experience more precisely. In his analyses, he found a non-significant effect for years of job tenure and job knowledge, but a significant beta-coefficient of .17 (p<.05) for tasks experience ratings and job knowledge.

6. Methods

The following paragraphs describe the sample and the instruments used in this study to answer the research questions.

6.1. Sample

For the following analyses, valid data from 268 students at the beginning of their post-secondary training from two German federal states was used. Only cases with full data were included in the analyses. Participants who had indicated putting minimal effort into taking the test were excluded from the analyses. Data collection took place in fall 2015 in the classrooms of the technical schools. The vocational test, the fluid intelligence test, and a questionnaire were administrated successively on one day. Numerical codes instead of names were used to ensure confidentiality. Participants had the opportunity to look up their results on a website a couple of weeks after the testing session.

Participants were aged between 19 and 49 years (two participants did not specify their age) with a mean value of 25.2 years (SD 4.6). As the majority of the students were male, information on gender was not gathered. 75 percent of the participants held an intermediate school leaving certificate, 20.1 percent a higher school leaving certificate (admission for university entrance), and 4.5 percent held a basic school leaving certificate (one participant did not indicate educational level). For 89 percent of the sample, information was available on their initial apprenticeship. Students named 20 different training occupations in all. A third of these apprenticeships usually take place in craft and 36.9 percent in industrial training environments. Work experience ranged from zero to 24 years with a mean of 3.5 years (SD 3.1).

6.2. Instruments

During the project, we conducted a test on vocational knowledge and a survey, including, among other things, a measurement of achievement motivation, the duration of work experience, and the frequency of specific tasks performed at the previous job.

6.3. Vocational knowledge test

To assess the vocational knowledge of the students entering post-secondary training, we designed a paper and pencil test containing 37 items. The test incorporated many multiple choice items, but also items for which test-takers had to assign terms to an illustration or to write down a short explanation (see Figure 1 for example items). For test development, we applied a content-driven construction process analyzing the curricula of the post-secondary training and those of initial VET in electronic occupations. The three content areas of “fundamentals of electronics”, “electronic systems”, and “control engineering” were considered for the test instrument. In addition, experts from vocational schools and training companies reviewed the items.

Finally, 12 to 13 items were retained for each content dimension. The testing time was limited to 80 minutes.

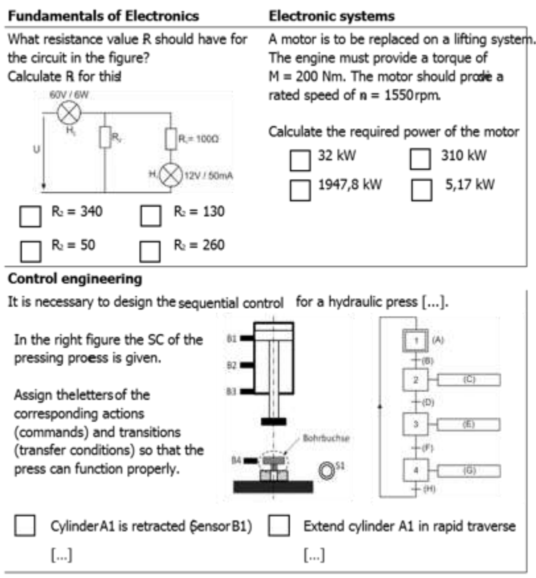

Figure 1. Example items of the vocational knowledge test

6.4. Fluid intelligence

Fluid intelligence was assessed using four subtests (series, classification, matrices, topologies) of the Culture Fair Intelligence Test - Scale 3 [23]. Each of these subtests provided 10 to 14 items with figural material to test for deductive reasoning skills. Instructions from the manual were applied for the testing procedure. A sum score was calculated for each subtest.

6.5. Prior knowledge

As the study started at the beginning of the post-secondary training, we could not directly assess the knowledge gained during the apprenticeship. However, we asked participants to indicate the grade of their written final examination as a proxy for prior vocational knowledge. The grades range from 0 to 100, with higher values indicating a better performance. The examination in electronic VET occupations captures knowledge in the planning and construction of machines, analyzing machines, as well as the fundamentals of economics and politics.

6.6. Achievement motivation

Achievement motivation was assessed with the 10-item scale from the Unified Motive Scales [24]. Both a German and English version are available. An example item is: “For me it is important to maintain high standards for the quality of my work”. Participants rated the items on a scale from 1 “strongly disagree” to 6 “strongly agree”.

6.7. Work experience

Participants were asked to indicate the number of years that they had worked in a job related to their initial training occupation.

6.8. Task-related work experience

Referring to Longoria [10], we tried to capture work experience by means of a task-related measure. We asked participants to indicate the frequency of specific tasks performed at their last job during the last five years. A list of 22 tasks was administered, for example “working with electronic systems and machines” or “carrying out technical calculations” and for each item students needed to decide on a 6-point Likert scale as to how frequently they had performed this task, from 1 “never” to 6 “very frequently”.

7. Results

Before answering the research questions, it was necessary to carry out several calculations. First, the IRT scaling procedure of the vocational test items was briefly delineated. Then, an exploratory factor analysis was performed out of the 22 task items to identify components of relevant tasks. Information on mean values, standard deviations, reliabilities and intercorrelations are shown in Table 2. These analyses were performed using SPSS 18. Following this, structure equation modeling was used to calculate an explanatory model for the influence of the distinct factors on vocational knowledge. Vocational knowledge, fluid intelligence, achievement motivation, and two task components entered the model as latent variables as this enables the consideration of measurement errors. For this reason, measurement models for the latent variables had to be calculated in advance.

7.1. Vocational test scaling procedure

The 37 items of the vocational test were fitted to a one-parametric item response model [25]. Using item response modeling, item and person parameters can be calculated at the same time [26]. Four items had to be excluded from the model due to bad model fit indices. Two competing models —a one-dimensional and a three-dimensional model with the latter differentiating between the dimensions of fundamentals of electronics, electronic systems, and control engineering—were calculated. The one-dimensional model revealed a $\chi2=11470.5$ (df=37). The information criteria were AIC=11545 and BIC=11683. For the three-dimensional model a $\chi2=11118.7$ (df=42) and an AIC=11203 and BIC=11360 were calculated. Therefore, the three-dimensional model represented a significant better fit ($\Delta\chi2=351.8$ Δdf=5) to the empirical data. For further analyses, person parameters (centered on zero) were used for each of the three dimensions of the vocational knowledge test.

7.2. Exploratory factor analysis of the tasks

The questionnaire encompassed 22 working tasks derived from job descriptions and empirical analyses of the typical tasks performed in the occupational field of electronics technicians [12]. To concentrate on items that are closely related, an exploratory factor analysis (principal component analysis, Varimax rotation) was carried out. In accordance with the Eigenvalue criteria, six factors were extracted that explained 61.1 percent of the total variance. Table 1 shows the loadings (>.3) of the items on the six factors. The first factor was called “working with machines” and comprised four items with loadings >.5. Another factor on “quality assurance” encompassed three items with loadings >.6. A third factor was extracted and called “checking and measuring” and had two items strongly loading on it. A fourth factor mainly comprised items regarding meetings and teaching and learning tasks, and was therefore named “meeting and learning”. A fifth factor consisted of six items related to project management and calculation tasks. The sixth factor contained items referring to programming tasks. However, the items regarding “assembling wires” and “learning, reading” could not be easily assigned to one of the six factors. For further analyses, two factors and their respective items were used: The work with machines factor encompassed tasks that referred to dealing with electronic machines and automation systems that was the most closely related to the vocational knowledge captured by the test. In contrast, project management tasks were unrelated to the test content, and correctly so, as accomplishing project management tasks should not result in a deeper understanding of the fundamentals of electronics or electronic systems. However, both components were used in the explanatory model to test the assumptions outlined in section 4.

Table 1. Loadings of the task items on the six factors extracted from the exploratory factor analysis

	Factor 1 "Working with machines"	Factor 2 "Quality assurance"	Factor 3 "Checking and measuring"	Factor 4 "Meeting and learning"	Factor 5 "Project manage-ment"	Factor 6 "Pro-gram-ming"
Work with machines	**.846**					
Identify malfunctions in machines	**.829**					
Repair machines	**.559**					
Assemble switchgears	**.706**					-.330
Solder circuits		**.713**				
Manufacture preliminary models		**.661**			.385	
Quality management		**.617**				
Checking and measuring			**.848**			
Analyze measurement data			**.839**			
Meetings with clients and team members				**.675**		
Team leadership				**.781**		
Train apprentices				**.668**		
Learning, reading				.468		.559
Plan machine extensions					**.739**	
Analyze processes					**.514**	
Project planning			.415		**.641**	
Technical calculations					**.691**	
Expense budgeting and billing					**.623**	
Engineering drawing					**.727**	
Program systems	.349				.402	**.610**
Program programmable logic control unit	.459				.391	**.555**
Assemble wires				.353		-.724

7.3. Descriptives

Table 2 shows the descriptives of the variables used in the study and their intercorrelations based on manifest variables. In addition, values on the diagonal represent—when a calculation was possible—reliability estimates according to Cronbach's alpha. The scales for achievement motivation and the task dimensions achieved good reliabilities (α=.76 to α=.87). However, the items of the test of fluid intelligence did not reach satisficing reliability estimates (α=.63). Intercorrelations between the vocational knowledge dimensions were positive and significant and, as expected, the dimensions also revealed significant positive correlations with fluid intelligence and with the grade from the final examination. The task dimensions also significantly correlated with each other, but the relationship was weak (r=.187). Working with machines frequently correlated positively with having knowledge in electronic systems and control engineering. Experiences in both task components went hand-in-hand with higher achievement motivation. The years of work experience did not correlate with any of the other variables.

As expected, the cognitive antecedents of knowledge acquisition correlated with each other and with the knowledge dimensions as they all represent crystallized intelligence that has been developed from fluid intelligence. In contrast to the assumptions made in paragraph 4, achievement motivation was not related to vocational knowledge.

In a next step, the unique effect of each variable on the vocational knowledge was investigated with the aid of structure equation modeling.

Table 2. Descriptives and Pearson correlations between the manifest variables used in the study

	N	M	SD	1	2	3	4	5	6	7	8
1 Fluid intelligence[a]	268	26	4.24	*.63*							
2 Vocational knowledge: fundamentals of electronics	268	.117	1.28	**.334****	-						
3 Vocational knowledge: electronic systems	268	.071	1.24	**.279****	**.216****	-					
4 Vocational knowledge: control engineering	268	.072	1.56	**.344****	**.278****	**.333****	-				
5 Achievement motivation[b]	268	4.58	.69	-.025	-.018	.071	.025	*.87*			
6 Years of work experience	268	3.46	3.09	-.056	-.060	-.081	-.097	-.018	-		
7 Task: working with machines[b]	268	3.68	1.28	.106	.091	**.227****	**.275****	**.245****	.104	*.76*	
8 Task: project management[b]	268	2.29	1.01	.002	-.038	.054	.023	**.196****	.038	**.187****	*.80*
9 Prior knowledge: final written examination in initial VET	213	79.1	9.16	**.143***	**.325****	**.200****	**.309****	-.005	-.031	.097	.099

Note. a=sum score of the total test b=mean value of the assigned items; **p<.01 *p<.05

7.4. Structure equation modeling

Structure equation modeling is a statistical technique that combines multiple regression analysis with exploratory factor analysis [27]. It enables complex models to be verified by means of comparing a theoretical matrix and an empirical covariance matrix. The quality of the match between the theoretical and empirical matrix is evaluated using several fit indices and in reference to their recommended cut-off-values [e.g. 28]. In addition, structure equation modeling integrates latent variables that are measured using multiple manifest indicators, thus facilitating the inference regarding “true” relationships between variables because the model statistically accounts for measurement error. Measurement models and the explanation model were realized with Mplus7.

7.5. Measurement models

Before fitting an explanatory model, measurement models for each latent variable and their respective indicators need to be estimated. The measurement model of fluid intelligence was built out of the sum scores provided by the four subtests. This measurement model showed an excellent fit (N=268; $\chi2$=.277; df=2; p>.05; CFI=1.000; RMSEA=.000). Ten items measured the construct of achievement motivation. This measurement model indicated an acceptable fit (N=268; $\chi2$=80.74; df=34; p<.01; CFI=.956; RMSEA=.072) with one covariance between items 1 and 2. The two task components extracted from the exploratory factor analysis were replicated with confirmatory factor analysis. The two components of working with machines and project management were calculated simultaneously and showed an acceptable fit (N=268; $\chi2$=90.37; df=34; p<.01; CFI=.928; RMSEA=.079). Finally, the construct of vocational knowledge was measured using the person estimator scores for each of the three vocational knowledge dimensions as indicators. This measurement model was exactly identified and, therefore, no fit indices could be calculated.

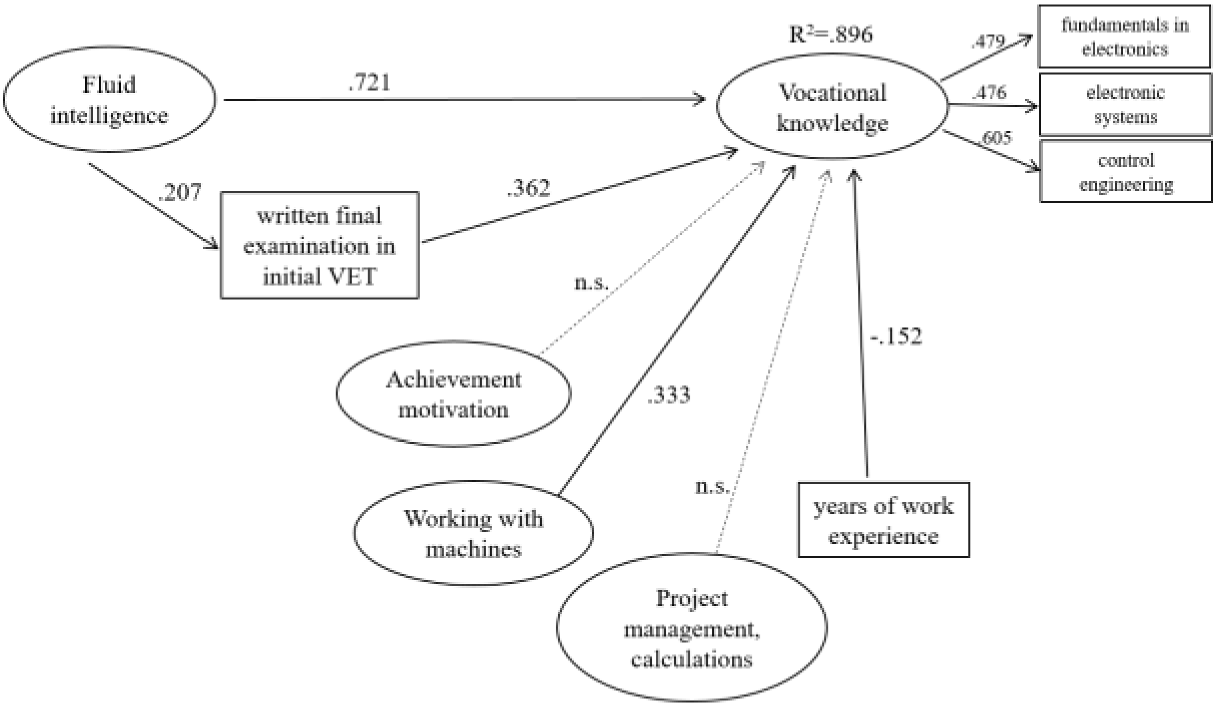

Figure 2. Explanation model of the vocational knowledge at the beginning of post-secondary training

7.6. Explanation model

The measured variables were all integrated in the explanation model to estimate their unique impact on vocational knowledge at the beginning of the post-secondary training. Figure 2 shows the complete model with standardized path coefficients and—for the sake of clarity—the standardized loadings for the latent construct of vocational knowledge only. The overall model showed a good fit (N=268; $\chi2$=543.65; df=371; p<.01; CFI=.919; RMSEA=.042). Nearly 90 percent of the total variance of the vocational knowledge could be explained by the variables in the model.

The model in Figure 2 shows a strong direct and a small, but significant, indirect effect of fluid intelligence on vocational knowledge (standardized indirect effect of .075, p<.05, using the Delta method implemented in Mplus). The years of work experience revealed a significant negative effect on vocational knowledge. Consequently, students with more years of work experience achieved lower scores on the knowledge test. Nevertheless, and in line with the assumptions, work experience in working with machines reveal a positive effect on vocational knowledge, whereas experience in project management and calculations did not have any effect. Finally, and in contrast to expectations, achievement motivation did not explain any additional variance.

The results in Figure 2 show that individuals benefit from experience in tasks that were closely related to the knowledge captured by the test. The question was then posed if whether this equally held true for those individuals with more years of work experience. More specifically, it addressed the existence of an interaction effect between task experience, working with machines and years of work experience. An additional model was calculated integrating this interaction term. The results revealed a non-significant interaction effect (.009, p>.05), indicating that students with divergent years of work experience did not benefit differently from experience with machines. However, this result has to be interpreted very carefully as the variable of years of work experience is distributed in a very skewed way and is thereby detrimental to the key assumption of normal distributed variables in structural equation modeling [27].

8. Discussion

The present study sought to gain insights regarding the influence of central cognitive and non-cognitive impact factors on the vocational knowledge for a sample of 268 German students at the beginning of post-secondary training in electronics. Overall, the analyses document that post-secondary training will gain importance because future growth primarily depends on the skills and competencies linked to these certificates. However, educational research has concentrated less on the analysis of competence development in this educational path. For this reason, this issue was addressed by illuminating the relevant determinants of competencies in post-secondary VET. The results illustrate the dominant role of cognitive prerequisites for the acquisition of vocational knowledge in post-secondary training. Furthermore, students performed worse with a higher number of years spent in the workforce, while test performance was enhanced if a student had experience with work tasks relating to the knowledge captured by the test.

The dominant role of fluid intelligence documented by the data corresponds with the theoretical approaches suggested by Ackerman [1] and Cattell [16] and is consistent with the research on the relevance of general mental ability for training success [19]. In a further step, it would be interesting to investigate the predictive power of fluid intelligence and vocational knowledge for the vocational knowledge at the end of the post-secondary training. The importance of fluid intelligence will presumably reduce due to the increased amount of prior knowledge that individuals can refer to. In addition, instead of analyzing the role of fluid intelligence as a single construct, it could be investigated as to whether diverse intelligence components addressing the verbal, numerical, or figural facets improve the prediction of vocational knowledge. For technical vocational knowledge, it can be assumed that particularly figural cognitive abilities are useful.

Figure 2 shows a negative impact for the years of work experience on the vocational knowledge. It can therefore be claimed that students who worked for a couple of years before entering post-secondary training performed weaker because they might have lost the knowledge gained in initial VET. In contrast, knowledge acquisition seemed to be easier for those individuals entering post-secondary training almost directly after finishing initial VET. However, the effect has to be interpreted with caution, as the variable is skewed and, as required by structure equation modeling [27], not normally distributed. Bivariate correlations revealed zero correlations for the years of work experience and the three knowledge dimensions. Therefore, further analyses considering the role of years of work experience for knowledge acquisition are needed.

Complementing the years of work experience variable, two additional variables were taken into account that captured the task-related experience in a job as proposed by Longoria [10]. In line with expectations, experiences with tasks that were closely related to the vocational knowledge revealed a positive effect, whereas experiences with tasks that were irrelevant for the tested knowledge had no effect. Obviously, dealing with specific tasks enhances the understanding of their conceptual knowledge basis. It would be worthwhile to challenge this effect by using an additional knowledge test on the knowledge of project management and calculations. In this way, differentiated relationships between knowledge and task-experiences could be investigated.

To address the role of non-cognitive traits and interests as suggested in Ackerman's theory [1], the construct of achievement motivation was selected for the prediction of vocational knowledge. It is likely that the desire to strive for success and to perform well affects performance in a voluntary test.

However, achievement motivation neither had any additional effect in the model nor revealed any significant correlation with the knowledge dimensions. It is possible that achievement motivation was not relevant for knowledge acquisition in post-secondary training, or it could be that the sample was restricted to highly-motivated individuals only. In fact, participants scored rather high on achievement motivation (mean value 4.58) with a small standard deviation (.069) supporting the latter supposition. Another possible explanation is that the construct of achievement motivation was already incorporated in the knowledge test. Consequently, by working hard and concentrating on the test, participants expressed their will to perform well although the test results did not have any effect on their grades. In future research, further motivational variables (e.g. self-efficacy, intrinsic motivation) and personality traits (e.g. Big Five) should be considered to clarify the relevance of non-cognitive antecedents. In addition, "test-taking effort" should be taken into account as a moderating variable.

As another milestone in the project, we aim at analyzing the relationships between vocational knowledge at the beginning and the end of the post-secondary training, as well as problem-solving skills assessed using a computer-based simulation of a real automation system. For instance, we would like to test the assumption of close associations between the knowledge dimension and the problem-solving dimension documented in similar studies [13]. Again, the role of cognitive and non-cognitive impact factors will be taken into account. It would be interesting to know whether work experiences, fluid intelligence, and prior knowledge gained in initial VET still affect vocational knowledge at the end of training.

A fundamental limitation of the study is the selection of the sample of students in electronics as it represented only a small selection of students in post-secondary training in two German federal states. Of course, replication studies with representative samples are desirable and it would be useful to further investigate post-secondary training courses, for example in health or commerce.

From a practical point of view, the presented results reveal that the vocational knowledge at the beginning of post-secondary training is highly dependable on cognitive antecedents, such as prior knowledge gained in initial VET, the extent of experience with machines and automation systems, and the years of work experience. For the students who performed low in initial VET, who do not have much work experience regarding automation systems, or who spent a longer time in the workforce before entering post-secondary VET, it might be more difficult to catch up with their peers. Offering these individuals preparatory courses to revive their knowledge is therefore conducive. In addition, testing their vocational knowledge at the beginning of the training might help them to realize and reflect upon their knowledge gaps and to activate further learning processes.

9. Acknowledgements

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