be suffering from? (*3 minutes*)

5. Depression: The mother of a friend died three days ago. He tells you that he feels sad and dulled and loses interest in most activities. During work, he has to deal with diminished concentration, even though this has never been a problem before. He only sleeps very lightly at night, because he often thinks about his dead mother. That is why he is often tired during the day and is lacking in motivation. What diagnosis would a psychotherapist give in this situation? (*7 minutes*)
    a. an episode of a major depression according to DSM IV
    b. a dysthymic disorder according to DSM IV
    c. separation anxiety according to DSM IV
    d. no disorder
6. Hemogram: You have received a laboratory print from your physician. Based on this hemogram, he has given you a certain diagnosis. However, you forgot what he has told you. What diagnosis has he given? Consider the hemogram for this. (*8 minutes*)

Parameter	Lower bound	Upper bound	Actual value
leucocytes	3,9/nl	10/nl	6,8/nl
erythrocytes	3,8/pl	5,2/pl	4,92/nl
hemoglobin	12 g/dl	16 g/dl	15,4 g/dl
hematocrit	0,35	0,47	0,44
MCV	82 fl	98 fl	90 fl
MCH	28 pg	32 pg	30 pg
MCHC	32 g/dl	36 g/dl	35 g/dl
thrombocytes	140/nl	440/nl	350/nl
triglycerides	40 mg/dl	175 mg/dl	170 mg/dl
cholesterol	150 mg/dl	200 mg/dl	230 mg/dl
uric acid	2,6 mg/dl	6,0 mg/dl	9 mg/dl
urea	13 mg/dl	43 mg/dl	33 mg/dl
creatinine	0,4 mg/dl	1,4 mg/dl	1,16 mg/dl
TSH	0,35 µIU/ml	2,50 µIU/ml	0,8 µIU/ml

a. Anemia

b. Hepatic cirrhosis

c. Gout

d. Diabetes

7. Grapefruit: In a magazine, you read that eating grapefruit in combination with certain drugs can lead to side effects. An acquaintance of yours is currently taking the cough medicine Dextromethorphan. What side effects might occur when he eats grapefruit while taking his medication? (*3 minutes*)

   a. Erectile dysfunction

   b. Congestion

   c. Bone marrow damage

   d. Dizziness

8. Scoliosis: The spine of your neighbor is curved as illustrated below. What is the correct label for this curvature? (*2 minutes*)

   a. Scoliosis

   b. Lordosis

   c. Kyphosis

   d. Arthrosis

9. Viper: During camp a teen has been bitten in the arm by a viper. You are the only person nearby. What would be the best course of action? (*3 minutes*)

   a. Remove the poison by sucking it out of the arm, keeping the arm still and calling the ambulance.

   b. Ligating the arm, keeping the person still and calling the ambulance.

   c. Keeping the arm on a splint, preventing the person from activities and calling the ambulance.

d. An ambulance is unnecessary for the bit of a viper. The person should simply rest for three to four hours.

10. Osteosynthesis: Your neighbor had an operation and shows you an X-ray image of the intervention. What surgical intervention is presented in the picture? Please name the medical term! (*8 minutes*)

11. Aphasia: You meet a woman with a speech disorder. She talks in a slow manner and her sentences are often disrupted by pauses. She talks with effort and seems to fight for every spoken word. You ask the woman what she has done yesterday. She seems to understand you just fine. When she wants to tell you what she did, she only stutters: "I… er… yesterday… son… er, no… daughter… garden… I sit sun, then… abbles… bicking abbles…" What kind of speech disorder is this? (*7 minutes*)

    a. Global aphasia
    b. Amnestic aphasia
    c. Wernicke's aphasia
    d. Broca's aphasia

12. Salbutamol: After a visit to the doctor, you get a spray of Salbutamol. Unfortunately, you cannot remember how to take it. (*3 minutes*)
    a. Daily in the morning
    b. Once a week
    c. Only in case of dyspnea
    d. Whenever a stomach-ache occurs
13. Total Endoprosthesis: A relative of yours needs a hip-TEP. What is the purpose of this intervention? (*2 minutes and 30 seconds*)
    a. To encourage the blood flow of the leg
    b. To treat an osteoarthritis
    c. To treat a femoral fracture
    d. To relieve the strain on the leg muscles

8.2. Additional Information on the Domain-Specific Knowledge Tests

8.2.1. Pilot Study

Development of the item pool: Due to the high time consumption and assumed decline of concentration, we decided to divide the item pool to create 2 parallel versions of the test, comparable in content and difficulty (version A and version B) and with anchor items that allowed us to link both versions on a common scale. A total of 118 items for health knowledge, 114 items for business knowledge, and 115 items for technology knowledge were used for the knowledge tests in the pilot study. For a detailed description of their content see Chapter 5.2.3. Each item was presented as a multiple choice question, with four answers of which one was correct. In order to minimize floor and ceiling effects, the items covered a broad range of difficulties. The content was chosen from the three years of VET, while the relative solution probability should always remain above the guessing probability of .25.

Sample: A sample of 292 students from medical assistant VET participated in the pilot study. The age of the 141 participants who completed version ranged from 16 to 35 (*M*=20.2, *SD*=2.7). Only one participant was male. The other 151 medical assistant students completed version B, with a mean age of 20.7 (*SD*=3.7) Again, there was only one male student in this group. A total of 431 business VET students, between 16 and 35 years of age, completed the business knowledge test. Version A was administered to a sample of 225 VET students (43.1% female) with a mean age of 21.5 (*SD*=2.7). Version B of the business knowledge test was completed by 205 students (49.3% female) with a mean age of 21.5 (*SD*=2.2). The third sample consists of 98 IT students between 17 and 35 years. The version A of the IT knowledge test was completed by 45 students of which only one was female. The mean age was 21.1 (*SD*=2.3) and 53 IT students completed version B, with 5 female students and a mean age of 21.6 (*SD*=3.2).

General Procedure and data analysis: The tests were presented in group sessions as paper-pencil tests. Version A and B were both distributed in each class, in order to mix the questions among the students. First, the participants were asked for some demographic data before being presented with about 60 domain-specific knowledge items. Overall, the testing time amounted to 90 minutes. Items with difficulties ≤ .25 and ≥ .95 or low item-total correlation ($r_{bis} \leq .25$) were deleted from further analysis. The remaining items had an average difficulty of .57 for the health test, .51 for the business test and .62 for the technology test.

With the remaining items two different measurement models could be analyzed. In order to evaluate the factorial structure of the knowledge tests, a one-dimensional model was compared to a model with three correlated factors. The WLSMV estimator was used for CFA which were conducted with Mplus. The two models were compared by χ^2 difference testing. Since the degrees of freedom (*df*) are estimated rather than computed in WLSMV estimation, the χ^2 difference test can't be calculated in a regular way for the WLSMV estimation. Instead, the DIFFTEST option of Mplus was used (Muthén & Muthén, 2012). The DIFFTEST revealed an advantage for the three-factor model for all three domains (health: $\Delta\chi^2(292) = 8.17$, $p = .04$; business: $\Delta\chi^2(431) = 24.85$, $p < .01$; technology: $\Delta\chi^2(98) = 13.4$, $p < .01$).

Sample items

Health knowledge test:

1. Ihr Freund hat seit Kurzem Schmerzen in beiden Armen, ein unangenehmes Engegefühl und Probleme beim Atmen. Schon bei geringe Anstrengung bekomme er keine Luft mehr und im Liegen sei es besonders schlimm. Auf das Versagen welches Organs könnten diese Symptome hindeuten?

Niere
Herz
Lunge
Leber

2. Pflege unter Berücksichtigung der physischen, psychischen und sozialen Bedürfnisse des Patienten – um welche Art der Pflege handelt es sich hierbei?

Ganzheitliche Pflege
Intensivpflege
Funktionspflege
Teilpflege

3. Für welche der genannten Krankheiten ist eine Schutzimpfung nötig?

Borreliose
Hepatitis C
Malaria
Keuchhusten

Business knowledge test:

1. Durch welche der folgenden marktkonformen Maßnahmen erreicht der Staat das wirtschaftspolitische Ziel einer Verbesserung der Beschäftigungslage?

Erhöhung des Angebots
Verringerung des Angebots
Erhöhung der Nachfrage
Verringerung der Nachfrage

2. Ein Einzelhandelsunternehmen erreichte im ersten Quartal des Jahres folgende Umsätze:

Januar	121.900,00 €

Februar 108.650,00 €

März 134.560,00 €

Wie hoch war der durchschnittliche Monatsumsatz?

121.703,33 €

121.700,00 €

121.666,67 €

121.550,00 €

3. Bei welchem Beispiel kann man betriebswirtschaftlich von einer Investition sprechen?

Familie Maier kauft einen neuen Kühlschrank.

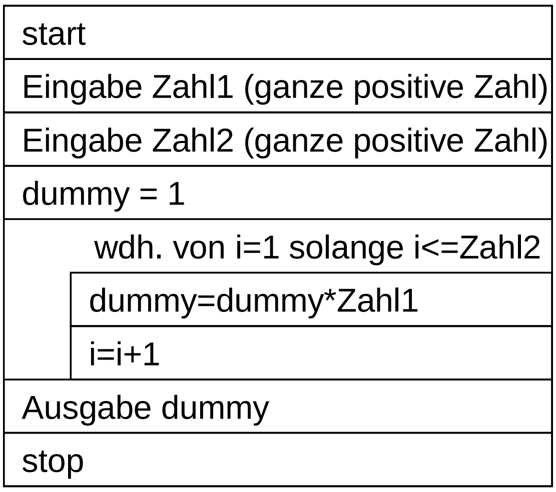
Familie Rossi lässt sich einen neuen, sparsamen Brenner in ihre Heizung einbauen und erhält dafür Fördermittel.

Die Elektrohandwerksfirma Weise kauft für die Werkstatt eine Tischbohrmaschine.

Giovanni kauft ein Fahrrad, um schneller zur Schule zu kommen.

Technology knowledge test:

1. Betrachten Sie das unten abgebildete Struktogramm:



Was wird in „dummy“ ausgegeben, wenn für „Zahl 1“ 4 und für „Zahl 2“ 3 eingegeben wird?

64

50

13

4

2. Sie kaufen ein Autorennspiel für den PC. Auf der Packung steht „Systemvoraussetzung: 2 GB RAM“. Ihr PC hat nur 1 GB RAM, aber Sie installieren das Spiel trotzdem. Als Sie es

spielen wollen, ruckelt und stockt es stark. Warum führt mangelnder Arbeitsspeicher zum Ruckeln?

Der PC muss Inhalte von der Festplatte laden, was länger dauert, als vom RAM zu laden.

Es kommt zu einer fehlerhaften Erkennung der Systemkomponenten, was zu technischen Problemen im Spiel führt.

Wenn zu wenig RAM zur Verfügung steht, können keine Updates für das Spiel heruntergeladen werden, wodurch nicht die volle Leistung in Anspruch genommen wird.

Bei mangelndem Arbeitsspeicher wird die Grafikkarte stärker belastet und es folgen Einbrüche der Bildwiederholungsrate.

3. Warum lässt sich das RGB-Verfahren der Farbdarstellung bei Druckern nicht anwenden?

Die Auflösung von Druckern reicht für dieses Farbverfahren nicht aus.

Der Farbverbrauch wäre zu hoch.

Drucker brauchen ein subtraktives Farbverfahren.

Bei diesem Verfahren lässt sich die Farbe Schwarz nicht herstellen.

4. Welche Komponente benötigen Sie für den Aufbau eines Twisted-Pair-Netzwerks?

Spleißbox

Firewall

Netzwerkkarte

DSL-Router

5. Sie benutzen eine Programmiersprache, in der die logischen Operatoren UND, ODER und NICHT zugelassen sind. Für die Codierung einer Verzweigung benötigen Sie eine Bedingung, die genau dann wahr ist, wenn einer der folgenden Fälle zutrifft:

Fall 1: Die Variable A ist kleiner als 0.

Fall 2: Die Variable A ist größer als 3500.

Kreuzen Sie den korrekten logischen Ausdruck an.

(A < 0) ODER (A >= 3500)

(A < 0) ODER (A > 3500)

(A < 0) UND (A > 3500)

(A < 0) UND NICHT (A < 3500)

6. Welche der folgenden Aussagen zur Defragmentierung einer Harddisk trifft zu?

Defragmentierung gruppiert Datenblöcke nicht logisch zusammenhängend, sondern zufällig.

Defragmentierung bringt Teile von aufgebrochenen Dateien wieder zusammen

Defragmentierung ist nichts anderes als Formatierung

Defragmentierung gruppiert und komprimiert mehrere Dateien zu einer einzigen

7. Für welches Kabelmedium zur Vernetzung von PCs würden Sie sich entscheiden, wenn es nicht auf hohe Störsicherheit ankommt und ein billiges Medium benutzt werden soll?

Shielded Twisted Pair (STP)

Unshielded Twisted Pair (UTP)

Glasfaserkabel

Koaxialkabel

8.2.2. Item Characteristics of the Domain-specific Knowledge Tests

Table 14. *Difficulties and Item-Total-Correlation for the Health Knowledge Items*

	1st year		2nd year		3rd year	
Item	*M*	r_{it}	*M*	r_{it}	*M*	r_{it}
A1B1C1	.69	.28	.67	.31	.85	.25
A2B21*	.82	.12	.06	.03	-	-
A3B17	.54	.48	.67	.25	-	-
A4B15	.25	.19	.42	.48	-	-
A5	.26	.23	-	-	-	-
A6	.88	.18	-	-	-	-
A7B3	.75	.29	.64	.33	-	-
A8B5C4	.67	.30	.73	.32	.82	.18
A9B6	.34	.20	.44	.43	-	-
A10B7	.62	.15	.63	.25	-	-
A11B9	.60	.30	.70	.29	-	-
A12	.87	.18	-	-	-	-
A13	.51	.42	-	-	-	-
A14*	.98	.11	-	-	-	-
A15B12C10	.68	.33	.82	.46	.69	.39
A16B13	.70	.10	.68	.18	-	-
A17	.55	.24	-	-	-	-
A18	.71	.32	-	-	-	-
A19	.81	.20	-	-	-	-
A20B16C6	.67	.29	.61	.37	.77	.30
A21	.82	.26	-	-	-	-
A22B26C28	.66	.23	.73	.21	.93	.28
A23B27C29	.50	.23	.40	.06	.59	.28
A24B28C26	.58	.40	.73	.28	.68	.25
A25B22	.82	.35	.86	.23	-	-
A26B25C30	.68	.31	.53	.04	.74	.47
A27B30C20	.78	.23	.81	.24	.75	.22
A28B11C31	.92	.28	.91	.26	.94	.20
A29B18	.71	.20	.83	.39	-	-
A30B10C8	.31	.40	.42	.40	.59	.38
B2C2	-	-	.52	.20	.62	.41
B4C3	-	-	.48	.31	.75	.30
B8C7	-	-	.53	.18	.70	.32
B14C14	-	-	.84	.49	.94	.18
B19C5	-	-	.23	.27	.46	.25
B20C16*	-	-	.06	.15	.88	.10
B23C22	-	-	.31	.31	.55	.44
B24C24	-	-	.81	.34	.64	.34
B29C21	-	-	.83	.31	.99	.26

C9	-	-	-	-	.77	.32
C11	-	-	-	-	.71	.21
C12	-	-	-	-	.42	.24
C13*	-	-	-	-	.97	.13
C15	-	-	-	-	.61	.30
C17	-	-	-	-	.64	.33
C18	-	-	-	-	.47	.41
C19	-	-	-	-	.92	.25
C23	-	-	-	-	.74	.37
C25	-	-	-	-	.67	.45
C27*	-	-	-	-	.13	.11

Note. M = mean difficulty; r_{it} = item-total correlation; Items marked with * were deleted in Study 3 (see item selection)

Table 15. *Difficulties and Item-Total-Correlation for the Business Knowledge Items*

	1st year		2nd year		3rd year	
Item	M	r_{it}	M	r_{it}	M	r_{it}
A1B1	.45	.33	.36	.26	-	-
A2a	.61	.38	-	-	-	-
A2b	.68	.39	-	-	-	-
A3B3C1	.60	.34	.67	.27	.75	.35
A4	.78	.32	-	-	-	-
A5B2C3	.51	.39	.42	.40	.57	.44
A6	.35	.31	-	-	-	-
A7	.81	.22	-	-	-	-
A8B21	.84	.10	.79	.34	-	-
A9*	.60	.04	-	-	-	-
A10	.38	.20	-	-	-	-
A11B22C5	.61	.46	.45	.36	.61	.17
A12B6C6	.53	.25	.61	.22	.71	.22
A13B7C7	.71	.44	.72	.46	.86	.39
A14B8	.24	.31	.35	.34	-	-
A15B10C9	.25	.20	.29	.21	.39	.24
A16B11	.63	.32	.66	.28	-	-
A17B15C16	.48	.37	.65	.26	.70	.16
A18B16	.49	.22	.53	.44	-	-
A19B19	.43	.37	.59	.25	-	-
A20	.36	.34	-	-	-	-
A21	.66	.33	-	-	-	-
A22	.40	.37	-	-	-	-
A23B5*	.56	.34	.46	.38	-	-

A24B24*	.33	.00	.28	.12	-	-
A25B26C22	.30	.25	.35	.26	.55	.32
A26B29C26	.44	.20	.47	.39	.59	.47
A27B27	.50	.15	.33	.23	-	-
A28B30	.74	.36	.71	.47	-	-
A29B4C28*	.56	.26	.53	.20	.55	.06
B9C8*	-	-	.35	.14	.25	.21
B12C12	-	-	.23	.17	.35	.30
B13C13*	-	-	.32	.31	.37	.33
B14C14*	-	-	.25	.06	.30	.15
B17C19	-	-	.22	.18	.45	.28
B18C17	-	-	.65	.46	.88	.41
B20C27*	-	-	.45	-.05	.50	.14
B23C4	-	-	.37	.32	.74	.48
B25C21	-	-	.54	.28	.66	.36
B28C25	-	-	.48	.45	.55	.45
C2	-	-	-	-	.51	.26
C10	-	-	-	-	.64	.43
C11	-	-	-	-	.47	.19
C15	-	-	-	-	.42	.41
C18	-	-	-	-	.42	.53
C20	-	-	-	-	.80	.41
C23	-	-	-	-	.59	.38
C24	-	-	-	-	.70	.27
C29	-	-	-	-	.26	.02

Note. M = mean difficulty; r_{it} = item-total correlation; Items marked with * were deleted in Study 3 (see item selection)

Table 16. *Difficulties and Item-Total-Correlation for the Technology Knowledge Items*

	1st year		2nd year		3rd year	
Item	M	r_{it}	M	r_{it}	M	r_{it}
A1B1	.50	.25	.49	.21	-	-
A2	.81	.18	-	-	-	-
A3B3C2	.55	.27	.66	.37	.73	.31
A4B6C5	.59	.39	.62	.44	.60	.35
A5B7	.38	.41	.41	.33	-	-
A6B8C7	.59	.48	.62	.63	.64	.42
A7	.55	.18	-	-	-	-
A8B9	.43	.39	.56	.48	-	-
A9B10	.62	.52	.67	.52	-	-
A10B11	.68	.25	.75	.25	-	-
A11	.51	.50	-	-	-	-

A12B12	.39	.32	.43	.33	-	-
A13	.69	.32	-	-	-	-
A14B15C16	.38	.34	.37	.37	.43	.50
A15B16	.77	.41	.79	.25	-	-
A16	.60	.20	-	-	-	-
A17B17C19	.62	.52	.68	.63	.58	.65
A18B18C22	.50	.30	.54	.48	.56	.35
A19B20C21	.27	.20	.42	.40	.60	.35
A20B22C24	.32	.16	.51	.35	.54	.35
A21	.44	.27	-	-	-	-
A22B23C25	.64	.36	.67	.27	.73	.15
A23B24C26	.71	.45	.75	.31	.79	.50
A24	.54	.59	-	-	-	-
A25B26	.40	.61	.53	.52	-	-
A26	.65	.48	-	-	-	-
A27B27*	.35	.30	.27	.21	-	-
A28B30C31	.52	.48	.66	.33	.64	.50
A29	.72	.34	-	-	-	-
A30	.61	.27	-	-	-	-
B2C1	-	-	.22	.15	.25	.15
B4C3	-	-	.41	.27	.59	.38
B5C4*	-	-	.57	.21	.39	-.04
B13C14	-	-	.54	.56	.79	.38
B14C15	-	-	.50	.27	.59	.31
B19C20	-	-	.58	.56	.55	.50
B21C23	-	-	.61	.44	.58	.27
B25C27*	-	-	.48	.02	.50	.38
B28C29*	-	-	.37	.21	.50	.19
B29C30	-	-	.63	.23	.75	.31
C6	-	-	-	-	.79	.46
C8*	-	-	-	-	.24	.00
C9*	-	-	-	-	.60	.00
C10	-	-	-	-	.24	.19
C11	-	-	-	-	.71	.38
C12*	-	-	-	-	.93	.04
C13*	-	-	-	-	.54	.15
C17	-	-	-	-	.58	.27
C18	-	-	-	-	.54	.27
C28	-	-	-	-	.64	.42

Note. M = mean difficulty; r_{it} = item-total correlation; Items marked with * were deleted in Study 3 (see item selection)

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