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Article — Published Version

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Vocations and Learning

Provided in Cooperation with:

Springer Nature

Suggested Citation: Schauer, Jennifer; Abele, Stephan; Etzel, Julian M. (2025) : Differential Development of Professional Knowledge and Problem-Solving Skills During VET: The Role of Cognitive Resources, School-Leaving Certificates, and Sociodemographic Background, Vocations and Learning, ISSN 1874-7868, Springer Netherlands, Dordrecht, Vol. 18, Iss. 1, <https://doi.org/10.1007/s12186-025-09367-4>

This Version is available at:

<https://hdl.handle.net/10419/323651>

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Differential Development of Professional Knowledge and Problem-Solving Skills During VET: The Role of Cognitive Resources, School-Leaving Certificates, and Sociodemographic Background

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Received: 25 April 2024 / Accepted: 13 February 2025
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Abstract

In this study, we investigated the development of apprentices' professional knowledge and problem-solving skills during the second half of dual vocational education and training (VET). We analyzed (1) the average level of development, (2) interindividual differences in this development, and (3) the effects of cognitive resources, school-leaving certificates, and sociodemographic background as covariates of the development. Professional knowledge ($n=473$) and problem-solving skills ($n=322$) were assessed towards the end of the second (T_1) and third year (T_2) of VET. Using latent change score analyses, we found (1) an average increase in professional knowledge, (2) substantial variance in change, and (3) associations between the apprentices' change and their cognitive resources (specifically, fluid intelligence and the prior level of professional knowledge). Beyond that, there were no effects of school-leaving certificates, socioeconomic status and migration background on the change between T_1 and T_2 but we found these covariates to be partly associated with the apprentices' prior level of professional knowledge at T_1 . As we detected large estimation uncertainties in the results for problem-solving skills, no reliable interpretation was possible for this outcome. In sum, our study reveals inconclusive findings on the effectiveness of VET programs in promoting learning and, at the same time, emphasizes the large heterogeneity in learning trajectories that needs to be accounted for in VET practice to improve success for all apprentices.

Keywords Development · Latent change score analysis · Problem-solving skills · Professional knowledge · Troubleshooting skills · Vocational education and training (VET)

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Introduction

Professional knowledge and *problem-solving skills* are essential for successfully carrying out professional tasks in an occupational domain. Automotive technicians, for instance, need knowledge of how a motor vehicle works, and they must be able to apply this knowledge to practical tasks (e.g., troubleshooting), which is referred to as problem-solving skills (e.g., Nickolaus & Seeber, 2013). These two outcomes are key objectives of vocational education and training (VET), such as the German dual VET. Regular dual VET lasts 36 to 42 months and is structured through occupation-specific regulations and curricula. It combines learning in vocational schools (40% of learning time) and companies (or inter-company training centres, 60% of learning time; Protsch & Solga, 2019). Formally, the learning contexts are equally responsible for imparting professional knowledge and problem-solving skills (Standing Conference of the Ministers of Education and Cultural Affairs of the Länder in the Federal Republic of Germany [KMK], 2013) but differ in the organization of learning (e.g., structured lessons and instruction in vocational schools versus less structured workplace learning in the companies).

To date, the existing research on the effectiveness of dual VET programs raises some concerns, as a substantive share of graduates does not achieve sufficient levels of professional knowledge and problem-solving skills as intended by the curricula (e.g., Lehmann & Seeber, 2013; Seeber & Seifried, 2019). For example, by the end of VET, a third of automotive technicians are only able to carry out routine troubleshooting tasks, while less than 15% can diagnose complex vehicle faults correctly and independently (Nickolaus et al., 2012). This suggests that dual VET does not sufficiently promote learning and development for all apprentices. This can affect their success in VET, their transition to qualified employment as well as their professional performance and development later on. It can also have an impact on societal outcomes such as securing a skilled workforce that contributes to economic development (e.g., Rausch et al., 2024).

Due to a lack of longitudinal research, there is little evidence on how apprentices develop in terms of professional knowledge and problem-solving skills throughout dual VET, to what extent apprentices differ in their development, and which factors explain interindividual differences in the development of professional knowledge and problem-solving skills. These questions are important to investigate to identify areas for improvement in VET and to develop measures that promote learning in terms of effectiveness, equality and equity. In general, the development of professional knowledge and problem-solving skills is affected by several factors (e.g., individual resources, training quality, or the structure of VET programs). In this study, we explicitly focused on the effects of micro- and individual-level factors, namely the apprentices' *cognitive resources*, *school-leaving certificates*, and *sociodemographic background*. We investigated the research questions raised above using longitudinal data on a cohort of automotive technician apprentices from the ManKobE study (*Mathematics and Science Competencies in Vocational Education and Training*; Retelsdorf et al., 2013).

Development of Professional Knowledge and Problem-Solving Skills During Dual VET

Previous research investigating the development of apprentices' professional knowledge and problem-solving skills largely suggested that they progressively develop and increase throughout VET (e.g., Abele, 2014; Atik, 2022; Atik & Nickolaus, 2016; Klotz et al., 2015; Rosendahl & Straka, 2011). However, a few studies also found stagnation (Rauner et al., 2014; Rauner & Ahrens, 2022), and even regressive tendencies (Rauner & Ahrens, 2022; Nickolaus & Ziegler, 2005). These inconsistencies may reflect stage-specific dynamics in development as there is evidence of substantial learning rates in earlier stages of VET (e.g., first year, Atik, 2022, Atik & Nickolaus, 2016), whereas lower development was found in later stages (e.g., Rauner et al., 2014). In addition, whereas progression was found for professional knowledge (e.g., Abele, 2014; Atik, 2022; Moehring et al., 2018), problem-solving skills appeared to develop less consistently (Gschwendtner et al., 2017; Nickolaus et al., 2012). This may indicate outcome-specific dynamics in development, but there has been little empirical research on this topic to date.

In general, longitudinal analyses of the development of professional knowledge and problem-solving skills during VET are still scarce. Although the aforementioned studies aimed to study development, they mainly relied on correlation-based analyses between two time points in VET or cohort comparisons without addressing development from a *within-subject perspective*. From such a perspective, development is referred to as the apprentices' intraindividual trajectories of change in professional knowledge and problem-solving skills between two or more time points in VET. In addition, the few existing longitudinal studies primarily assessed the average level of development across all apprentices within a cohort (e.g., Atik & Nickolaus, 2016; Nickolaus et al., 2012) which reflects a generalized measure of development but fails to capture that apprentices may exhibit different levels of development. Abele (2014) found that these interindividual differences exist in the development of professional knowledge (but did not investigate this matter for problem-solving skills). Beyond that, little is known about interindividual differences in the development of professional knowledge and problem-solving skills and about individual factors that may explain this heterogeneity in development.

Covariates of the Development of Professional Knowledge and Problem-Solving Skills

According to PPIK theory ('process, personality, interests and knowledge'; Ackerman, 1996), interindividual differences in the development of intellectual abilities in a certain domain are fostered by the individuals' level of general cognitive abilities (intelligence-as-process often referred to as fluid intelligence, Cattell, 1971), their prior knowledge and skills repertoire in this domain (intelligence-as-knowledge or crystallized intelligence, Cattell, 1971), and the time and effort spent on learning. Building on PPIK theory, Abele (2014) adapted these assumptions to the context of industrial-technical VET and specified which individual-level factors may influence the development of apprentices' professional knowledge and skills during VET. He

assumed and found that the development of professional knowledge and skills is influenced by (1) *cognitive resources* such as *fluid intelligence* and *domain-specific knowledge and skills*, and (2) *school-leaving certificates*. Neither the PPIK theory nor Abele (2014) took into account the (3) *sociodemographic background* of apprentices. However, given the significance of socioeconomic status (SES) and migration background for general education outcomes (e.g., Skopek & Passareta, 2021), we elaborated on these theories and assumed that these factors have a continuing impact on the development of professional knowledge and problem-solving during VET (Stocké et al., 2011).

Cognitive Resources– Fluid Intelligence and Domain-Specific Knowledge and Skills

Fluid intelligence describes an individual's general cognitive ability to process information such as reasoning (Cattell, 1971) and is assumed to be mostly unaffected by learning. Fluid intelligence has been found to explain interindividual differences in professional knowledge and problem-solving skills across many occupational domains (e.g., Abele, 2014; Atik, 2022; Seeber, 2014). However, its predictive validity decreased when *domain-specific knowledge and skills* were accounted for (e.g. Abele, 2014, Moehring et al., 2018). Domain-specific knowledge and skills can be considered a facet of crystallized intelligence (Cattell, 1971) that is related to the content and tasks of an occupational domain, and that is attributed to learning in either pre-vocational contexts or in VET, specifically (Atik, 2022; Klotz & Winther, 2016; Moehring et al., 2018; Neumann et al., 2013). As for the automotive domain, this can be physics knowledge acquired throughout general education (e.g., Etzel et al., 2024) as this school subject covers basics that are relevant to the automotive domain, and professional knowledge (e.g., how a motor vehicle works) that is directly related to the automotive domain and acquired throughout VET. These domain-specific facets of cognitive resources can facilitate the processing and organization of new information in vocational learning (*'knowledge-is-power' hypothesis*, e.g., Etzel et al., 2024; Moehring et al., 2018; Simonsmeier et al., 2021). Consistently, existing research suggested that domain-specific knowledge and skills are the strongest predictors of the levels of professional knowledge and problem-solving skills achieved throughout VET (e.g., Abele, 2014; Atik, 2022).

These associations suggest that apprentices who bring a higher level of general cognitive abilities to VET or have a higher level of (pre-existing) domain-specific knowledge and skills demonstrate a higher level of professional knowledge and problem-solving skills throughout VET. However, this does not provide information on how low- and high-achievers differ in their individual *development* of these outcomes during VET. According to the *'Matthew effect'* (Bast & Reitsma, 1998), apprentices with higher cognitive resources are expected to show advantages in development that are reflected in higher learning rates as they can make use of learning opportunities more effectively. This would suggest increasing achievement gaps within the cohort. However, there is almost no evidence of this phenomenon from the VET context (e.g., Petsch et al., 2014). On the contrary, previous studies found compensatory effects (i.e., apprentices with lower cognitive resources showed stronger development; Atik, 2022; Atik & Nickolaus, 2016; Nickolaus et al., 2012) or no differences

at all between low- and high-achievers (Abele, 2014). Given these inconclusive findings, further research on the role of cognitive resources in explaining interindividual differences in apprentices' development of professional knowledge and problem-solving skills is needed.

School-Leaving Certificates

Related to the role of cognitive resources, *school-leaving certificates* obtained at the end of general education are considered another relevant factor for vocational learning (Abele, 2014). On average, apprentices with higher certificates bring a higher level of cognitive resources to VET, which is presumably due to better opportunities to realize their cognitive potential in pre-vocational contexts (e.g., they spent more years learning in general education or attended more stimulating schools; Holtmann et al., 2023). The role of certificates in explaining differences in professional knowledge and problem-solving skills therefore is commonly assumed to be covered by differences in the apprentices' cognitive resources (e.g., Cerdà-Navarro et al., 2022). However, certificates also cover non-cognitive aspects such as engagement in education or self-efficacy beliefs that can play a distinct role in vocational learning (e.g., Baethge-Kinsky et al., 2016; Cerdà-Navarro et al., 2022). For example, due to negative experiences in pre-vocational contexts (e.g., repeating classes, rejection and disappointed expectations when searching for a training position), apprentices with low certificates may have internalised a "stigma of having failed and feeling less intelligent and capable" (Cerdà-Navarro et al., 2022, p. 6). This may lead to pessimistic expectations, resignation or a lack of engagement in vocational learning and, as a result, lower development and outcomes throughout VET. Moreover, as certificates are an important selection criterion in the transition from school to VET (e.g., Holtmann et al., 2017; Schauer & Abele, 2023), youths with higher certificates usually have higher chances of entering more stimulating and supportive environments (e.g., companies with higher training resources) which may benefit their development in VET. Therefore, differences in the development of professional knowledge and problem-solving skills may as well be explained by an interplay of '*selection and socialization effects*' (Häfeli et al., 1988).

Previous studies yielded inconsistent findings on the role that certificates play in the development of professional knowledge and problem-solving skills. Some studies found that they have no incremental predictive power for interindividual differences in the development of professional knowledge once cognitive resources were accounted for (Abele, 2014; Atik & Nickolaus, 2016). This suggests that respective associations must be traced back to the underlying differences in cognitive resources. In contrast, a couple of studies did find additional effects even after accounting for cognitive resources (e.g., Atik, 2022) suggesting that there are further aspects associated with certificates that are relevant to vocational learning. Therefore, the role of certificates in apprentices' development of professional knowledge and problem-solving skills remains open.

Sociodemographic Background

Theories on vocational learning as well as previous research have barely addressed the role of sociodemographic background in the development of professional knowledge and problem-solving skills. The few studies that tackled this question (Atik, 2022; Pieniak et al., 2023; Seeber, 2014) largely suggested that social disparities in vocational learning must be traced back to interindividual differences in cognitive resources due to restricted opportunities for youth from lower SES and migrant families to unfold their cognitive potential in pre-vocational contexts (e.g., restricted access to stimulating schools or private tutoring due to lower (non-)monetary family resources). Hence, they, on average, bring a lower level of cognitive resources into VET (e.g., Skopek & Passaretta, 2021) and therefore could be disadvantaged in vocational learning. This is also referred to as '*primary effects*' (Boudon, 1974). In addition, apprentices could be further disadvantaged by the aforementioned interplay of '*selection and socialization effects*' (Häfeli et al., 1988) as SES and migration background also influence access to training positions and (stimulating) learning environments (e.g., Busse, 2020; Protsch & Solga, 2016). (Deficits in) Language skills may additionally affect learning and reinforce disadvantages for apprentices with a migration background (Atik, 2022). However, to the best of our knowledge, to date, there are no longitudinal analyses directly addressing the question of how SES and migration background explain interindividual differences in the development of professional knowledge and problem-solving skills during VET.

The Present Study

Based on the theories and previous research discussed above, we identified three open aspects that we aimed to address in our study: First, there is little longitudinal research that has investigated development from a *within-subject perspective* depicting the apprentices' intraindividual trajectories of change in professional knowledge and problem-solving skills between two or more time points in VET. Moreover, previous studies mostly focussed on professional knowledge, but few examined the equally important outcome of problem-solving skills or included both outcomes to examine differences in their development. Second, little is known about interindividual differences in the development of these outcomes and to what extent apprentices exhibit different levels of development in professional knowledge and problem-solving skills. Third, the question of the extent to which cognitive resources, school-leaving certificates and sociodemographic background explain interindividual differences in the development of professional knowledge and problem-solving skills largely remained open, as previous studies have predominantly examined their associations with the apprentices' achievement levels at certain stages in VET but not with development from a within-subject perspective. Remarkably, theory and previous research have barely considered the role of sociodemographic background for vocational learning although there is reason to assume that their earlier influence on cognitive resources and outcomes from general education continues in VET.

Research question (RQ) 1. In this study, we first examined the extent to which apprentices develop their professional knowledge and problem-solving skills in VET by operationalizing development as the apprentices' intraindividual change between two time points in the second half of VET (towards the end of the second and third years of VET, specifically). Because VET programs intend to continuously promote both outcomes over the entire course of VET, we expected professional knowledge and problem-solving skills to further increase in this period (H1). By investigating both, professional knowledge and problem-solving skills, we aimed to explore differences in the development of these outcomes.

RQ2. In addition to the average level of development in professional knowledge and problem-solving skills, we examined interindividual differences in this development to investigate whether apprentices exhibited different levels of development or whether everyone learned roughly the same. Based on the (scarce) findings of previous studies (e.g., Abele, 2014), we expected to find significant variance in intraindividual change for both outcomes (H2).

RQ3. Lastly, we aimed to gain a better understanding of the role of *cognitive resources*, *school-leaving certificates*, and *sociodemographic background* in explaining interindividual differences in the development of professional knowledge and problem-solving skills. Here, we expected apprentices with higher levels of *cognitive resources* to show higher levels of development (H3) as theory emphasized the significance of cognitive resources, namely *fluid intelligence* and *domain-specific knowledge and skills* for vocational learning (Abele, 2014; Ackerman, 1996). In the case of *school-leaving certificates*, we assumed that apprentices with higher certificates show stronger development (H4). Considering their *sociodemographic background*, we expected apprentices with a *migration background* and lower *SES* to show lower levels of development (H5). Following on theory and previous research, we expected the effects of certificates, SES and migration background on the development of professional knowledge and problem-solving skills to be fully covered by interindividual differences in cognitive resources that mainly result from unequal opportunities in unfolding the individuals' cognitive potential in pre-vocational contexts (i.e., '*primary effects*', Boudon, 1974). However, due to possible alternative approaches (e.g., '*selection and socialization effects*', Häfeli et al., 1988) and inconsistencies in previous research, we aimed to explore whether there are additional effects beyond what is covered by differences in cognitive resources.

Our study focused on automotive technician apprentices. The automotive domain is of (inter-)national societal importance as it significantly contributes to the economy and employment. A skilled workforce and effective VET programs therefore are of practical relevance (e.g., Rausch et al., 2024). In Germany, automotive technicians are the most frequently chosen dual VET program among males and represent a significant share of dual apprenticeships (5% out of 1.2 million apprentices). Furthermore, the share of apprentices without or with a lower secondary certificate (35%) and without German nationality (12%, Kroll, 2024) is relatively high compared to other VET programs. We therefore assumed apprenticeship to be especially heterogeneous in terms of the characteristics under study which can support differentiated analyses and the generalizability of the results.

Methods

Participants

Our analyses were based on the subsample of automotive technician apprentices from the German study *Mathematics and Science Competencies in Vocational Education and Training* (ManKobE; Retelsdorf et al., 2013). Apprentices were tested and surveyed on three measurement occasions over the entire course of dual VET: One roughly three months into VET (T_0 , fall of 2012), a second towards the end of the second year of VET shortly before the intermediate exams (T_1 , spring of 2014), and a third towards the end of the third year of VET shortly before the final exams (T_2 , fall of 2015). Cognitive resources, certificates and sociodemographic background were assessed at T_0 . Professional knowledge and problem-solving skills were assessed at T_1 and T_2 (i.e., with a measurement interval of approximately one and a half years). For automotive technicians, problem-solving skills were operationalized as troubleshooting skills, specifically (see ‘*Test Materials*’). For the sake of clarity, we will keep to this term in the following.

For all analyses, we used data from participants who answered at least one item of the professional knowledge or troubleshooting skills assessment (respectively) at either measurement occasion. This means that we included participants in our analyses even when they only provided data at one measurement occasion but not the other (e.g., due to dropout from VET or unavailability on the assessment day, $n=164$ apprentices dropped out of the professional knowledge assessment between T_1 and T_2 , and $n=81$ apprentices dropped out of the troubleshooting skills assessment). In doing so, we ensured that our handling of missing data would protect our results against potential dropout effects (see ‘*Statistical Analyses*’).

The final sample consisted of $n=473$ participants who completed the professional knowledge assessment. Out of those, $n=322$ also completed the assessment on troubleshooting skills. Apprentices were predominantly male (95%). More than one-fourth of apprentices had a migration background. The majority either held a lower secondary certificate at maximum (including a few who left general education without any certificate) or an intermediate certificate. The sample composition was similar in terms of the professional knowledge and troubleshooting skills assessments (see Tables 1 and 2, no significant mean differences were found regarding the covariates under study), and consistent with data from public statistics and previous studies (e.g., Abele, 2014; German Federal Statistical Office, 2015).

Test Materials

Professional Knowledge and Troubleshooting Skills (T_1 and T_2)

Apprentices’ professional knowledge and troubleshooting skills were measured with tests that have been developed and validated in previous studies. Professional knowledge was assessed with paper-pencil tests (Nickolaus et al., 2016). The test booklets contained 55 tasks covering five areas in the automotive domain (engine, engine control, start/power/lightning, service, chassis). Troubleshooting skills encompass

Table 1 Professional knowledge ($n=473$)— descriptive statistics and correlation matrix

	<i>M</i>	<i>SD</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) T ₁ Level	0.00	1.00	1							
(2) T ₂ Level	0.28	1.40	0.88***	1						
(3) Fluid Intelligence	0.54	1.01	0.48***	0.49***	1					
(4) Physics Knowledge	0.31	1.21	0.54***	0.48***	0.62***	1				
(5) Intermediate Certificate	0.51	0.71	0.20**	0.15	0.27***	0.18**	1			
(6) Upper Secondary Cert.	0.13	0.36	0.22**	0.19*	0.34***	0.34*	- 0.39***	1		
(7) HISEI	44.91	17.37	0.13**	0.07	0.15**	0.21***	0.10*	0.23***	1	
(8) Migration Background	0.27	0.45	- 0.18**	- 0.18**	- 0.05	- 0.12*	- 0.09	0.10	- 0.19**	1

Note: For categorical variables, the mean values represent the percentage of apprentices with an intermediate or upper secondary certificate or with a migration background, respectively. Results are based on a latent baseline model including all variables. Levels of significance: * $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$.

Table 2 Troubleshooting skills ($n=322$)— descriptive statistics and correlation matrix

	<i>M</i>	<i>SD</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) T ₁ Level	0.00	1.00	1							
(2) T ₂ Level	0.18	0.90	0.82***	1						
(3) Fluid Intelligence	0.44	1.01	0.47***	0.32**	1					
(4) Physics Knowledge	0.39	1.24	0.49***	0.42***	0.62***	1				
(5) Intermediate Certificate	0.58	0.50	0.16	0.14*	0.16*	0.10	1			
(6) Upper Secondary Cert.	0.15	0.35	0.24***	0.25***	0.36***	0.36***	- 0.48***	1		
(7) HISEI	45.54	17.30	0.09	0.10	0.15*	0.25***	0.10*	0.23***	1	
(8) Migration Background	0.32	0.57	- 0.21	- 0.22*	- 0.07	- 0.14*	- 0.14*	0.10	- 0.23**	1

Note: For categorical variables, the mean values represent the percentage of apprentices with an intermediate or upper secondary certificate or with a migration background, respectively. Results are based on a latent baseline model including all variables. Levels of significance: * $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$.

detecting and diagnosing malfunctions and their causes in motor vehicles. Data was assessed using a computer-based motor vehicle simulation including ten test items (Gschwendtner et al., 2009). Specifically, participants were asked to carry out diagnoses based on four work assignments including different malfunctions (i.e., naming the causes of the malfunctions and justifying the solution) and six technical tasks (e.g., resistance measurement). Both, the paper-pencil and the computer-based test, were administered on T₁ and T₂. Test items were coded dichotomously (1 = *full credit*, 0 = *no credit*).

We examined the psychometric quality of both tests at each measurement occasion and optimized them for better comparability. Specifically, we estimated two-parameter logistic item response theory models (2PL-IRT; e.g. Embretson & Reise, 2000) for each test and each measurement occasion. We excluded all items that (1) did not load substantially on the latent factors and (2) yielded very different loadings across measurement occasions (i.e., differences > 0.30). The optimized tests consisted of 43 items for professional knowledge and eight items for troubleshooting skills.

Cognitive Resources: Fluid Intelligence and Physics Knowledge (T_0)

We included information on *fluid intelligence*, and *physics knowledge* as a facet of domain-specific knowledge acquired during general schooling. Both measures were assessed at the beginning of VET (T_0). Fluid intelligence was assessed using the established *Cognitive Ability Test* (CAT; Heller & Perleth, 2000). The CAT comprises three subtests for numerical, spatial and verbal abilities. We used individuals' weighted likelihood estimates (WLE; Warm, 1998) from a one-dimensional 2PL-IRT model as a measure of their general cognitive abilities (WLE-Reliability=0.90). Physics knowledge was assessed using tests from the *German Educational Standards in Mathematics and Physics* (Pant et al., 2013). Again, we used WLE estimates that were derived based on the coding procedures and item parameters of the test (WLE-Reliability=0.67).

School-Leaving Certificates (T_0)

Information on the apprentices' school-leaving certificates obtained at the end of general education was assessed at T_0 . For the analyses, we differentiated between apprentices with (1) a lower secondary certificate or without any certificate from general education (short: max. lower secondary certificate), (2) an intermediate certificate, and (3) an upper secondary certificate (i.e., university entrance certificate). The groups were represented by two distinct dummy variables each coded as 1 if apprentices had an intermediate or upper secondary certificate, respectively. Apprentices with max. lower secondary certificate each represented the reference group (i.e., coded as 0).

Sociodemographic Background: Socioeconomic Status and Migration Background (T_0)

Information on the apprentices' sociodemographic background was assessed at T_0 . Specifically, we included information on socioeconomic status (SES) and migration background. SES was assessed via the *International Socio-Economic Index of Occupational Status* (ISEI; Ganzeboom, 2010; Ganzeboom et al., 1992). The ISEI combines information on the parents' occupation, income and education and represents their socioeconomic position and resources (Ehmke & Siegle, 2005). We combined information from both parents and considered only the highest score (HISEI). Migration background was specified using the information on the apprentices' and their parents' country of birth. Information was coded dichotomously as 1 if the participant or at least one of their parents was not born in Germany, and 0 otherwise. We decided on this approach as a pragmatic approximation to migration-specific disparities because our data did not allow for more differentiated analyses.

Statistical Analyses

All analyses were estimated with *Mplus* (version 8.6, Muthén & Muthén, 1998–2017). The clustering of apprentices in school classes was accounted for by using the

'*TYPE = COMPLEX*' option to obtain robust standard errors. There was no information available for clustering by training companies.

Missing data were handled via full information maximum likelihood (FIML) estimation. This method makes use of all available information in the data (i.e., all study variables) and yields unbiased results when the missing mechanism is missing at random (MAR; Enders, 2022). In common longitudinal designs, such as the one used in this study, the MAR assumption is often violated because the variable that contains missing values at a later measurement occasion (e.g., professional knowledge at T_2) is often the same variable that is responsible for the missingness in the first place (e.g., professional knowledge at T_1 , because dropping out of the study may be related to having lower scores at T_1). This is a threat to the validity of analyses of change, because failing to appropriately take systematic study dropout into account may lead to biased results. To alleviate this, Graham (2003, 2009) proposed to include variables that are related to the missing mechanism in the analysis. When this is done, the missing data can be considered MAR, conditional on the observed data. Empirical studies have shown that this procedure yields results that substantially reduce attrition bias and that are superior to listwise deletion (i.e., only including participants who provided data at both measurement occasions; e.g., Enders & Bandalos, 2001; Jorgensen et al., 2018). Overall, we used the state of statistical procedures for handling missing data to minimize the risk of bias in our analyses.

Analysis of Measurement Invariance

As a preliminary step, we examined the longitudinal measurement invariance of the tests on professional knowledge and troubleshooting skills. Measurement invariance is typically considered a prerequisite for longitudinal analyses to ensure that constructs have the same meaning across measurement occasions (Putnick & Bornstein, 2016). The degree of invariance is defined at different levels of strictness, depending on which parts of the model are constrained to be invariant over time (configural invariance: fixed factor structure; metric invariance: fixed factor structure and item loadings; scalar invariance: fixed factor structure, item loadings, and thresholds; Meredith, 1993). We estimated subsequent longitudinal 2PL-IRT models with increasingly stricter equality constraints. Thereafter, we compared the respective models based on the Bayesian Information Criterion (BIC), and $RMSEA_D$ as a measure of approximate fit for model comparisons (Savalei et al., 2023). Models with smaller BIC values are preferred (Raftery, 1995; Vrieze, 2012). For the $RMSEA_D$, values ≤ 0.08 are considered as indications of 'fair fit'. Values ≤ 0.10 are still considered to indicate 'mediocre fit' (MacCallum et al., 1996).

Latent Change Score Analyses

Second, we investigated the apprentices' development of professional knowledge and troubleshooting skills (for each outcome separately) by estimating consecutive latent change score (LCS) 2PL-IRT models with invariant measurement parts across time. The model specification is depicted in Fig. 1. LCS models are characterized by an additional latent change factor (Δ) that is included through a node factor (i.e., a

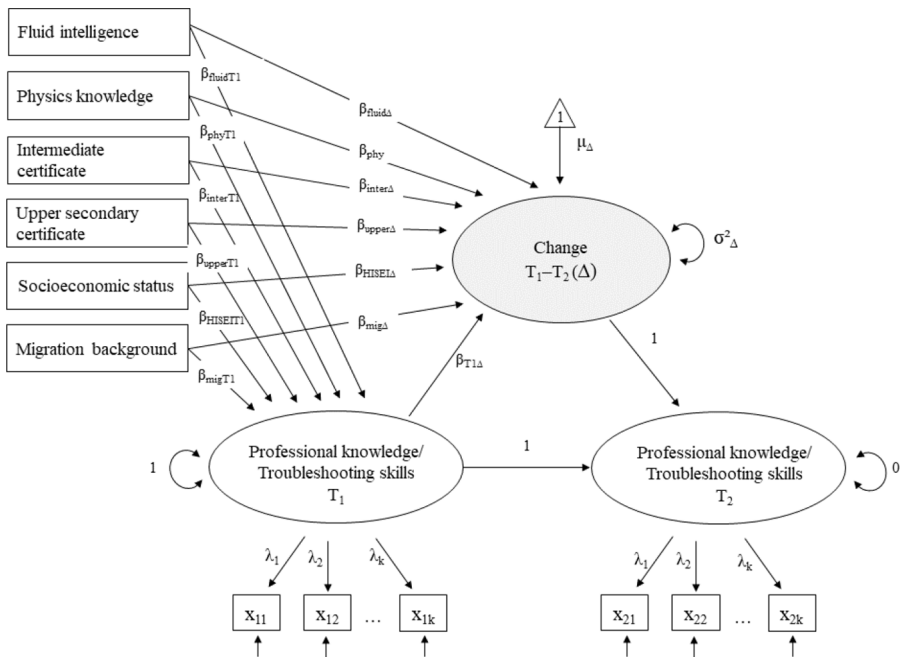


Fig. 1 Latent change score analyses—specification of measurement and structural model

latent variable without observed indicators; Klopck & Wickrama, 2020). The latent change factor is identified by (1) fixing the paths from the T_1 to the T_2 latent variable to one, (2) fixing the path from the change factor to T_2 to one, (3) fixing the T_2 variance to zero, and (4) freely estimating the mean (μ_Δ) and variance (σ_Δ^2) of the change factor. One advantage of the LCS approach is that it directly models the average level of intraindividual change (μ_Δ) and the degree of interindividual differences in intraindividual change (σ_Δ^2) as a latent variable. This makes it possible to include covariates of change into the model and to directly estimate their associations with intraindividual development in the construct under study.

The analysis models were structured in four consecutive steps: (1) We fitted baseline models without covariates. Here, we estimated the mean (μ_Δ) and variance (σ_Δ^2) of the latent change factor. In subsequent steps, we added (2) fluid intelligence and physics knowledge, (3) the certificate dummies, and (4) HISEI and migration background. We specified their effects on both, the T_1 level of professional knowledge and troubleshooting skills (e.g., $\beta_{fluidT1}$ for fluid intelligence) as well as on change from T_1 to T_2 (e.g., $\beta_{fluid\Delta}$). Importantly, all models included a directed path between T_1 and the change factor ($\beta_{T1\Delta}$) to account for the role of the pre-existing domain-specific professional knowledge and skills acquired during VET for subsequent development.

Table 3 Analyses of measurement invariance (model comparison)

	Professional knowledge ($n=473$)					Troubleshooting skills ($n=322$)				
	ΔLL	Δdf	LR_p	$RMSEA_D$	ΔBIC	ΔLL	Δdf	LR_p	$RMSEA_D$	ΔBIC
Metric vs. configural	105.19	43	≤ 0.001	0.06	-168.05	3.21	8	0.20	0.00	-40.71
Scalar vs. metric	129.00	41	≤ 0.001	0.07	-123.67	15.41	6	0.02	0.06	-13.75

Note: LL=Model Log-Likelihood, LR_p =p-value of the Log-Likelihood-Ratio test (equal to the chi-square test)

Table 4 Results of latent change score analyses

	a) Professional knowledge ($n=473$)					b) Troubleshooting skills ($n=322$)				
	M1b	M2a	M3a	M4a		M1b	M2b	M3b	M4b	
	Baseline model	Cognitive resources	Certificates	Sociodemographic background		Baseline model	Cognitive resources	Certificates	Sociodemographic background	
T₁ Level (of professional knowledge/troubleshooting skills)										
$\beta_{Intercept}$ Fluid intelligence		0.24** (0.09)	0.20 (0.11)	0.19 (0.11)			0.26* (0.11)	0.24* (0.10)	0.22* (0.10)	
$\beta_{Intercept}$ Physics knowledge		0.38** (0.08)	0.36** (0.08)	0.36** (0.08)			0.31*** (0.07)	0.28* (0.08)	0.30* (0.08)	
$\beta_{Intercept}$ Intermediate certificate (Ref.: Max. lower secondary)		0.40*** (0.09)	0.10 (0.06)	0.11* (0.06)				0.13 (0.13)	0.17 (0.11)	
$\beta_{Intercept}$ Upper secondary certificate (Ref.: Max. lower secondary)			0.06 (0.10)	0.10 (0.09)				0.11 (0.12)	0.15 (0.09)	
$\beta_{Intercept}$ Socioeconomic status (HISEI)				-0.04 (0.04)					-0.08 (0.10)	
$\beta_{Intercept}$ Migration background (Ref.: Without)				-0.13** (0.05)					0.02 (0.12)	
Adj. R ²		0.33	0.33	0.34			0.26	0.28	0.30	
T₂-T₁ Development (change in professional knowledge/troubleshooting skills)										
β_{Δ} Intercept (mean change)	0.41* (0.17)	0.51* (0.23)	0.75** (0.24)	1.02*** (0.31)		0.26 (0.29)	0.21 (0.34)	-0.01 (0.43)	0.40 (0.50)	
σ^2_{Δ} Residual variance (variance in change)	0.89*** (0.06)	0.87*** (0.07)	0.85*** (0.07)	0.84*** (0.06)		0.83*** (0.25)	0.78*** (0.26)	0.76* (0.27)	0.65** (0.22)	
β_{T_1} T ₁ Level	0.33*** (0.09)	0.30*** (0.11)	0.30* (0.12)	0.29* (0.13)		-0.41 (0.31)	-0.47 (0.35)	-0.45 (0.36)	-0.42 (0.37)	
β_{Δ} Fluid intelligence		0.18*** (0.12)	0.27* (0.11)	0.27* (0.12)			-0.13 (0.18)	-0.24 (0.19)	-0.28 (0.20)	
β_{Δ} Physics knowledge		-0.10*** (0.10)	-0.06 (0.13)	-0.07 (0.13)			0.15 (0.17)	0.09 (0.18)	0.06 (0.17)	
β_{Δ} Intermediate certificate (Ref.: Max. lower secondary)			-0.17 (0.12)	-0.15 (0.12)				0.15 (0.15)	0.13 (0.12)	
β_{Δ} Upper secondary certificate (Ref.: Max. lower secondary)			-0.15 (0.13)	-0.11 (0.11)				0.23 (0.18)	0.27 (0.20)	
β_{Δ} Socioeconomic status (HISEI)				-0.09 (0.11)					-0.09 (0.10)	
β_{Δ} Migration background (Ref.: Without)				-0.07 (0.10)					-0.35* (0.09)	
Adj. R ²	0.11	0.12	0.15	0.15		0.16	0.21	0.23	0.33	

Note: Standardized estimates, standard errors in brackets. Levels of significance: * $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

Findings

Measurement Invariance

The results of the measurement invariance tests are depicted in Table 3. For both outcomes, the scalar measurement invariance models yielded the lowest BIC. In addition, model comparisons based on the $RMSEA_D$ indicated a fair approximate fit for all comparisons. Therefore, formal requirements for comparing latent means over time were fulfilled and the scalar invariance models were used as a baseline for all subsequent steps.

Development of Professional Knowledge and Troubleshooting Skills

The results of all LCS models are presented in Table 4. In the first step, we investigated the mean levels of development of professional knowledge and troubleshooting skills within the cohort ($\hat{\mu}_{\Delta}$) as well as the variance in development ($\hat{\sigma}^2_{\Delta}$).

Professional knowledge. Concerning the average level of apprentices' development in professional knowledge between T₁ and T₂, we found a substantial significant mean change ($\hat{\mu}_{\Delta}=0.41$, $SE=0.17$, $p \leq .05$) suggesting an average increase in professional knowledge within the cohort. In addition, we found significant variance in change ($\hat{\sigma}^2_{\Delta}=0.89$, $SE=0.06$, $p \leq .001$, all estimates reported in M1a). This indicates that the apprentices exhibited different levels of development that may be

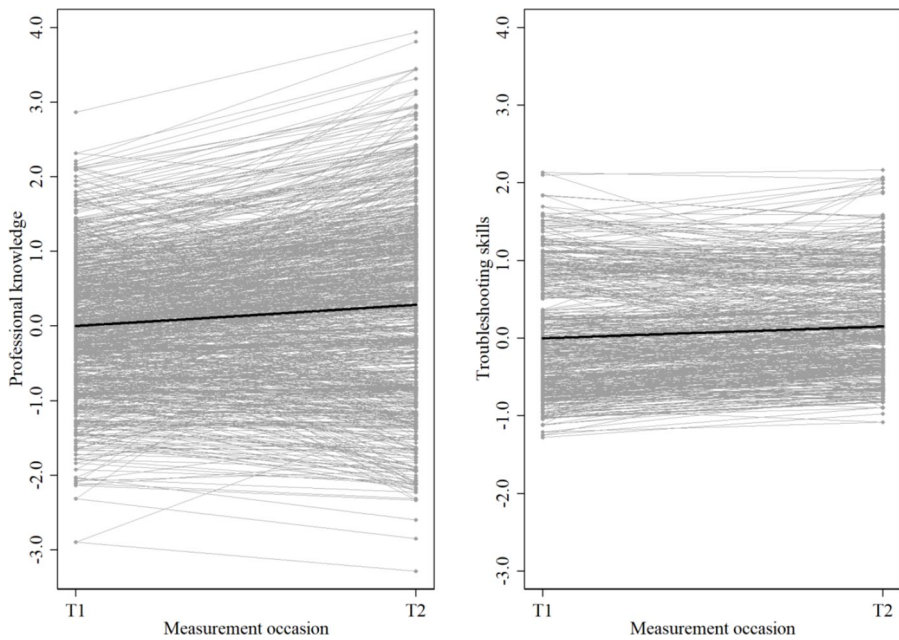


Fig. 2 Apprentices' trajectories of development in professional knowledge and troubleshooting skills.
Note: Factor scores derived from baseline model (M1a/b)

explained by the impact of the covariates examined later on. This heterogeneity in development is illustrated in Fig. 2, in which the change trajectories are shown by plotting the T_1 and T_2 factor values derived from the base models. Each grey line represents an apprentice and their trajectory of change in terms of professional knowledge and troubleshooting skills between T_1 and T_2 . It can be seen that even when the apprentices had the same initial level of professional knowledge, they exhibited different levels of change. The bold black line represents the average level of change between the mean values of T_1 and T_2 .

Troubleshooting skills. Our analyses also revealed significant variance in the apprentices' longitudinal trajectories of troubleshooting skills ($\hat{\sigma}^2_{\Delta}=0.83$, $SE=0.25$, $p\leq.001$; see Fig. 2). However, the estimate for the mean change in troubleshooting skills between T_1 and T_2 was not statistically significant, due to a large standard error ($\hat{\mu}_{\Delta}=0.26$, $SE=0.29$, $p=.36$, all estimates reported in M1b). This suggests that even though this effect descriptively indicates a slight improvement in apprentices' troubleshooting skills, it is subject to high uncertainty. Consequently, this result should be treated with caution and not be interpreted as reliable and generalizable evidence of an average improvement in troubleshooting skills.

Covariates of the Development of Professional Knowledge and Troubleshooting Skills

To investigate the extent to which the interindividual differences in development can be explained by the individual-level factors under study, we estimated the effects of the apprentices' prior level of professional knowledge and troubleshooting skills at T_1 (M1), fluid intelligence and physics knowledge (M2), certificates (M3), and SES and migration background (M4) on the change between T_1 and T_2 . In addition, we investigated the effects of the covariates considered in M1 to M4 on the T_1 level of professional knowledge and troubleshooting skills.

Professional knowledge. Our analyses revealed that heterogeneity in the development of professional knowledge between T_1 and T_2 was significantly associated with the apprentices' T_1 level of professional knowledge ($\hat{\beta}_{T1\Delta}=0.33$, $SE=0.09$, $p\leq.001$, M1a). This effect persisted across all models. It indicates that apprentices with a priory higher level of professional knowledge showed higher increases in professional knowledge between T_1 and T_2 . In Fig. 2, this is visible in the diverging trajectories for apprentices with high and low levels of professional knowledge at T_1 . The resulting pattern mirrors a “fan-spread” (Walberg & Tsai, 1983) that indicates an increase in the heterogeneity of professional knowledge within the cohort over time (i.e., a significant difference between the variances of the latent factors at T_2 and T_1 , $\hat{\sigma}^2_{T2-T1}=0.31$, $SE=0.12$, $p\leq.05$). Additionally accounting for the other covariates, we only found a significant effect of fluid intelligence on the change between T_1 and T_2 ($\hat{\beta}_{fluid\Delta}=0.27$, $SE=0.11$, $p\leq.05$, M4b). This indicates that apprentices with higher general cognitive abilities showed a higher level of development in professional knowledge.

Concerning the covariates' effects on the T_1 level of professional knowledge, we found small to moderate effects of fluid intelligence ($\hat{\beta}_{fluidT1}=0.24$, $SE=0.09$) and physics knowledge ($\hat{\beta}_{phyT1}=0.40$, $SE=0.09$, both $p\leq.001$; M2a). This suggests that apprentices who entered VET with higher cognitive resources showed higher levels of professional knowledge towards the end of the second year of VET. The effect of fluid intelligence became non-significant after including certificates (M3a), HISEI and migration background (M4a), whereas that of physics knowledge remained significant across all models. There were no distinct effects of certificates on the T_1 level of professional knowledge beyond what could be explained by differences in cognitive resources. However, additionally controlling for HISEI and migration background revealed a small effect of the dummy for intermediate certificates ($\hat{\beta}_{interT1}=0.11$, $SE=0.06$, $p\leq.05$, M4a) indicating that apprentices with an intermediate certificate tended to have a higher T_1 level of professional knowledge than those with a lower or no certificate from general education. In addition, there was a small negative effect of migration background on the T_1 level ($\hat{\beta}_{migT1}=-0.13$, $SE=0.05$, $p\leq.01$, M4a). This indicates that, even after accounting for differences in cognitive resources, certificates and SES, apprentices with a migration background were expected to have a slightly lower level of professional knowledge towards the end of the second year of VET.

Troubleshooting skills. For troubleshooting skills, the effect of the T_1 level on the change between T_1 and T_2 was not statistically significant ($\hat{\beta}_{T1\Delta} = -.41$, $SE = 0.31$, $p = .19$, M1b) and, again, we detected a large standard error indicating substantial uncertainty in this estimate. For both reasons, the effect cannot be interpreted meaningfully or generalized to the population. Concerning the other covariates, we found a significant effect of migration background ($\hat{\beta}_{mig\Delta} = -.35$, $SE = 0.09$, $p \leq .01$, M4b) suggesting that apprentices with a migration background showed a weaker development even after controlling for differences in the prior level of troubleshooting skills and the other covariates. Considering the covariates' effects on the T_1 level of troubleshooting skills, we only found significant effects of fluid intelligence ($\hat{\beta}_{fluidT1} = 0.22$, $SE = 0.10$, $p \leq .05$) and physics knowledge ($\hat{\beta}_{phyT1} = 0.30$, $SE = 0.08$, $p \leq .001$, M4b) indicating that apprentices with a higher level of these cognitive resources showed a higher level of professional knowledge towards the end of the second year of VET.

Discussion

Differential Development of Professional Knowledge and Troubleshooting Skills during VET

In this study, we investigated automotive technician apprentices' development of professional knowledge and troubleshooting skills during the second half of dual VET. We operationalized development from a *within-subject perspective* that made it possible to directly target the apprentices' intraindividual change in professional knowledge and troubleshooting skills between two time points in VET towards the end of the second (T_1) and third year (T_2). More specifically, we analyzed the average level of intraindividual change of professional knowledge and troubleshooting skills within the cohort during this period (RQ1), interindividual differences in intraindividual change (RQ2), and the role of cognitive resources, school-leaving certificates, and sociodemographic background for explaining these interindividual differences (RQ3). In latent change score analyses, we examined these questions for each outcome separately. While our findings for professional knowledge were robust, the respective findings for troubleshooting skills were characterized by larger uncertainty (due to larger standard errors). In the following sections, we thus focus primarily on the interpretation of the robust findings for professional knowledge before addressing possible explanations for the less reliable results for troubleshooting skills.

Progress and Heterogeneity in the Development of Professional Knowledge

Concerning RQ1, we found that professional knowledge increased over the second half of VET which supports our assumption in H1. As for RQ2, we found significant variance in this change indicating that apprentices exhibited different levels of development in professional knowledge throughout the second half of VET. This is consistent with H2 in which we expected to find these interindividual differences in development. Considering RQ3, we found that the variance in development can

be explained by the apprentices' cognitive resources, more specifically *fluid intelligence* and their *prior level of professional knowledge*, whereas we found no effects of *physics knowledge* acquired in general schooling. Our findings thus largely support H3, according to which we assumed a stronger development for apprentices with a higher level of cognitive resources. After accounting for interindividual differences in cognitive resources, there were no distinct effects of *school-leaving certificates*, *SES* and *migration background* on the development of professional knowledge during the second half of VET. This supports our assumption that potential disparities in development related to these factors must be traced back to underlying differences in cognitive resources (H4 and H5). However, our analyses revealed that physics knowledge, school-leaving certificates, and migration background explained differences in the apprentices' level of professional knowledge towards the end of the second year of VET.

Our findings are largely in line with previous research that found a continuous development of professional knowledge during VET (e.g., Atik, 2022; Atik & Nickolaus, 2016). Even if our analyses do not allow any qualitative statements to be made about the extent of development and the level of professional knowledge attained, the results indicate that VET still effectively promotes learning in this area in the second half of VET. The findings on the variance in the development of professional knowledge, at the same time, highlight that there is substantial heterogeneity in development which was indicated in earlier studies (e.g., Abele, 2014). Here, theories and previous studies emphasized the role of *cognitive resources* in explaining these interindividual differences in (the development of) professional knowledge (Abele, 2014; Ackerman, 1996). In terms of *fluid intelligence*, our results suggest that even in the second half of VET, apprentices benefit from their general cognitive abilities which may help them process and organize new information. Surprisingly, this seemed to be less the case for *physics knowledge* acquired in general schooling which covers important basics within the automotive domain and therefore was expected to be relevant for vocational learning. Instead, our results indicate that the *professional knowledge* that is more closely related to the automotive domain and explicitly acquired during VET gains in importance for subsequent development. This is largely in line with theory and previous studies (e.g., Abele, 2014; Rosendahl & Straka, 2011). At the same time, our analyses reveal that both these facets of domain-specific cognitive resources are interrelated as we found that apprentices with higher levels of physics knowledge consistently showed higher levels of professional knowledge towards the end of the second year of VET. Therefore, it can be assumed that (1) school-based knowledge is particularly important in earlier stages of VET when apprentices learn basic professional knowledge in their occupational domain, and (2) cognitive advantages seem to cumulate throughout VET and therefore, school-based knowledge indirectly pays off even at the end. Looking more closely at the T_1 effect of the apprentices' prior level of professional knowledge on the subsequent development of this outcome, our findings indicate a '*Matthew effect*' (Bast & Reitsma, 1998). This means that higher-achieving apprentices expand their advantages in professional knowledge and, in consequence, achievement gaps appear to increase over the second half of VET. Probably, higher-achieving apprentices can make use of learning opportunities in VET more effectively. However, as Simonsmeier et al. (2021) discuss, the effects

of prior knowledge on subsequent development and the underlying mechanisms tend to be heterogeneous and still need to be better understood. Our study does not allow any specific conclusions to be drawn at this point.

Our findings indicate that *school-leaving certificates* obtained at the end of general schooling make no additional contribution to explaining interindividual differences in the development of professional knowledge in the second half of VET beyond what is covered by differences in cognitive resources. It can therefore be assumed that apprentices with different educational levels but similar levels of cognitive resources will develop equally in terms of professional knowledge. Here, our findings support theory and earlier studies in which the role of certificates has largely been attributed to their associations with cognitive resources (e.g., Abele, 2014; Atik & Nickolaus, 2016). Notably, we found that apprentices with intermediate certificates showed a small advantage in the level of professional knowledge towards the end of the second year of VET that was not attributed to differences in cognitive resources. This may be explained by further (non-cognitive) aspects such as a higher level of engagement in VET (Cerdà-Navarro et al., 2022) or '*selection and socialization effects*' (Häfeli et al., 1988) from more supportive learning environments which, however, we cannot directly conclude from our analyses.

The non-significant effects of *SES* and *migration background* on the development of professional knowledge in the second half of VET can be interpreted similarly: Our findings suggest '*primary effects*' (Boudon, 1974) in vocational learning meaning that the role of sociodemographic background tends to be mediated by underlying inequalities in cognitive resources that emerged from pre-vocational contexts (e.g., Skopek & Passaretta, 2021). However, our analyses revealed disadvantages for apprentices with a migration background in their level of professional knowledge towards the end of the second year of VET. These migration-specific disparities seemed to persist over the second half of VET as we did not find any differences in development that would indicate compensation. Their disadvantages in professional knowledge were evident after taking into account '*primary effects*' (i.e., disparities in cognitive resources and certificates, Boudon, 1974). Therefore, other influencing factors such as (deficits) in language skills (e.g. Atik, 2022) or '*selection and socialization effects*' (i.e., selection and development in less conducive learning environments; Häfeli et al., 1988) could be alternative explanations, which again we cannot derive directly from our study.

To summarize, our findings on the development of professional knowledge indicate that there is progress in this important outcome during VET, but also considerable heterogeneity in development. There are groups of learners who are at risk of falling behind in the development of professional knowledge, such as apprentices with a low level of cognitive resources, and apprentices with a migration background. To effectively support these learners and respond to their different needs, it is crucial to identify potential challenges early through valid diagnostics. This enables targeted interventions that promote vocational learning and contribute to the achievement of VET objectives. In addition, adaptive teaching and learning are essential in VET to respond to the varying needs of learners and ensure equitable learning opportunities (e.g., Abele, 2014).

Inconclusive Insights into the Development of Troubleshooting Skills

The interpretation and generalization of our results on troubleshooting skills are considerably more difficult. Although we optimized our analyses by carefully analyzing and selecting the test items and by taking measurement errors into account through a robust latent variable approach, there was a considerable degree of uncertainty that resulted in mostly non-significant effects due to relatively large standard errors. This severely limits the interpretability of our findings on the development of troubleshooting skills during the second half of VET. A possible reason for this could be the high difficulty of the troubleshooting test. This assumption is supported by the relatively low solution rates for the majority of the test items within our sample. Specifically, a high level of difficulty may have led to an insufficient coverage of reliable information over the full range of the latent variable, and, thus, to a higher degree of uncertainty. Because this particular test has been validated and successfully used in other studies (e.g., Gschwendtner et al., 2009, Abele et al., 2014), we consider a mismatch between the test requirements and the specific conditions of the ManKobE study design to be the most plausible explanation for this outcome. Specifically, the troubleshooting test was administered toward the end of an extensive test battery, which may have led to cognitive fatigue among participants (e.g., Ackerman & Kanfer, 2009; Lindner et al., 2024).

Limitations and Future Research

The methodological caveats concerning our analyses on troubleshooting skills underscore the need for replication studies that carefully consider the test requirements and conditions to avoid overtesting and ensure data quality. To address the identified limitations, future studies should consider administering complex troubleshooting tests without too many additional measures (e.g., questionnaires and additional tests), to minimize the potential effects of cognitive fatigue. Optimizing the test by including more items with medium and low difficulty levels or simplifying the complexity of the test (e.g., shorter instructions, multiple-choice response formats) could additionally help enhance its diagnostic quality. These adjustments could not only improve the validity and reliability of the test but also provide deeper insights into the mechanisms underlying (the assessments of) troubleshooting skills. Furthermore, troubleshooting skills are a highly relevant facet of automotive technicians' problem-solving skills but there are further problem-solving tasks (e.g., repair, maintenance, Rausch et al., 2024), and respective skills facets that we did not consider in this study. Future research should take the complexity of problem-solving (skills) in the automotive domain into account and evaluate the effectiveness of VET in teaching a wide array of different problem-solving skills.

A more general methodological limitation of our analyses that should be addressed in future research is the fact that all covariates were modelled using manifest test scores (e.g., WLE scores for the physics test) in order not to overload the already quite complex modelling approach. While this is a common approach in research based on performance tests scaled with the Rasch model or more complex IRT models, manifest variables are not free from measurement error. They may introduce

noise that attenuates the effect sizes and reduces power (e.g., Nimon et al., 2012). Consequently, the effect sizes containing the physics test scores may be considered conservative estimates of the true effect sizes.

Concerning the covariates under study, it has to be noted that there are further impacts on vocational learning that we did not take into account in our study. At the individual level, for instance, theories emphasize the role of domain-specific interests and argue that professional knowledge and skills will develop particularly well in domains that correspond to the apprentices' interests as they will be more motivated and persistent in learning (e.g., Ackerman, 1996). In the case of migration background, specifically, we have mentioned migration-specific aspects (e.g., language skills) that are not directly reflected in our study. Future research should explore these aspects as well as the mechanisms that may lead to migration-specific disparities in vocational learning in more detail (e.g., Vieze et al., 2023). Hereby, distinguishing between first- and second-generation migrants—i.e., whether the apprentices themselves have direct migration or refugee experience (first-generation) or were born and raised in the host country to migrant parents (second-generation)—could provide deeper insights into the challenges these groups face, as these distinctions often reflect differences in educational biographies and socialization processes (e.g., Busse, 2020). This would not only contribute to theories on vocational learning that largely do not account for sociological factors such as migration background but also to a better understanding of these learners' needs and appropriate measures in VET practice. Lastly, future research needs to consider *institutional impacts* from vocational schools and company workplaces (e.g., training quality) on the development of professional knowledge and problem-solving skills. These were also not covered in our study and, in general, have not yet been much investigated as covariates of the development of these outcomes (e.g., Nickolaus et al., 2015). In general, studies on the organization of learning and the implementation of curricula in companies and vocational schools could expand our understanding of how the learning contexts contribute to the development of professional knowledge and problem-solving skills.

Future studies addressing the points discussed here could further enhance our understanding of how professional knowledge and problem-solving skills develop during dual VET, as well as the individual and institutional factors that contribute to interindividual differences. Such research holds the potential to advance theory and drive improvements in VET practices. Comparative studies exploring these issues across different VET programs would be particularly valuable, as they could bolster the reliability and generalizability of findings.

Authors' Contributions All authors contributed to the article and approved the submitted version. Conceptualization: all authors; Methodology: JeS and JME; Formal analysis and investigation: JeS and JME. Writing - original draft preparation: JeS; Writing - review and editing: all authors; Supervision: StA and JME.

Funding Open Access funding enabled and organized by Projekt DEAL.

Declarations

Conflicts of Interest We have no conflicts of interest to declare. The research *reported* in this article is part of the project “Mathematics and Science Competencies in Vocational Education and Training”, which was funded by the Leibniz Association (Grant No.: SAW-2012-IPN-2). The datasets generated and analyzed during the current study are not publicly available. Data can be made available from the corresponding author on request.

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