

# What Affects Vocational Competencies in German Post-secondary VET?

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## Abstract

*This paper aims at investigating the role of cognitive and non-cognitive impact factors on vocational knowledge at the beginning of post-secondary training in a German sample. Although the relevance of post-secondary training for the future economy is documented, little is known about competence development after initial VET in Germany. Therefore, the study seeks to highlight vocational knowledge acquisition that is crucial for future job performance. Referring to Ackerman's PPIK theory [1], the roles of fluid intelligence, prior knowledge, and achievement motivation are investigated. In addition, the relevance of work experience is addressed using different measurements. Structure equation modeling reveals the dominant role of cognitive impact factors on knowledge acquisition, while, in contrast to expectations, achievement motivation does not have any effect. Experiences performing tasks that are closely related to the knowledge captured by the test do have a significant positive effect on knowledge acquisition, whereas experiences in divergent tasks do not. The results provide evidence that those students who do not have specific work experience or who spent a longer time in the workforce might benefit from additional preparatory courses to catch up on necessary knowledge.*

## 1. Introduction

Education is a key factor in equipping people with the essential skills and competencies that they need to deal with upcoming economic and social challenges as well as to facilitate innovation and growth [3]. Formal education usually takes place along different tracks. School, university, and initial vocational education and training (VET) represent well-trodden educational paths in most countries. However, the educational path of post-secondary VET is less defined and less established [3]. Analyses published by the European Centre for the Development of Vocational Training (CEDEFOP) [4] demonstrate that the occupational group of "technicians and associate professionals" that is closely linked to post-secondary training will be highly important in the future economy. In general, the analyses predict a shift toward more skill-intensive jobs and a decline in traditional manual or routine jobs. They forecast the highest demand in job

opportunities for the group of technicians and associate professionals compared to the other occupational groups (e.g. professionals, clerks, craft and related trade workers). According to the analyses' calculation, nearly two-thirds of future employment growth will be linked to the occupational group of technicians and associated professionals. Therefore, post-secondary training opportunities will grow in importance because they equip people with the skills and competencies needed in the future.

Educational research can contribute to this by shedding light on the process of competence development in post-secondary VET. For example, research can provide evidence on how competence development occurs after initial VET and how competencies in post-secondary training are structured [5], or how competence is impelled by cognitive and non-cognitive determinants.

The present paper addresses the latter research question for a sample of 268 German students at the beginning of their post-secondary training in electronics. Using structure equation modeling, it aims at clarifying the role of students' cognitive prerequisites, motivation, and particularly the role of their work experience in vocational competencies. Initially, section 2 briefly provides some information about post-secondary training in Germany and section 3 outlines the research on competence assessment. Information on the research questions and the theoretical background are given in sections 4 and 5. Research methods and results are presented in paragraphs 6 and 7. Finally, section 8 summarizes the results and provides perspectives.

## 2. Post-secondary VET in Germany

Vocational education and training (VET) plays a key role in the German educational system. After finishing secondary school programs, approximately 60 percent of young people opt for an initial VET program. Post-secondary vocational education and training follow up initial VET and addresses individuals who intend to broaden their skills and knowledge and who would like to obtain another vocational certificate. Usually, individuals achieve another vocational certificate that is assigned to the tertiary level 5B according to the International Standard Classification of Education (ISCED). 13 percent of individuals who finished an initial VET

program decide to continue with a post-secondary training program [3]. In Germany, post-secondary training programs are available in a vast variety of occupational fields, e.g. in health and social occupations, in clerical occupations and in technical occupations. These are regulated by the federal Vocational Training Act, by the chambers of commerce and industry, or by the federal states.

The training programs offered by the federal states take place at trade and technical schools for two years (full-time) or three to four years (part-time) and are free of charge. To enter such a training program, individuals require a first certificate in a recognized training occupation relevant to the intended specialization and at least one year of work experience. According to the training regulations, post-secondary training enables participants to retain or deepen their vocational competencies, prepares them to assume more responsibility and management functions at the workplace and, in this way, facilitates job promotion [3]. According to the OECD, these training programs are crucial for responding to the economy's increasing demand for higher vocational skills. In addition, they present a valuable career development function as they build on the learning processes started in initial VET and the individuals' work experience [3].

There is empirical evidence that graduates from post-secondary training pursue successful careers. For example, a study involving graduates from post-secondary training documented that they often achieve leadership positions, even more often than graduates holding a bachelor's degree [6]. Data from another graduate survey revealed that 62 percent received a job promotion or increased responsibilities [7]. In addition, graduates earn on average 25 percent more than employees with initial VET certificates [8]. Furthermore, unemployment rates for tertiary B degree holders are among the lowest in the OECD [3], thereby indicating the strong labor market demand for these competencies.

For the most part, the labor market success of employees with a post-secondary degree is well documented, though little is known about competence development from initial to post-secondary VET and about the relevant antecedents. To the best of the author's knowledge, Zinn and Wyrwal [5] conducted the only study addressing competence development in post-secondary VET using extensive and sophisticated assessing tools. They measured the domain-specific knowledge of a representative sample of students at the beginning of their post-secondary training in structural engineering. Highly heterogeneous skills, competencies, and work experience were revealed in the sample.

### 3. Assessment of vocational competencies in VET

In Germany, much research has been conducted on the assessment of competencies in educational contexts. Since the end of the 1980s, new monitoring strategies for governmental intervention have resulted in a stronger focus on the "outputs" of educational processes from elementary education through secondary to tertiary and vocational education [9]. Klieme et al. [9] defined the role of research as to "render this educational productivity measurable, to develop models that can explain how educational processes take place, evaluate their effectiveness and efficiency, and propose and analyze strategies for intervention." To measure these educational outputs, the concept of competence has been introduced. Although there is not just one definition of the competence construct, it is commonly agreed that they are domain-specific, cognitive dispositions that are acquired via learning processes, and are useful for solving domain-specific tasks or problems [9]. Providing profound evidence on competencies in varying educational contexts, researchers develop competence models as well as measurement instruments. In the context of test development, innovative measurement concepts involve computer-based assessment tools that bring about various advantages in test application and test reporting. For example, it is possible to simulate complex and dynamic real-life situations and to implement specific tasks that allow domain-specific competencies to be captured.

Computer-based simulations are particularly conducive for competence assessment in VET since learning does not only occur in vocational schools but also at workplaces and in the working processes of training companies.

Researchers dealing with competence assessment in German VET mainly focus on the assessment of relevant vocational competencies, which should be developed according to the respective curricula at the end of a usual three-year initial apprenticeship. One goal of research is to theoretically and empirically distinguish the central subdimensions of vocational competencies. Researchers generally describe competencies and their components in terms of declarative, academic, or fact-oriented knowledge on the one hand and as procedural, tacit, or "action-oriented" knowledge on the other. However, there is much debate regarding the distinction between different knowledge components and their relationship with work performance. According to Longoria [10], a clear distinction between declarative and procedural knowledge cannot be made because job knowledge always comprises both declarative and procedural components. He defined job knowledge as "technical information about objects and concepts required to do the job and the

knowledge of processes and judgmental criteria necessary for efficient and correct action on the job". Other researchers pointed out that procedural knowledge in particular seems to be valuable for competent performance in work environments [11].

In VET research, diverse test instruments are applied to capture declarative (and partly procedural) vocational knowledge and problem-solving competencies in simulated work contexts. More "traditional" (mostly paper and pencil) test instruments comprising multiple choice items are used alongside innovative computer-based tools that attempt to represent work environments with typical work tasks and problems that participants have to solve.

Prospective electronics technicians often work in the field of automation technology, be it in the craft sector (e.g. electrical installation companies, waterworks) or in the industry sector (e.g. automobile or chemical industry). More specifically, they are responsible for maintaining automation systems, for detecting and resolving equipment malfunctions, installing electrical control systems, and analyzing software programs [12]. Therefore, a key task in this occupational field is to solve analytical problems concerning system malfunctions. The German research group of Walker, Link, and Nickolaus assessed such analytical competencies (and partly more constructive ones) of prospective electronics technicians with an authentic computer simulation [13]. To address the academic, declarative (and, at the same time, to some extent procedural knowledge elements, as those two dimensions could not be separated empirically in the industrial-technical field [13]), written paper and pencil tests were used.

Although much effort was undertaken to address distinct knowledge dimensions with appropriate test instruments, the empirical relationship between apprentices' performance in both tests at the end of the apprenticeship in various technical training occupations is quite strong ( $r=.61$  to  $r=.86$ ) [13]. Presumably, at least in technical occupations, declarative knowledge and problem-solving competencies are related to each other. This is because declarative knowledge facilitates problem solving in that reverting to the relevant concepts and rules needed to tackle a specific problem. This assumption is also supported by Dye et al. [14], who documented the relevance of job knowledge for job performance, particularly when job-specific knowledge is closely related to the tasks performed in the job.

To summarize, it can be claimed that the assessment of vocational competencies plays a prominent role in providing evidence on the output of formal (and informal) vocational training processes. Researchers have provided a portfolio of elaborate and sophisticated test instruments to

address both declarative knowledge and action-oriented competencies typically required at workplaces. Empirical data show relatively strong relationships between the distinct dimensions of vocational competencies, at least in technical training occupations. It is clear that profound vocational knowledge is crucial for successful behavior at work.

#### 4. Research questions and hypotheses

In cooperation with the University of Stuttgart, the German Federal Institute for Vocational Education and Training is currently conducting a research project aimed at investigating competence development after initial VET. More specifically, we are conducting a longitudinal study comprising approximately 300 students in post-secondary VET, 100 apprentices in initial VET, and 100 students in a bachelor program. One research goal encompasses investigating and comparing both the declarative knowledge and the technical problem-solving competencies in electronics and automation systems in the samples mentioned. Focusing on the students in post-secondary VET, we would like to gain insights into how declarative knowledge and problem-solving competencies develop from the beginning to the end of the training. Furthermore, we are interested in the importance of cognitive and non-cognitive impact factors because "there is clearly a need for differentiated research related to the acquisition of many facets in the wide array of vocational competencies" [15]. Seeber and Lehmann [15] argue that even the role of cognitive antecedents, such as general mental ability or reading and competencies in mathematics, is still unclear.

The present paper deals with the question of how vocational knowledge at the beginning of a post-secondary training course is influenced by the students' cognition, achievement motivation, and work experience. Referencing Ackerman [1] and Cattell [16], fluid intelligence is expected to have a dominant impact on knowledge acquisition. When considering the cognitive antecedents of knowledge acquisition, prior knowledge must also be taken into account [15].

However, Sembill et al. [17] stated that "the acquisition of knowledge of any kind is also reliant on non-cognitive processes". Ackerman equally stressed the importance of personality traits and interests for building knowledge in his PPIK theory [1]. In the present paper, achievement motivation was selected as a valuable trait, representing ambition and the will to be successful and to master challenging tasks. Individuals scoring high on achievement motivation are expected to work harder and achieve better on the vocational knowledge test. The role of work experience is likewise further investigated in this paper. Employees should ordinarily accumulate vocational knowledge with the

years of work experience due to their encounters with different working tasks and processes. However, the amount of knowledge retained and deepened at work might also depend on the concrete tasks that have to be performed. Therefore, referring to Longoria [10], work experience measured on a task-level should be more predictive when related to the vocational knowledge captured in the test.

## 5. Theoretical background

Regarding the theoretical background, references are made to Ackerman's PPIK [1] (intelligence-as-process, personality, interests, and intelligence-as-knowledge) theory. In this developmental theory, Ackerman [1] described how knowledge develops by integrating fluid intelligence as well as personality traits and interests. More specifically, Ackerman drew on Cattell's [16] idea to distinguish between fluid and crystallized intelligence. Fluid intelligence was considered to be "an expression of the level of complexity of relationships which an individual can perceive and act upon when he does not have recourse to answers to such complex issues already stored in memory" [16]. Therefore, fluid intelligence refers to the detection of analogies and relationships as well as on the ability to draw inferences. In contrast, Cattell [16] conceptualized crystallized intelligence as the capability to "operate in areas where the judgements have been taught systematically or experienced before". In his investment theory, Cattell [16] presumed that individuals resort to their fluid intelligence to build crystallized intelligence. Ackerman worked with these ideas and suggested an integrated theoretical model in which fluid or process intelligence affects the acquisition of crystallized intelligence or knowledge. Ackerman's knowledge concept was much broader than the one used by Cattell as he assumed that "there are probably as many domains of knowledge as there are occupations (and non-occupational pursuits as well)" [1]. Therefore, domain-specific knowledge tests are useful for precisely capturing this component. According to Ackerman, however, "the amount of knowledge acquired in a particular topic area by any individual becomes limited by the prior domain-specific knowledge repertoire (and related domain knowledge - in a sense of transfer-of-knowledge) of that individual" [1].

Furthermore, the PPIK theory also considered non-cognitive determinants. Ackerman pointed out the importance of the Big Five personality traits and the interest dimensions proposed by Holland [18] for knowledge acquisition. Regarding their causal influence, he admitted that there is probably not a clear causal relationship between intelligence and personality and that "abilities and interests develop in tandem, such that ability level determines the

probability of success in a particular task domain, and personality/interests determine the motivation for attempting the task" [1].

A huge body of evidence documents the relevance of both general intelligence and prior knowledge for training success. For example, Schmidt and Hunter [19] documented the relevance of general mental ability (GMA) for the prediction of training success in their meta-analysis, calculating a correlation coefficient of  $\rho=.56$ . They concluded that "the major direct causal impact of mental ability has been found to be on the acquisition of job knowledge. That is, the major reason more intelligent people have higher job performance is that they acquire job knowledge more rapidly and acquire more of it" [19].

Overall, the relevance of the Big Five personality traits as well as for Holland's interest dimensions [18] on job or training performance is well documented [20], [21]. However, the focus of the study was a selected sample of students participating in technical post-secondary training and it is assumed that this sample was somewhat restricted regarding its vocational interests. For this reason, a motivational construct was selected that might facilitate learning throughout the training and the effort invested in learning. Achievement motivation is an appropriate motivational construct that can be defined as "one's motivation to achieve success; enjoyment of surmounting obstacles and completing tasks undertaken; the drive to strive for success and excellence" [22]. In their meta-analysis, Robbins and his colleagues [22] revealed a corrected validity coefficient of  $\rho=.303$  for achievement motivation and college performance.

The present paper places particular emphasis on the role of work experience for acquiring job-related knowledge as the students in the sample usually enter post-secondary training with a divergent amount of work experience [5]. As Longoria [10] outlined, it is a widespread assumption that knowledge and skills are somehow gained automatically with the years spent in a work environment. In contrast, as they could only document small correlations for the years of work experience,  $\rho=.18$  with job performance and  $\rho=.01$  with training performance, Schmidt & Hunter [19] thought it possible that new job knowledge is only acquired during the first five years in a job and that this process ends after that. Nevertheless, Longoria [10] asserted that "it is not simply experience that matters in predicting job performance, but what a worker learns as a consequence of that experience". Consequently, he suggested an innovative way to appropriately capture work experiences rather than simply counting the years spent in a job. Instead, he assumed that the relationship between work experience and knowledge depends on task characteristics. He therefore proposed task experience ratings in order to capture work

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 administered 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.

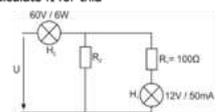
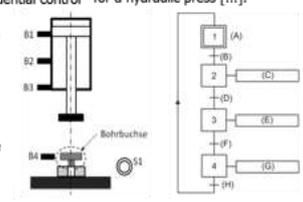
Fundamentals of Electronics	Electronic systems				
What resistance value $R$ should have for the circuit in the figure? Calculate $R$ for this 	A motor is to be replaced on a lifting system. The engine must provide a torque of $M = 200 \text{ Nm}$ . The motor should provide a rated speed of $n = 1550 \text{ rpm}$ . Calculate the required power of the motor <table border="0"> <tr> <td><input type="checkbox"/> 32 kW</td> <td><input type="checkbox"/> 310 kW</td> </tr> <tr> <td><input type="checkbox"/> 1947,8 kW</td> <td><input type="checkbox"/> 5,17 kW</td> </tr> </table>	<input type="checkbox"/> 32 kW	<input type="checkbox"/> 310 kW	<input type="checkbox"/> 1947,8 kW	<input type="checkbox"/> 5,17 kW
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Control engineering					
It is necessary to design the sequential control for a hydraulic press [...]. In the right figure the SC of the pressing process is given. Assign the letters of the corresponding actions (commands) and transitions (transfer conditions) so that the press can function properly. 					
<input type="checkbox"/> Cylinder A1 is retracted (sensor B1) <input type="checkbox"/> Extend cylinder A1 in rapid traverse [...]    [...]					

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  $\chi^2=11470.5$  (df=37). The information criteria were AIC=11545 and BIC=11683. For the three-dimensional model a  $\chi^2=11118.7$  (df=42) and an AIC=11203 and BIC=11360 were calculated. Therefore, the three-dimensional model represented a significant better fit ( $\Delta\chi^2=351.8$   $\Delta df=5$ ) 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	<b>.846</b>					
Identify malfunctions in machines	<b>.829</b>					
Repair machines	<b>.559</b>					
Assemble switchgears	<b>.706</b>					-.330
Solder circuits		<b>.713</b>				
Manufacture preliminary models		<b>.661</b>			.385	
Quality management		<b>.617</b>				
Checking and measuring			<b>.848</b>			
Analyze measurement data			<b>.839</b>			
Meetings with clients and team members				<b>.675</b>		
Team leadership				<b>.781</b>		
Train apprentices				<b>.668</b>		
Learning, reading				.468		.559
Plan machine extensions					<b>.739</b>	
Analyze processes					<b>.514</b>	
Project planning			.415		<b>.641</b>	
Technical calculations					<b>.691</b>	
Expense budgeting and billing					<b>.623</b>	
Engineering drawing					<b>.727</b>	
Program systems	.349				.402	<b>.610</b>
Program programmable logic control unit	.459				.391	<b>.555</b>
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 ( $\alpha=.76$  to  $\alpha=.87$ ). However, the items of

the test of fluid intelligence did not reach satisfying reliability estimates ( $\alpha=.63$ ). 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 <sup>a</sup>	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 <sup>b</sup>	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 <sup>b</sup>	268	3.68	1.28	.106	.091	.227**	.275**	.245**	.104	.76	
8 Task: project management <sup>b</sup>	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 ( $N=268$ ;  $\chi^2=.277$ ;  $df=2$ ;  $p>.05$ ;  $CFI=1.000$ ;  $RMSEA=.000$ ). Ten items measured the construct of achievement motivation. This measurement model indicated an acceptable fit ( $N=268$ ;  $\chi^2=80.74$ ;  $df=34$ ;  $p<.01$ ;  $CFI=.956$ ;  $RMSEA=.072$ ) 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 ( $N=268$ ;  $\chi^2=90.37$ ;  $df=34$ ;  $p<.01$ ;  $CFI=.928$ ;  $RMSEA=.079$ ). 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.

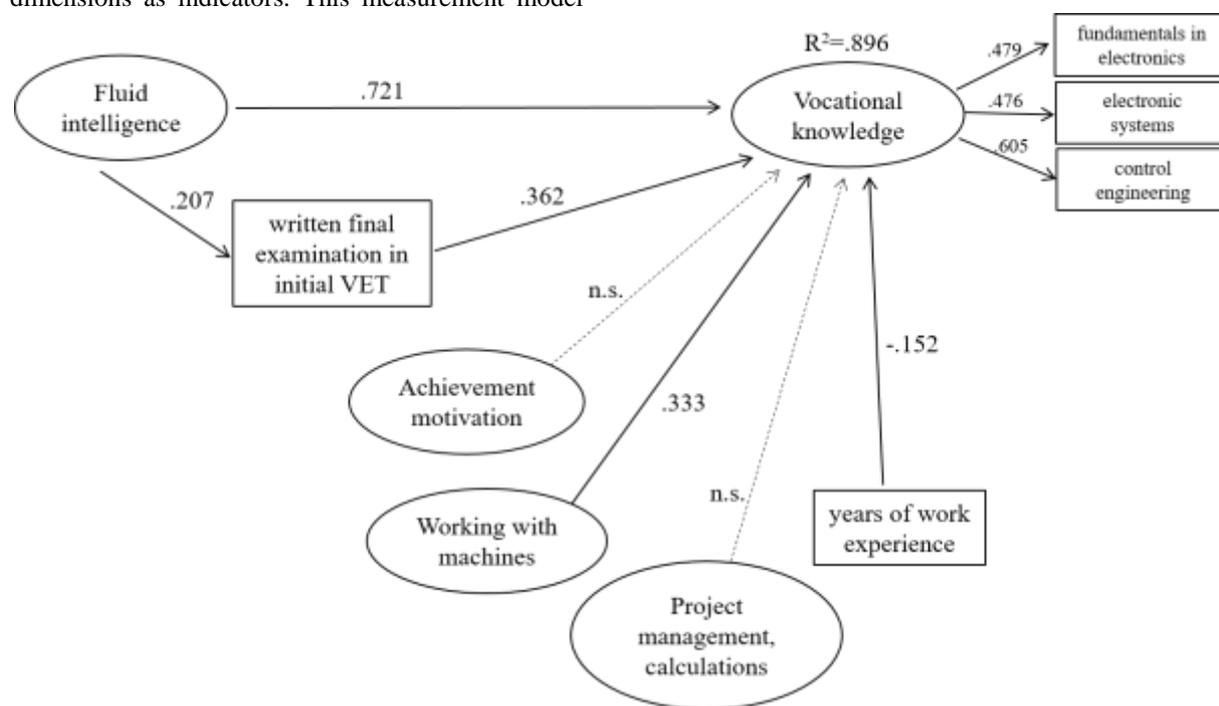


Figure 2. Explanation model of the vocational knowledge at the beginning of post-secondary training

## 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 ( $N=268$ ;  $\chi^2=543.65$ ;  $df=371$ ;  $p<.01$ ;  $CFI=.919$ ;  $RMSEA=.042$ ). 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.

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## 10. References

- [1] Ackerman, P. L. (1996) 'A Theory of Adult Intellectual Development: Process, Personality, Interests, and Knowledge', *Intelligence* 22, pp. 227–257.
- [2] OECD, (2015) 'OECD Innovation Strategy 2015. An Agenda for Policy Action', OECD Publishing, Paris, <https://www.oecd.org/sti/OECD-Innovation-Strategy-2015-CMIN2015-7.pdf> [Access Date: 21 August, 2017].
- [3] Fazekas, M. & Field, S. (2013) 'A Skills beyond School Review of Germany. OECD Reviews of Vocational Education and Training', OECD Publishing; <http://dx.doi.org/10.1787/9789264202146-en> (21 August 2017).
- [4] CEDEFOP (2012) 'Future skills supply and demand in Europe: Forecast 2012', Research paper No. 26, Publications Office of the European Union, Luxembourg.
- [5] Zinn, B., Wyrwal, M. (2014) 'Ein empirisches Erklärungsmodell zum fachspezifischen Wissen von Schülern bei Einmündung in die bautechnische Fachschule [An empirical explanation model for the domain-specific knowledge of students upon entering technical school]', *Zeitschrift für Berufs- und Wirtschaftspädagogik* 110 (4), pp. 529–548.
- [6] Flake, R., Werner, D., Zibrowius, M. (2016) 'Karrierefaktor berufliche Bildung. Eine empirische Untersuchung der Einkommens- und Arbeitsmarktperspektiven von Fachkräften mit Fortbildungsabschluss im Vergleich zu Akademikern [Career factor VET. An empirical investigation of the wages and labor market perspectives of skilled employees with a postsecondary degree compared to university graduates]', <http://www.iwkoeln.de/studien/gutachten/beitrag/regina-flake-dirk-werner-michael-zibrowius-karrierefaktor-berufliche-fortbildung-263655> [Access Date: 21 August, 2017].
- [7] Deutscher Industrie- und Handelskammertag (DIHK) (2014) 'Aufstieg mit Weiterbildung. 8. Umfrage unter Absolventen der IHK-Weiterbildungsprüfungen [Job promotion via further training. 8. Survey on graduates of the examinations of the German chamber of industry and commerce]', DIHK Verlag, <https://www.dihk.de/themenfelder/aus-und-weiterbildung/weiterbildung/weiterbildungspolitik/umfragen-und-prognosen/weiterbildungserfolgsumfrage-2014> [Access Date: 21 August, 2017].
- [8] Hall, A., (2013) 'Fortbildungs-versus Hochschulabschluss: Einkommen im Vergleich [Post-secondary training certificate versus university certificate: Wages by comparison]', *Berufsbildung in Wissenschaft und Praxis* 5, pp. 4-5.
- [9] Klieme, E., Hartig, J., Rauch, D. (2008) 'The Concept of Competence in Educational Contexts', in Hartig, J., Klieme, E., Leutner, D. (Ed.) 'Assessment of Competencies in Educational Contexts', Hogrefe, Göttingen, pp.3–22.
- [10] Longoria, R.G. (1997) 'The Relationship Between Work Experience and Job Knowledge: A Theoretical and Empirical Reexamination', PhD diss., Rice University.
- [11] Sternberg, R.J., Wagner, R.K., Williams, W.M., Horvath, J.A. (1995) 'Testing common sense', *American Psychologists* 50(11), pp. 912–927.
- [12] BMBF (Federal Ministry of Education and Research) (2009) 'Feasibility Study VET-LSA. A comparative analysis of occupational profiles on VET programmes in 8 European countries – International report', Federal Ministry of Education and Research, Bonn Berlin.
- [13] Walker, F., Link, N., Nickolaus, R. (2016) 'A multidimensional structure of domain-specific problem-solving competencies of electronics technicians for automation technology', *Empirical Research in Vocational Education and Training*, <http://ervet-journal.springeropen.com/> [Access Date: 21 August, 2017].

- [14] Dye, D. A., Reck, M., McDaniel, M. A. (1993) 'The Validity of Job Knowledge Measures', *International Journal of Selection and Assessment* 1(3), pp. 153–157.
- [15] Seeber, S., Lehmann, R. (2013) 'Basic competencies as determinants of success in commercial apprenticeships', in Beck, K., Zlatkin-Troitschanskaia, O. 'From Diagnostics to Learning Success', Sense Publishers, Rotterdam, pp.75–83.
- [16] Cattell, R.B. (1987) 'Intelligence: Its's Structure, Growth and Action', North Holland, Amsterdam.
- [17] Sembill, D., Rausch, A., Kögler, K. (2013) 'Non-Cognitive Facets of Competence. Theoretical Foundations and Implications for Measurement', in Beck, K., Zlatkin-Troitschanskaia, O. 'From Diagnostics to Learning Success', Sense Publishers, Rotterdam, pp.199–212.
- [18] Holland, J. L. (1997) 'Making vocational choices. A theory of vocational personalities and work environments' (3rd ed.), Psychological Assessment Resources, Odessa Florida.
- [19] Schmidt, F. L., Hunter, J. E. (1998) 'The Validity and Utility of Selection Methods in Personnel Psychology: Practical and Theoretical Implications of 85 Years of Research Findings', *Psychological Bulletin* 124(2), pp. 262–274.
- [20] Barrick, M.R., Mount, M.K. (1991) 'The Big Five Personality Dimensions and Job Performance: A Meta-Analysis', *Personnel Psychology* 44, pp. 1–26.
- [21] Van Iddekinge, C.H., Putka, D.J., Roth, P.L., Lanivich, S. E. (2011) 'Are You Interested? A Meta-Analysis of Relations Between Vocational Interests and Employee Performance and Turnover', *Journal of Applied Psychology* 96(6), pp. 1167–1194.
- [22] Robbins, S.B., Le, H., Davis, D., Lauver, K., Langley, R., Carlstrom, A. (2004) 'Do Psychosocial and Study Skill Factors Predict College Outcomes? A Meta-Analysis', *Psychological Bulletin* 130(2), pp. 261–288.
- [23] Weiß, R.H. (1971) 'Grundintelligenztest CFT 3 [Culture Fair Intelligence Test. Scale 3]' Hogrefe, Göttingen.
- [24] Schönbrodt, F. D., Gerstenberg, F. X.R. (2012) 'An IRT analysis of motive questionnaires: The Unified Motive Scales', *Journal of Research in Psychology* 46, pp. 725–742.
- [25] Nitzschke, A., Velten, S., Dietzen, A., Nickolaus, R. (in press) 'Motive, Vorerfahrungen und kognitive Eingangsvoraussetzungen von Technikerschülern und Technikerschülerinnen [Motives, prior experiences and cognitive prerequisites of prospective technicians]', *Zeitschrift für Berufs- und Wirtschaftspädagogik*.
- [26] Wilson, M., De Boeck, P., Carstensen, C. H. (2008) 'Explanatory Item Response Models: A Brief Introduction', in Hartig, J., Klieme, E., Leutner, D. (Ed.) 'Assessment of Competencies in Educational Contexts', Hogrefe, Göttingen, pp. 91–120.
- [27] Ullman, Jodie B. (2014) 'Structural Equation Modeling', in Tabachnick, B. G., Fidell, L. S. 'Using multivariate statistics', Pearson, Boston, pp. 731–836.
- [28] Hu, L., Bentler, P. (1999) 'Cutoff criteria for fit indices in covariance structure analysis: conventional criteria versus new alternatives', *Structural Equation Modeling* 6, pp. 1–55.