Empirical Research in Vocational Education and Training

RESEARCH Open Access

General digital competences of beginning trainees in commercial vocational education and training

Stefanie Findeisen[1*] and Steffen Wild[2]

*Correspondence: stefanie.findeisen@uni-konstanz.de
[1] Department of Economics, University of Konstanz, Universitätsstrasse 10, 78464 Konstanz, Germany
Full list of author information is available at the end of the article

Abstract

Against the background of digital transformation processes that are currently changing the world of work, this paper examines general digital competences of beginning trainees in commercial vocational education and training (VET) programs. We are particularly interested in factors influencing digital competence profiles. From survey data including $N=480$ trainees in one federal state in Germany, we were able to identify three different competence profiles (based on the trainees' self-assessment of their general digital competence). Initial descriptive analysis reveals differences between competence profiles of different training professions (industrial clerks and retail salespersons reach higher competence levels than salespersons). However, regression results indicate that these differences can be explained by differences in school leaving certificates. Contrary to prior empirical evidence, we find no significant effect of trainees' gender. Finally, the frequency of certain private digital activities (e.g. using office programs, conducting internet searches) affects digital competence profiles. Implications for both VET programs and further research are discussed.

Keywords: Vocational education and training, Trainees, Digital competences, DigComp

Introduction

Importance of digital competences of beginning trainees in VET

Digital transformation processes are currently changing the world of work (Arnold et al. 2016; Autor 2015; Frey and Osborne 2017). The increasing use of technology affects organizational structures as well as communication and collaboration processes and fosters a trend towards knowledge-based work activities (Baethge et al. 2003; van Laar et al. 2017). The growing importance of technology poses new requirements with respect to skills and competences of the workforce. There is an increasing need for interdisciplinary skills (e.g. problem solving, creativity, critical thinking, learning skills)—typically referred to as 21st-century skills (see e.g. Voogt and Roblin 2012)—and for digital competences (Arnold et al. 2016; Autor 2015; Brolpito 2018; van Laar et al. 2017).

VET programs are supposed to foster the competences required to successfully engage in professional situations (Avis 2018; Seeber 2016). However, to successfully shape digital transformation processes training companies are in need of trainees who start their training program with solid digital competences (Härtel et al. 2018). The on-going COVID pandemic additionally increases the need for digital competences, as health regulations require the use of digital tools in both the workplace (e.g. communication and collaboration) and vocational schools (e.g. distance learning formats) during the training program.

While it is often assumed that these days adolescents naturally possess certain digital competences, Kirschner and De Bruyckere (2017) illustrate that the idea of information-skilled digital natives, who readily apply technology because they grew up in a digital world, is a myth. In fact, studies among young people during general education in Germany reveal deficits with regard to digital competences (Bos et al. 2014; Eickelmann et al. 2019; Härtel et al. 2018). However, there is still a lack of empirical evidence on digital competences of adolescents at the start of VET programs (Härtel et al. 2018). Our study aims to address this research gap by examining the level of general digital competences of trainees when they enter their training program. In addition, we are interested in factors that explain different competence levels. We specifically examine the extent to which competence differences can be explained by individual characteristics as well as prior learning processes of adolescents. The study focuses on the most popular field of VET in Germany (in terms of yearly numbers of beginning trainees) and examines trainees in three commercial VET programs: industrial clerks, retail salespersons, and salespersons.

Conceptualizing digital competence

A wide range of terms are used by different authors to conceptualize individuals' abilities to use information and communication technology (ICT) (Ilomäki et al. 2016). In the following, we will refer to the concept of digital competence. Digital competence can be defined as 'confident, critical and creative use of ICT to achieve goals related to work, employability, learning, leisure, inclusion and/or participation in society' (Ferrari 2013). In a slightly broader approach, Ilomäki et al. (2016) define digital competence as consisting of '(1) technical competence, (2) the ability to use digital technologies in a meaningful way for working, studying and in everyday life, (3) the ability to evaluate digital technologies critically, and (4) motivation to participate and commit in the digital culture'. A widely used conceptualization of digital competence is provided by the European Digital Competence Framework (DigComp) (Ferrari 2013). Based on the claim that every citizen needs digital competences to participate in an increasingly digitalized society, the framework distinguishes between five areas of digital competence (Ferrari 2013):

1. Information (browsing, searching and filtering information; evaluating information; storing and retrieving information).
2. Communication (interacting through technologies; sharing information and content; engaging in online citizenship; collaborating through digital channels; netiquette; managing digital identity).
3. Content creation (developing content; integrating and re-elaborating; copyright and licenses; programming).

4. Safety (protecting devices; protecting data and digital identity; protecting health; protecting the environment).
5. Problem solving (solving technical problems; identifying needs and technological responses; innovating and creatively using technology; identifying digital competence gaps).

This conceptualization has to be regarded as a generic framework (Ferrari 2013). In line with the general differentiation between domain-general and domain-specific competences (see e.g. Löfgren et al. 2019; Seeber 2016; Winther and Achtenhagen 2009), Wilbers (2019) distinguishes between four different types of digital competences: (1) general digital competences, (2) professional digital competences, (3) digital competences that are specific to the field of work and (4) digital competences that are profession-specific. The general digital competences are regarded as generic and span all educational sectors, like competences described in the DigComp framework.

The focus of our study is the commercial VET sector, where digital transformation leads to changes regarding both supplier and customer relations as well as internal processes (e.g. storage and inventory management systems) and also work equipment (Kupfer and Jaich 2019; Seeber et al. 2019). Routine tasks become less important for professions in this field (e.g. salespersons, retail salespersons or industrial clerks) (Bergmann 2019; Utecht 2019). At the same time, computer-assisted operations as well as the use and interpretation of digital data gain importance (Jordanski 2019). Specific digital competences for these professions contain, for instance, the application of (new) digital information and communication technologies, the use of hardware and software (e.g. office packages) and dealing with data protection issues (Bergmann 2019; Jordanski 2019; Utecht 2019).

Profession-specific digital competences (industrial clerks: e.g. handling big data, using Enterprise Resource Planning (ERP) systems (Bergmann 2019; Traub and Leppert 2019; Wilbers 2019); *retail salespersons*: e.g. understanding digital networks, conducting information searches (Holz and Leppert 2019; Kupfer and Jaich 2019); *salespersons*: e.g. communication with customers, general willingness to learn (Kupfer and Jaich 2019; Schmelter 2019)) are expected to be fostered during the course of the respective VET program. However, in order to successfully manage the digital transformation processes in the commercial field, training companies need beginning trainees who already possess a solid level of general digital competence (Härtel et al. 2018). To assess general digital competences of beginning trainees, the DigComp framework seems to be a suitable approach, especially since the framework includes several aspects that are also relevant for commercial training programs (e.g. content creation via office packages, safety aspects). As such, we believe that the competences measured using the DigComp framework are a solid base for a successful start in commercial training programs and the acquisition of profession-specific digital competences.

Determinants of digital competence: theoretical model

The development of digital competence can be theoretically described as depicted in Fig. 1. This model builds on the framework for the International Computer and Information Literacy Study (ICILS) and depicts the acquisition of digital competence (here:

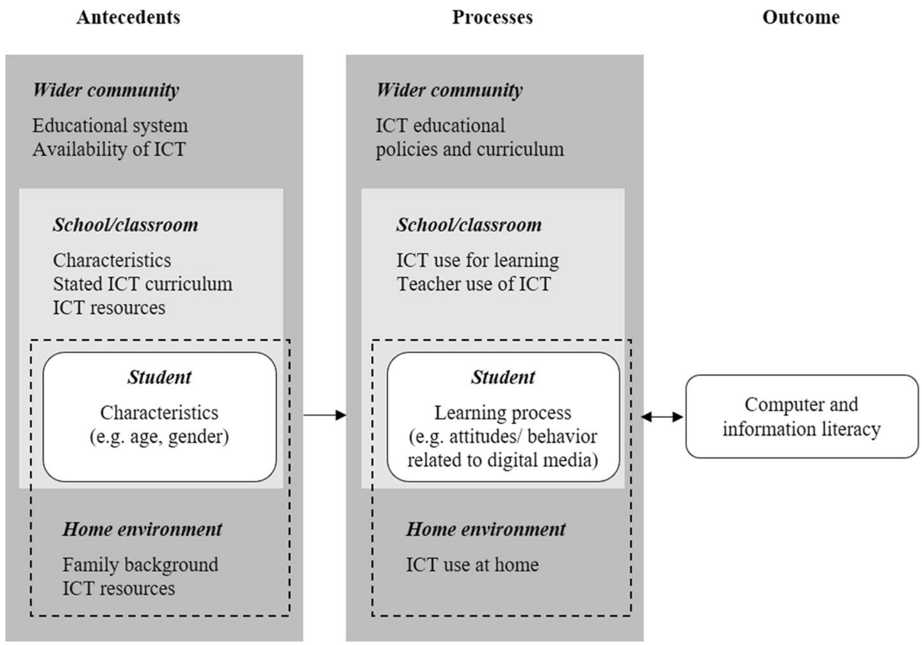

Fig. 1 Theoretical model of the acquisition of computer and information literacy (adapted from Fraillon et al. 2020, p. 7)

“Computer and information literacy”) based on a classic input-process-outcome model (see e.g. Fraillon et al. 2020; Heldt et al. 2020). The model assumes that input factors (antecedents) directly affect learning processes (process), learning processes, in turn, are expected to correlate with digital competence (outcome)—hence, they affect digital competences and are also influenced by competences (Heldt et al. 2020).

The model also distinguishes between four levels that are relevant for the acquisition of digital competence: (1) the wider community (characteristics of the educational system, policies and curricula), (2) the school/classroom (characteristics of the school, classroom instruction), (3) the home environment (family background, e.g. migration background, and ICT access at home), and (4) the individual student (student characteristics, learning process and level of performance). The ICILS framework deliberately includes individuals’ learning processes outside of school as digital competence is not only acquired in the school context. The model also accounts for the fact that antecedents and processes might be determined by factors on higher levels (e.g. ICT education policies determine schools’ ICT resources) (Fraillon et al. 2020).

In our study, we are interested in the individual level, hence, in the role of characteristics and learning processes of adolescents on the acquisition of digital competence. Existing empirical evidence on the impact of individual factors is reported in the following section.

Determinants of digital competence of adolescents: empirical evidence

The International Computer and Information Literacy Study (ICILS) repeatedly reports deficits regarding digital competences among German adolescents (Bos et al. 2014; Eickelmann et al. 2019). In this comparative international study, German 8th grade students demonstrate only rudimentary competence levels. Compared to other countries represented in the ICILS, Germany ranks in the middle range. However, there is no significant change regarding digital competences between the 2013 and the 2018 survey.

When it comes to determining factors of digital competences, several studies have examined the effects of gender. The ICILS finds that for the German sample, girls possess significantly higher digital competences than boys. In fact, none of the other countries that are part of the study report advantages of male participants compared to females (Gerick et al. 2019). These findings are supported by other studies that also find advantages for females regarding digital competences (e.g. Siddiq and Scherer 2019). However, there is also empirical evidence suggesting higher digital competences of males (e.g. Goldhammer et al. 2013) as well as studies finding no gender effect (Hatlevik and Christophersen 2013).

Moreover, education seems to be related to digital competence. As Hatlevik and Christophersen (2013) demonstrate for a group of students in upper secondary schools in Norway ($N=4087$), the study program (vocational vs. general education) significantly predicts digital competences. The authors perceive the study program as an indicator of academic aspiration and illustrate that students in general educational tracks significantly outperform vocational track students with regard to digital competence. This replicates findings of previous studies (Calvani et al. 2012; Hatlevik 2010). For the German context, Wild and Schulze Heuling (2020) indicate that students in cooperative higher education programs demonstrate higher digital competences than students in VET. Furthermore, Hatlevik et al. (2015b) find that for a sample of ninth grade students in Norway ($N=852$)—apart from family background—prior academic achievement (grades achieved in the most important school subjects) is the most important predictor of digital competence.

When it comes to the effect of learning opportunities, Zhong (2011) finds from PISA data that both ICT access at home and at school significantly predict adolescents' self-reported digital competence. However, the effect of ICT access at home is higher than the school effect and the students' previous experience in using a computer significantly predicts digital competence.

Empirical evidence on digital competences of trainees in VET is still scares. There is, however, one study from 2013 on the internet use of German trainees, finding that participants do well when it comes to navigating through the internet (orienting themselves on an unknown website, registering for a platform with their email address) (Burchert et al. 2013). With respect to those tasks, the authors found no differences between different types of VET programs (technical vs. commercial trainees). However, all the trainees experienced difficulties when it comes to searching for information and reading web content. Furthermore, the results reveal that the trainees use the internet mainly for communication and information. While there is a high affinity to use the internet for private purposes, internet use for professional reasons in the workplace is less common. This is true for the search of information and even more so for the use of internet forums, blogs, or online videos. When facing a problem, the trainees prefer consulting experienced colleagues or other trainees before trying internet searches.

Furthermore, in a small interview study among trainees in healthcare professions ($N=3$), Evangelinos and Holley (2015) demonstrate-based on the DigComp framework—that trainees perceive themselves as fairly capable with respect to ICT tasks. However, their activities cover only a narrow field of technology use, mainly for private purposes (e.g. communication via social media), and they overestimate their digital competence and fail to recognize skills necessary for the workplace.

Research questions

The empirical evidence described above mainly focuses on general education programs. For the context of VET, reliable findings are missing. Moreover, in face of the repeatedly reported deficits regarding general digital competences of adolescents (in Germany), it seems worthwhile to examine digital competences of beginning trainees in VET as well as factors predicting different competence profiles. This is the purpose of our study. We focus on beginning trainees in commercial VET in Germany. The professional field of *Commercial Services, Trade, Distribution, Hotel and Tourism* is the largest field in terms of the number of beginning trainees in the federal state of Baden-Wuerrtemberg (2018: 11,914 beginning trainees). Within this field we focused on the three professions with the highest numbers of beginning trainees: industrial clerks [*Industriekaufmann/frau*] (2018: 3,219 beginning trainees), retail salespersons [*Kaufmann/frau im Einzelhandel*] (3,649 beginning trainees), and salespersons [*Verkäufer/in*] (2,575 beginning trainees). This allows us to compare trainees in three different, yet similar professions. Hence, we can, for instance, expect fairly similar interests of adolescents applying to these training programs (e.g. affinity towards the use of digital media). At the same time, these three professions typically vary with regard to trainees' characteristics, especially regarding school leaving qualification, and to some extent gender and age (see Table 7 in the Appendix). Hence, it is of interest to analyze whether trainees in these professions differ regarding digital competence and to what extend differences can be explained by individual characteristics.

This study aims to answer the following research questions:

1. Which digital competence profiles do trainees in commercial VET possess at the beginning of their VET program?
2. Which factors predict general digital competences of beginning trainees in commercial VET?

Research Question 1 focuses on the identification of heterogeneity among beginning trainees. Research Question 2 focusses on predictors of the level of general digital competence. Based on the theoretical framework depicted in Fig. 1, there are several possible predictors. This study focuses on analyzing factors on the student level. Hence, we expect trainees' competence profiles to be influenced by (1) individual characteristics and (2) trainees' learning processes related to digital activities. Regarding individual characteristics, we examine the effect of trainees' age, gender and educational qualification. Furthermore, we are interested in differences between the three training professions we include in our analysis. Among the three professions, a training program for industrial clerks is the most highly regarded. For instance, training companies typically select applicants with higher educational qualifications for this program (two thirds possess higher education entrance qualifications; see Appendix Table 7) than for the other two training programs. Our study aims to examine, whether differences between trainees in these three training programs also occur with respect to general digital competences. Also, we examine, to what extend these differences can be explained by individual characteristics.

Apart from individual characteristics, we analyze the impact of adolescents' learning opportunities related to digital activities. Since we focus on beginning trainees in the first couple of months into the training program, participants did not yet have the opportunity to significantly benefit from profession-specific learning processes in both the training company and the vocational school. Hence, we focus on general digital competences as well as learning opportunities prior to/outside of the VET program (experiences from digital activities at home or in school). As it is not uncommon to complete more than one training program, we control for previously completed training programs of trainees. In doing so, we can take into account if trainees did have access to vocational learning opportunities regarding digital activities.

Methodology

Research design and instruments

We collected data from 480 trainees in commercial VET programs during their first months into a vocational training program. Data collection lasted from October 2018 to February 2019 and covered five vocational schools and 22 classes in the federal state of Baden-Wuerttemberg (convenience sampling). Participation was voluntary, and a privacy policy was adhered to. There were no incentives for participation.

During the survey, participants answered a modified instrument designed by Müller et al. (2018) with 24 items based on the DigComp framework (Ferrari 2013) to measure the following five components of digital competence: (1) Information, (2) Communication, (3) Content creation, (4) Safety, and (5) Problem solving. The items for each dimension are displayed in Table 1. For each item, the trainees indicate whether they are able to complete the task described (e.g. online transfer of money) or how they would describe their behavior (e.g. changing passwords regularly). Hence, each item is assessed dichotomously (0: I am not able to complete this task/I do not do this regularly/I do not recognize this; 1: I am able to complete this task/I do this regularly/I do recognize this). Since the questionnaire aims at a general assessment of digital competence and is designed to be applicable to a wide range of individuals, the survey participants assess their digital competence on a rather broad level. Hence, they are not asked, for instance, to distinguish between private and professional behavior.

The use of self-reports, of course, falls short of elaborate performance-based competence measures that are increasingly state-of-the-art in commercial vocational education and training research (e.g. Seeber 2016; Seifried et al. 2020). However, due to limited testing time, a thorough performance-based assessment of trainees' digital competence was not possible in this study. A self-report questionnaire had the advantages of time and cost effectiveness. Additionally, in other fields of vocational education (e.g. health care; see Evangelinos and Holley 2014, 2015), the DigComp framework was used as well. Overall, in view of the focus of our study, this approach seems to be suitable for the assessment of general digital competences.

Table 1 DigComp dimensions and items (translation and original wording)

Item in English	Item in German
Information	*Informationsverarbeitung*
Internet research	Internetrecherchen
Data transmission between devices	Datenübertragung zwischen Geräten
Use of multiple sources	Nutzung mehrerer Quellen
Recognition of advertisements	Erkennen von Werbeanzeigen
Considering search results, beyond the first page	Beachtung von Suchtreffern über die erste Seite hinaus
Communication	*Kommunikation*
Online bank transfers	Online-Überweisung
Recognizing fake news	Erkennen von Fake News
Posting information on social networks	Inhalte in soziale Netzwerke einstellen
Handling hostility on social networks	Umgang mit Anfeindungen über soziale Netzwerke
Content creation	*Erstellen von Inhalten*
Creating texts (word processing programs)	Texte erstellen (Textprogram)
Performing calculations (spreadsheet program)	Berechnungen erstellen (Tabellenprogram)
Creating a presentation	Präsentationserstellung
Designing web applications	Webanwendungen gestalten
Programming	Programmieren
Safety	*Schutz und Sicherheit*
Awareness that services/apps transfer data	Bewusstsein, dass Dienste/Apps Daten weitergeben
Regular updates of antivirus software	Regelmäßiges Update der Antivirensoftware
Changing passwords regularly	Regelmäßiger Passwortwechsel
Problem solving	*Problemlösung*
Installation of devices	Installation von Geräten
Establishment of a (home)network	Einrichtung (Heim-)Netzwerk
Helping others with internet/computer problems	Anderen bei Internet- und PC-Problemen helfen
Connecting hardware to a device	Hardware anschließen
Learning to use new program versions	Mich in neue Programmversionen einarbeiten

Text in the introduction: 'Think about your digital skills. What can you do, recognize and what is your behavior?'

To evaluate the measurement quality of the used instrument, we applied the IRT-based approach by Birnbaum (1968). In detail, we used Yen's Q3-Index with a cut-off point of 0.2 to check the local independence assumption (Yen 1993). For the items Designing web applications and Programming, this assumption was violated (Yen's Q3-Index = 0.34). However, as the knowledge necessary for designing web applications is not identical to the knowledge required for programming in general, from a content point of view, we decided against excluding either of the items. All the other items were below the cut-off point (Yen's Q3-Index < 0.2). Moreover, the scales revealed fair reliability (see also Table 2): *Information* (EAP/PV-Reliability = 0.74; 5 Items; example of an item: 'Data transmission between devices'), *Communication* (EAP/PV-Reliability = 0.68; 4 items; example of an item: 'Recognizing fake news'), *Content creation* (EAP/PV-Reliability = 0.74; 5 items; example of an item: 'Designing web applications'), *Safety* (EAP/PV-Reliability = 0.63; 3 items; example of an item: 'Regular updates of antivirus software') and *Problem solving* (EAP/PV-Reliability = 0.73; 5 items; example of an item: 'Learning to use new program versions').

Next, we checked for the multidimensionality of the instrument by the estimation of four different models: (1) a one-dimensional 1 PL model, (2) a one-dimensional 2 PL

Table 2 Reliability of and intercorrelations (Spearman) between the scales of digital competence

Scales	Number of items	EAP/PV	1	2	3	4	5
1. Information	5	0.74	–				
2. Communication	4	0.68	0.69	–			
3. Content creation	5	0.74	0.57	0.59	–		
4. Safety	5	0.63	0.49	0.50	0.46	–	
5. Problem solving	5	0.73	0.56	0.55	0.58	0.52	–

EAP/PV = Expected-a-posteriori/plausible value reliability

All correlations are significant ($p < 0.01$)

Table 3 Confirmatory factor analysis nested model comparisons

	AIC	*BIC*	*LL*	*Deviance*	*df*	*Δχ2*	*Δdf*	*p*
One dimension 1 PL model	10,479.46	10,575.46	− 5216.73	10,433.46	23			
Five dimensions 2 PL model	10,159.15	10,384.53	− 5025.57	10,051.15	54	382.31	31	< 0.001
One dimension 2 PL model	10,337.01	10,520.66	− 5124.50	10,249.01	44			
Five dimensions 2 PL model	10,159.15	10,384.53	− 5025.57	10,051.15	54	197.87	10	< 0.001
Five dimensions 1 PL model	10,240.87	10,395.30	− 5083.43	10,166.87	37			
Five dimensions 2 PL model	10,159.15	10,384.53	− 5025.57	10,051.15	54	115.72	17	< 0.001

AIC Akaike information criterion, *BIC* Bayesian information criterion, *LL* log-likelihood, *1 PL* Rasch Model, *2 PL* Birnbaum Model

model, (3) a five-dimensional 1 PL model (competence structure given in Table 2), and (4) a five-dimensional 2 PL model. We used the Akaike information criterion (AIC), Bayesian information criterion (BIC), Log-likelihood (LL), and Deviance to analyze model fit. The different models analyzed and the corresponding fit indices are displayed in Table 3. Based on χ^2-difference tests, we specifically tested the multidimensional model with five competence dimensions (2 PL model) against the three other models: (1) the model with one competence dimension (1 PL model) ($\chi^2 = 382.31$; $df = 31$; $p < 0.001$), (2) the model with one competence dimension (2 PL model) ($\chi^2 = 197.87$; $df = 10$; $p < 0.001$), and at last (3) the five-competence dimension 1 PL model ($\chi^2 = 115.72$; $df = 17$; $p < 0.001$). We found that model fit was significantly higher for the five-competence dimension 2 PL model compared to all other alternative models. Hence, further analyses were based on the model with five dimensions and a 2 PL structure.

Spearman intercorrelations (r_s) between the five dimensions varied between $r_s = 0.46$ and $r_s = 0.69$ (see Table 2). The lowest correlation existed between Content creation and Safety ($\mathrm{r_s} = 0.46$). The highest correlation was between Information and Communication ($r_s = 0.69$).[1]

To assess trainees' learning processes and learning opportunities (see Research Question 2), we also used an instrument by Müller et al. (2018). Here, the participants indicated which activities they performed regularly (once or several times a week). Based on face validity aspects we categorized the four items 'using searching tools on the internet to find content/information', 'viewing online videos (e.g. YouTube)', 'using digital maps

[1] In a prior study, the instrument was also tested on a sample of more than 1,000 persons in VET and higher education institutions with similar measurement quality (Wild and Schulze Heuling 2021).

and route guidance systems (e.g. Google Maps)', and 'using learning opportunities on the internet (e.g. online course, learning languages online)' as Collecting information and learning. Moreover, we clustered three items to the aspect Communication and collaboration ('using instant messaging services (e.g. WhatsApp, Threema, Telegram)', 'using cloud services (e.g. Dropbox, Google Drive, Amazon Drive)', and 'collaborating within a team via online tools (e.g. Google Docs, Microsoft SharePoint)'). In the category Generating content, we summarized the items 'using office programs (e.g. Word, Excel, PowerPoint)' and 'reading blogs and forums or creating blog entries'. The participants were asked to select all activities they regularly perform and leave unchecked the activities they do not perform (regularly) (dichotomous classification). Again, the questionnaire did not explicitly distinguish between private learning processes and work-related learning processes, however, since the trainees were only a couple of weeks/months into the training program when they filled out the questionnaire, we expect learning processes regarding digital activities to rather occur during their leisure time.

Sample

Table 4 gives a summary of the sample of 480 trainees collected in the course of this study. The sample consists of 205 industrial clerks, 145 retail salespersons, and 130 salespersons. Of all participants, 61% were female, 37% male, and 2% could not be assigned to either male or female. On average, the trainees were $M = 19.38$ ($SD = 2.35$) years old. Eleven percent of the trainees successfully completed a VET program in a different profession before starting the current program. The trainees are trained in three different commercial professions: School leaving certificates varied. Almost 43% had a General Certificate of Secondary Education [*Realschule*]. About 20% had a lower school leaving certificate [*Hauptschule*]. The rest gained a higher education entrance qualification (*Abitur*: 18%) or technical college entrance qualification (*Fachhochschulreife*: 18%).[2]

We found a significant difference in the training professions with respect to gender (χ^2 (4) = 13.75, $p \leq 0.01$, *Cramér's* $V = 0.12$). The ratio of female trainees is higher among industrial clerks (69%) and retail salespersons (59%) than among salespersons (52%). Further analyses reveal significant differences between the trainees' school leaving certificate in different professions (χ^2 (8) = 197.67, $p \leq 0.001$, *Cramér's* $V = 0.45$). An equal share (33%) of industrial clerks had a school leaving certificate at General Certificate of Secondary, advanced technical college entrance qualification, and general university entrance qualification (Abitur). Most retail salespersons had a General Certificate of Secondary Education (61%). For salespersons, there was a higher frequency of lower school leaving certifications (48%) and General Certificate of Secondary Education (40%). Finally, there were differences between the training professions in relation to former vocational apprenticeships (χ^2 (2) = 6.50, $p \leq 0.05$, *Cramér's* $V = 0.12$). A successfully completed VET program was most common among salespersons (16%), compared to 12% for retail salespersons and 7% for industrial clerks. More detailed information for

[2] Comparing the sample characteristics with official data on beginning trainees by the German "Berufsbildungsinsitut" (BIBB; https://www.bibb.de/dienst/dazubi/de/1871.php) shows that the sample—apart from the share of trainees who completed a prior apprenticeship—seems to be highly representative of the population of beginning trainees for the three professions (see Table 7 in the Appendix for details), which overall justifies the convenience sampling approach chosen in this study.

Table 4 Sample characteristics for different training professionals ($N = 480$)

	Proportion/mean (*M*) with standard deviation (*SD*) in parenthesis			
	Industrial clerks ($n = 205$)	**Retail salespersons ($n = 145$)**	**Salespersons ($n = 130$)**	**Total sample ($n = 480$)**
Sex				
Male	31%	38%	46%	37%
Female	69%	59%	52%	61%
Diverse	0%	3%	2%	2%
Age	19.21 (1.97)	19.38 (2.62)	19.66 (5.59)	19.38 (2.35)
Prior vocational apprenticeship				
Yes	7%	12%	16%	11%
No	93%	88%	84%	89%
School leaving certificate				
Dropout	0%	1%	3%	1%
Lower school certification (Hauptschule)	1%	22%	48%	20%
General Certificate of Secondary Education (Realschule)	33%	61%	40%	43%
Advanced technical college entrance qualification (Fachhochschulreife)	33%	8%	4%	18%
University entrance qualification (Abitur)	33%	8%	5%	18%
Collecting information and learning				
Using searching tools on the internet to find content/information	76%	55%	39%	59%
Viewing online videos	68%	70%	69%	69%
Using digital maps and route guidance systems	49%	41%	35%	43%
Using learning opportunities on the internet	10%	17%	15%	14%
Communication and collaboration				
Using instant messaging services	83%	73%	67%	76%
Using cloud services	21%	17%	18%	19%
Collaborating within a team via online tools	6%	8%	12%	8%
Generating content				
Using office programs	72%	23%	20%	43%
Reading blogs and forums or creating blog entries	19%	21%	15%	19%

each professional path—also regarding digital activities and learning opportunities—is presented in Table 4.

Data analysis

In the first step, we analyzed trainees' digital competences separately for each profession. We report descriptive data based on boxplots. To test the differences of the five competence dimensions between different training professions, we used the Kruskal–Wallis-tests and the post-hoc-tests of Dunn (1964) with Bonferroni correction. Next, we applied a latent profile analysis (LPA) with the aim of grouping homogenous participants into heterogeneous groups (Oberski 2016; Vermunt and Magidson 2002). As decision criteria, we used the Aikake information criterion (AIC) and the Bayesian information criterion (BIC). In addition, we checked for the entropy values closest to 1 (Asparouhov and Muthen 2018; Celeux and Soromenho 1996), and also used the diagonal of the average latent class probabilities for most likely class membership as a selection criterion. For the latter, the cut-off criterion was an assigned class of above 80 percent (Jung and Wickrama 2008; Rost 2006).

To analyze the research questions described in Sect. 2, we used an ordinal regression (Hosmer et al. 2013). This type of regression is a sub-type of logistic regression where the dependent variable is ordered. These analyses differ with regard to calculations of probabilities. While a logistic regression provides probabilities that a variable will take on a specific value, ordered logit provides probabilities that values will fall below a certain threshold. To check the robustness of the results, we estimated nested models with 500 bootstraps. Multicollinearity was not a problem in the estimated models ($VIF \leq 1.48$ for all variables used).

Five participants provided no information on socio-demographic data; these participants were excluded from the regression analysis. Apart from that, the data set contained only single missing values regarding the variables age and gender (nine missings each). Hence, we decided not to impute missing data (Tabachnick and Fidell 2013). When analyzing the effect of school leaving certificates, we excluded dropouts ($n = 6$) and grouped together the two different types of higher education entrance qualification (general university entrance qualification [*Abitur*] and advanced technical college entrance qualification [*Fachhochschulreife*]). We estimated the LPA using the software R with packages 'idyLPA' and 'tidyverse'. All other analyses were carried out in STATA (Version 14) and SPSS (Version 27).

Results

Preliminary analysis and latent profile analysis

Figure 2 shows boxplots for the five digital competences and the three different training programs ($N = 480$). In detail, the analyses show that industrial clerks tend to have the highest standardized theta scores of digital competences, retail salespersons rank second, and salespersons show the lowest scores. This order holds for three of the five competence dimensions: *Information* ($Md_{Salespersons} = -0.47 < Md_{Retail\_salespersons} = -0.19 < Md_{Industrial\_clerks} = 0.41$), *Communication* ($Md_{Salespersons} = -0.36 < Md_{Retail\_salespersons} = -0.12 < Md_{Industrial\_clerks} = 0.21$), and *Content creation* ($Md_{Salespersons} = -0.31 < Md_{Retail\_salespersons} = -0.16 < Md_{Industrial\_clerks} = 0.16$). For the dimensions *Safety*, salespersons reach the lowest score ($Md_{Salespersons} = -0.15$), but retail salespersons and industrial clerks are on the same level ($Md = 0.25$). However, regarding the dimension *Problem solving*, retail salespersons reach the highest median ($Md_{Retail\_Salespersons} = 0.16$), before industrial clerks ($Md_{Industrial\_clerks} = 0.11$) and salespersons ($Md_{Salespersons} = -0.23$). The Kruskal–Wallis-tests indicate significant differences between the training professions for all five dimensions: *Information* ($H(2) = 40.20$, $p < 0.001$), *Communication* ($H(2) = 27.87$, $p < 0.001$), *Content creation* ($H(2) = 24.92$, $p < 0.001$), *Safety* ($H(2) = 23.64$, $p < 0.001$) and *Problem solving* ($H(2) = 11.31$, $p < 0.01$). A pairwise comparison according to Dunn (1964) was used to test differences between the three professions in detail. For the dimension *Information*, the results show significant differences between salespersons and retail salespersons ($z = -2.99$, $p < 0.01$), salespersons and industrial clerks ($z = 6.30$, $p < 0.001$)

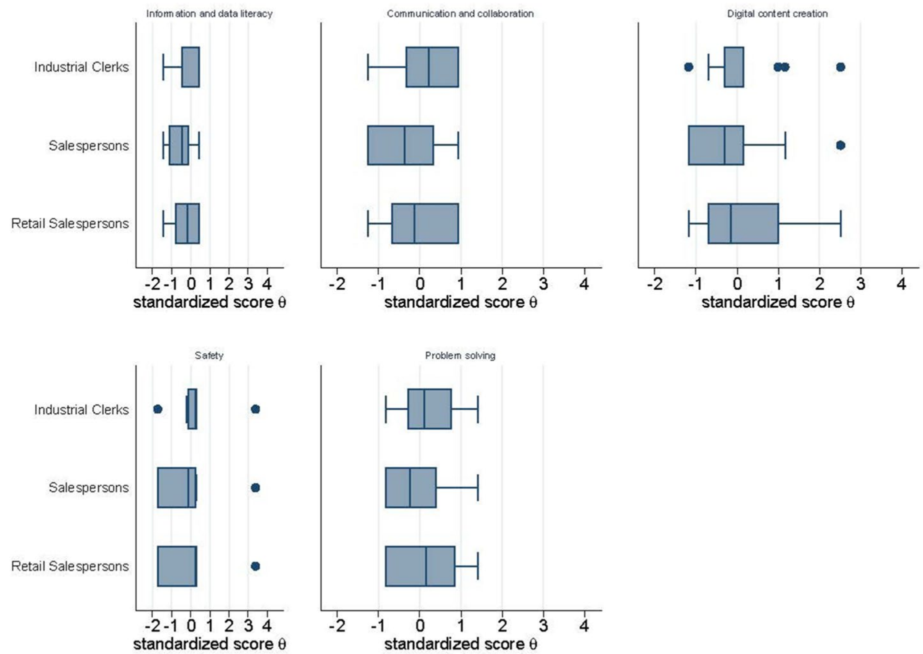

Fig. 2 Distribution of digital competences by profession (standardised score of theta)

as well as retail salespersons and industrial clerks ($z = 3.18$, $p < 0.01$). For the dimension *Communication* significant differences are revealed between salespersons and industrial clerks ($z = 5.14$, $p < 0.001$) as well as between retail salespersons and industrial clerks ($z = 3.15$, $p < 0.01$). For *Content creation* we again find significant differences between salespersons and industrial clerks ($z = 4.99$, $p < 0.001$) as well as between salespersons and retail salespersons ($z = -2.89$, $p < 0.05$). Similar results are found for *Safety* (salespersons and industrial clerks: $z = 4.82$, $p < 0.001$; salespersons and retail salespersons: $z = -3.26$, $p < 0.01$) as well as *Problem solving* (salespersons and industrial clerks: $z = -3.15$, $p < 0.01$; salespersons and retail salespersons: $z = 2.75$, $p < 0.05$).

Using a latent profile analysis (LPA), we identify profiles of digital competences. In the analysis, we test different amounts of profiles (one to five profiles) against each other. Table 5 provides the fit statistics. The results show that AIC and BIC decrease from the solution with one profile to five profiles. However, entropy suggests a solution with three profiles (highest entropy value = 0.93 for a three profile solution). The same is true for the diagonal of the average latent class probabilities for most likely class membership. The highest minimum (96%) and highest maximum (98%) are reached in the solution with three profiles. Based on these results we decided to distinguish three competence profiles for further analysis.

Figure 3 depicts the three profiles for the five digital competences. The first profile (line dashed dotted) comprises 22% of the sample and shows the lowest digital competences in all five dimensions. For further analysis, we call this profile *low competence level profile*. A second profile (43% of the sample) achieves the highest values in all five competence dimensions. We call this profile *high competence level profile*. The values of a third profile (35% of the sample) lie between the two previous described profiles in all dimensions (dotted line). We name this profile medium competence level profile.

Table 5 Fit statistics of latent profile analysis ($N=480$)

Number of profiles	*AIC*	*BIC*	Entropy	Minimum average latent class probabilities for most likely latent class membership	Maximum average latent class probabilities for most likely latent class membership
1	6292.033	6333.771	–	–	–
2	5502.042	5568.822	0.874	0.947	0.975
3	5333.306	5425.129	0.933	0.957	0.983
4	5110.385	5227.251	0.863	0.873	0.943
5	5034.353	5176.262	0.845	0.783	0.980

AIC Akaike information criterion, *BIC* Bayesian information criterion

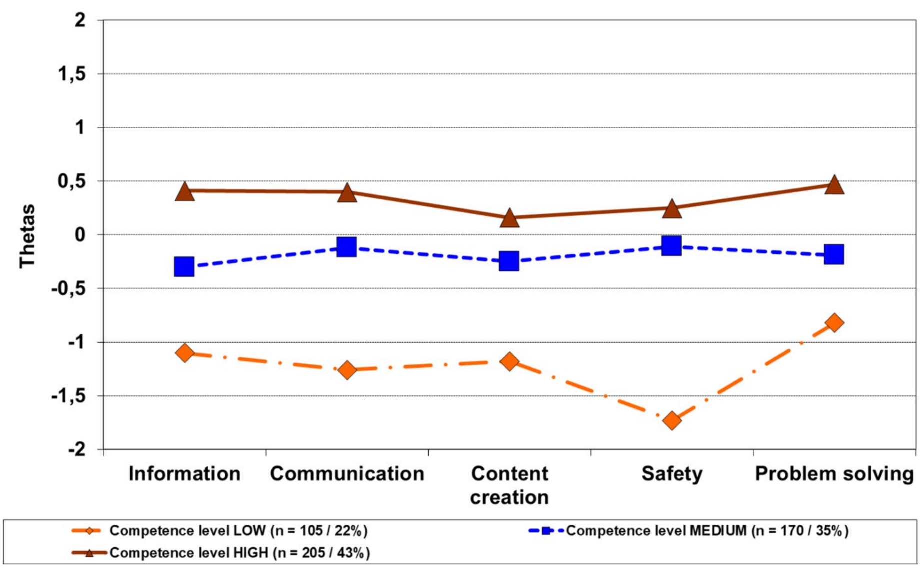

Fig. 3 Latent profile analysis of digital competences with three profile solution

Regression results

To examine our research questions, we applied ordinal regression analyses ($n=460$). Table 6 reports the regressions results. Model 1 includes trainees' professional path as well as their individual characteristics (*Pseudo* $R^2=0.05$; *Nagelkerke* $R^2=0.10$; *Cox & Snell* $R^2=0.11$). In this model, we find a significant effect of the trainees' profession on general digital competences. The probability of being in a higher profile of digital competences (*odds ratio* [*OR*]) is almost four times higher for industrial clerks ($OR=4.22$; $p<0.001$) and about twice as high for retail salespersons ($OR=2.26$; $p<0.01$), as compared to salespersons. Participants' gender does not significantly affect their digital competences. Furthermore, there is a marginally significant effect of the trainees' age. Each additional year increases the odds ratio to belong to a higher profile by 9% ($OR=1.09$; $p<0.10$). However, as the results of Model 2 indicate, the effect of both age and training profession can be explained by differences in school leaving certification. The age effect becomes insignificant in Model 2, when controlling for school leaving certificates, and the differences in probability to belong to a higher profile are reduced to $OR=2.06$ ($p<0.05$) for industrial clerks. A likelihood ratio test between Model 1 and Model 2

Table 6 Ordinal regression of digital competence profile with 500 bootstraps ($n = 460$)

	Model 1 Odds ratio	Model 2 Odds ratio	Model 3 Odds ratio
Professional path (ref. = salespersons)			
Industrial clerks	3.93 (0.90)***	2.06 (0.64)*	1.03 (0.35)
Retail salespersons	2.10 (0.52)**	1.59 (0.46)	1.42 (0.43)
Sex (ref. = male)			
Female	0.89 (0.17)	0.92 (0.19)	0.96 (0.20)
Diverse	2.11 (5.87)	2.01 (5.50)	3.07 (10.50)
Age	1.09 (0.05)#	1.03 (0.05)	0.99 (0.05)
Vocational apprenticeship	0.48 (0.15)*	0.50 (0.17)*	0.71 (0.27)
School leaving certificates (ref. = lower school leaving certificate [*Hauptschule*])			
Certificate of secondary education [*Realschule*]		2.25 (0.68)**	2.01 (0.59)*
Higher education entrance qualification [*Fachhochschulreife* or *Abitur*]		3.58 (1.38)**	3.06 (1.16)**
Collecting information and learning			
Using searching tools on the internet to find content/information			1.98 (0.44)**
Viewing online videos			1.23 (0.32)
Using digital maps and route guidance systems			1.43 (0.33)
Using learning opportunities on the internet			0.53 (0.17)*
Communication and collaboration			
Using instant messaging services			2.82 (0.79)***
Using cloud services			1.54 (0.42)
Collaborating within a team via online tools			0.87 (0.36)
Generating content			
Using office programs			2.63 (0.62)***
Reading blogs and forums or creating blog entries			2.16 (0.58)**
Pseudo R^2	0.05	0.06	0.17
Nagelkerke R^2	0.10	0.14	0.35
Cox & Snell R^2	0.11	0.13	0.30

Standard errors in parenthesis; #$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

yields evidence of a modest improvement in model fit (*Pseudo* $R^2 = 0.06$; *Nagelkerke* $R^2 = 0.14$; *Cox & Snell* $R^2 = 0.13$; χ^2 $(2) = 14.88$, $p < 0.001$). In Models 1 and 2, a former degree in another VET program significantly decreases the odds to belong to a higher profile by 50 percent (Model 2: $OR = 0.50$; $p < 0.05$).

In Model 3, we included different digital activities (learning processes) (Research Question 2). A likelihood ratio test between Model 2 and Model 3, again, shows a modest improvement in model fit (*Pseudo* $R^2 = 0.17$; *Nagelkerke* $R^2 = 0.35$; *Cox & Snell* $R^2 = 0.30$; χ^2 $(9) = 104.46$, $p < 0.001$). In Model 3 (see also Table 6), the effect of the trainees' profession becomes entirely insignificant. Instead, school leaving certificates explain a significant amount of the differences in digital competence. Compared to a lower school leaving certificate, the trainees with a certificate of secondary education are twice as likely ($OR = 2.01$, $p < 0.05$) and trainees with a higher education entrance qualification are three times as likely ($OR = 3.06$, $p < 0.01$) to belong to a higher competence profile. Compared to Model 1 and 2, the effect of a former training program becomes insignificant.

When it comes to digital activities and learning opportunities, for the dimension Collecting information and learning, we find a significant positive effect for 'using searching tools on the internet to find content/information' ($OR = 1.98$; $p < 0.01$) and surprisingly, a significant negative effect for 'using learning opportunities on the internet' ($OR = 0.53$; $p < 0.05$). Regarding the dimension *Communication and collaboration,* the item 'using instant messaging services' has a significant positive effect ($OR = 2.82$; $p < 0.001$). Finally, the items 'using office programs' ($OR = 2.63$; $p < 0.001$) and 'reading blogs and forums or creating blog entries' ($OR = 2.16$; $p < 0.01$) of the dimension generating content have a positive effect.

Table 6. Ordinal regression of digital competence profile with 500 bootstraps ($n = 460$).[3]

Discussion

General discussion

The aim of this study was to examine profiles of general digital competences of beginning trainees as well as factors (individual characteristics and learning opportunities) influencing the digital competences of beginning trainees. Against the background that training companies can benefit from trainees who begin their training program with a certain level of digital competence, we claim that the competences measured using the DigComp framework form the basis for a successful start in commercial training programs and the acquisition of profession-specific digital competences during the VET program. Our analysis is based on beginning trainees in three different commercial VET programs and cannot be generalized to other VET programs. For the sample examined, we identified three different profiles of digital competence that can be characterized as low (22% of the sample), medium (35%), and high digital competences (43%). Initial results point towards significant differences regarding digital competences between different training professions. In detail, both industrial clerks and retail salespersons seem to outperform salespersons for each of the five dimensions of digital competence. However, further analysis demonstrate that these effects can be explained by differences in the trainees' school leaving qualifications. When controlling for school leaving certificates, the only effect that remains is an advantage of industrial clerks compared to salespersons. This effect also becomes insignificant when controlling for learning processes (digital activities). The finding is also in line with results from research showing that prior academic achievement is the most relevant predictor of digital competence (e.g. Hatlevik et al. 2015b).

We find no significant effect of gender on general digital competences of beginning trainees in commercial VET programs. Although most studies on gender effects pointed towards significant effects in favor of female students in general education programs, this result could not be replicated for trainees in VET. This finding might be explained by the assessment method that is based on self-reports (see also Sect. 5.2). With regard

[3] Please note that we did not exclude the category *diverse* (gender) from the analysis although there is only a rather small number of participants indicating diverse gender. Although there is a risk of high standard error for the category *diverse* in the regression analysis, we did not want to systematically exclude trainees with diverse genders due to ethical reasons. In order to perform a robustness check, we re-ran the regression without the category *diverse* and the results did not change. The only two minor changes in the alternative model concern the significance levels of *vocational apprenticeship* ($p < 0.10$) and *higher education entrance qualification* ($p < 0.001$).

to digital competences, it is well documented in prior research that male participants report higher self-efficacy regarding advanced digital skills (e.g. Gerick et al. 2019). This bias could overshadow differences that might exist in favor of female participants.

Moreover, there is no significant effect of the trainees' age, once we control for school leaving certificates. Hence, the mere age does not seem to matter with respect to trainees' general digital competence.

Furthermore, our results indicate that trainees who already participated in a prior VET program do not have a higher probability of belonging to a higher competence profile once individual learning processes are controlled for. This variable was used as a control variable to account for prior experiences regarding digital activities in vocational contexts. An insignificant effect could indicate that participants did not take their digital activities during prior training programs into account when reporting their learning processes.

Finally, our results reveal certain effects of the trainees' digital activities or (general) learning opportunities on digital competences. In line with expectations, trainees who regularly (1) use searching tools on the internet to find content/information, (2) use office programs, and (3) read blogs and forums or create blog entries reach higher profiles of digital competences. These three learning opportunities can be expected to be directly related to general digital competences. We also find a positive effect of the regular use of instant messaging services. This finding might be explained by a general affinity toward the use of digital tools and might therefore be related to general digital competences. Surprisingly, the regular use of learning opportunities on the internet is negatively related to general digital competences. This might be attributed to the fact that trainees do not perceive this activity to be relevant for the development of digital competence. However, further research is necessary to examine this relationship. Finally, the regular use of cloud services and the collaboration within a team via online tools do not significantly affect general digital competences. This finding can probably be explained by the assessment method. The DigComp framework does not account for these or similar aspects when assessing general digital competences.

Limitations and future research

This study has several limitations that need to be considered when interpreting the results. First, as already mentioned in Sect. 3.1 the use of self-reports contains certain limitations regarding the validity of digital competence assessment. A major disadvantage of self-reports is that the respondents might have distorted self-perceptions. This could lead to severe overestimations of their own abilities. However, several studies reveal that students' ICT self-efficacy positively predicts digital competence (Hatlevik et al. 2015a, 2018). Hence, it can be assumed that self-reports can at least be used as an indicator for actual digital competence.

Moreover, our study focused on trainees' general digital competences, as we focused on beginning trainees and aimed at an assessment of their starting conditions. Also, the study focused on the sector of commercial VET. Hence, we are neither able to draw any conclusions regarding profession-specific digital competences (e.g. handling big data, using ERP systems that are especially relevant to industrial clerks; see Sect. 1.2) nor regarding other fields of VET or other training professions.

Another limitation refers to the assessment of learning opportunities. These were, again, assessed at a rather general level. Unfortunately, due to limited test time, we did not gather additional information about the context where digital activities took place. It would have been especially helpful to know, which prior training program participants completed and which digital activities they performed during prior training. A more distinct assessment of digital activities would generally be of interest, for instance, as the results of Burchert et al. (2013) point to differences in the trainees' internet use for private and professional purposes.

Finally, we do not have information on the trainees' success during the VET program or on their performance on the job. This information could be useful to relate differences in the level of general digital competence at the start of the training program to training outcomes or to competence development during VET.

Overall, future research endeavors should focus on the development of profession-specific digital competences over the course of the VET program, preferably using longitudinal designs. Hereby, it would be interesting to examine the role of trainees' starting conditions (general digital competence) for the acquisition of further profession-specific digital competences and training success. When it comes to antecedents and learning processes relevant for the development of digital competence, the theoretical framework in Fig. 1 would need to be expanded by two additional levels: the vocational school and the training company.

Implications

Based on the results reported above, there are certain implications for VET programs. Since, 22% of our sample demonstrate low competence levels regarding general digital skills at the start of the VET program, there is a need to foster digital competences during VET. This seems to be especially relevant for salespersons who show the lowest profile of the professions examined. This would imply implementing new learning formats into VET. Such learning formats that allow for flexible use and are independent of time and location include, for instance, mobile learning, social learning and game-based learning (de Witt 2012; Seufert et al. 2012). They have the potential to foster professional competences, to improve the cooperation between different places of learning in VET, or to enable collaboration between employees working in separated branch offices (de Witt 2012; Seufert et al. 2012). Consequently, trainers and teachers in VET also need relevant competences to implement these learning formats (e.g. Attwell and Gerrard 2019; Wilbers 2012). Additionally, teachers should be trained to instruct trainees in the use of digital tools for the specific profession. However, as mentioned in Sect. 5.2, before implementing new learning formats and training teachers and trainers, there is a need for an assessment of domain- or even job-specific digital competences of trainees that can guide respective changes in VET programs.

Appendix

See Table 7.

Table 7 Comparison of sample characteristics and trainee characteristics based on BIBB data

	Proportion/mean (*M*) with standard deviation (*SD*) in parenthesis					
	Industrial clerks		**Retail salespersons**		**Salespersons**	
	Sample	**Beginning trainees[a]**	**Sample**	**Beginning trainees**	**Sample**	**Beginning trainees**
N	205	2619	145	3375	130	2475
Sex						
Female	69%	63%	59%	51%	52%	51%
Age	19.21 (1.97)	19.7	19.38 (2.62)	20.7	19.66 (5.59)	20.0
Prior vocational apprenticeship						
Yes	7%	3%	12%	29%	16%	4%
School leaving certificate						
Dropout	0%	1%	1%	3%	3%	5%
Lower school certification (Hauptschule)	1%	1%	22%	26%	48%	49%
General Certificate of Secondary Education (Realschule)	33%	33%	61%	53%	40%	38%
Advanced technical college entrance qualification (Fachhochschulreife) or university entrance qualification (Abitur)	66%	64%	16%	18%	9%	5%

[a] Numbers referring to all trainees in the federal state of Baden-Wuerttemberg, who started the respective training program in 2020

Acknowledgements
Not applicable.

Authors' contributions
SF and SW developed the research questions. SF and SW discussed and executed the research design. SW performed the data analysis. SF wrote the first draft of the manuscript. All authors read and approved the final manuscript.

Funding
No funding was received for this study.

Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Department of Economics, University of Konstanz, Universitätsstrasse 10, 78464 Konstanz, Germany. [2]Chair of Psychological Diagnostics, Faculty 13 Rehabilitation Sciences, Dortmund University of Technology, Emil-Figge-Str. 50, 44227 Dortmund, Germany.

Received: 4 August 2021 Accepted: 10 January 2022
Published online: 19 January 2022

References
Arnold D, Arntz M, Gregory T, Steffens S, Zierahn U (2016) Herausforderungen der Digitalisierung für die Zukunft der Arbeitswelt. ZEW policy brief 8
Asparouhov T, Muthen B (2018) Variable-specific entropy contribution. https://www.statmodel.com/download/UnivariateEntropy.pdf
Attwell G, Gerrard A (2019) The training and professional development of teachers in use of digital technologies in Vocational Education and Training. In: Stalder BE, Nägele C (eds) Trends in vocational education and training research,

Vol. II: Proceedings of the European Conference on Educational Research (ECER), Vocational Education and Training Network (VETNET), pp 38–44

Autor DH (2015) Why are there still so many jobs? The history and future of workplace automation. J Econ Perspect 29:3–30. https://doi.org/10.1257/jep.29.3.3

Avis J (2018) Socio-technical imaginary of the fourth industrial revolution and its implications for vocational education and training: a literature review. J Vocat Educ Train 1–27. https://doi.org/10.1080/13636820.2018.1498907

Baethge M, Buss K-P, Lanfer C (2003) Konzeptionelle Grundlagen für einen Nationalen Bildungsbericht—Berufliche Bildung und Weiterbildung/Lebenslanges Lernen. BMBF, Berlin

Eickelmann B, Bos W, Gerick J, Goldhammer F, Schaumburg H, Schwippert K, Senkbeil M, Vahrenhold J (eds) (2019) ICILS 2018 Deutschland: computer- und informationsbezogene Kompetenzen von Schülerinnen und Schülern im zweiten internationalen Vergleich und Kompetenzen im Bereich Computational Thinking. Waxmann, Münster, New York

Bergmann M (2019) Zukünftige Kompetenzanforderungen in der Ausbildung von Industriekaufleuten: Die Sicht der Arbeitgeber. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. epubli, Berlin, pp 147–158

Birnbaum A (1968) Some latent trait models and their use in inferring an examinee's ability. In: Lord FM, Novick MR (eds) Statistical theories of mental test scores. Addison-Wesley, Reading, pp 397–479

Bos W, Eickelmann B, Gerick J, Goldhammer F, Schaumburg H, Schwippert K, Senkbeil M, Schulz-Zander R, Wendt H (2014) ICILS 2013: computer- und informationsbezogene Kompetenzen von Schülerinnen und Schülern in der 8. Jahrgangsstufe im internationalen Vergleich. Waxmann, Münster

Brolpito A (2018) Digital skills and competence, and digital and online learning. European Training Foundation, Turin

Burchert J, Katterfeldt E-S, Schulte S, Zeising A (2013) Azubis online.: Über die Kompetenzen und Motive der Nutzung des Internets in der Ausbildung. Medien + Erziehung 57:97–107

Calvani A, Fini A, Ranieri M, Picci P (2012) Are young generations in secondary school digitally competent? A study on Italian teenagers. Comput Educ 58:797–807. https://doi.org/10.1016/j.compedu.2011.10.004

Celeux G, Soromenho G (1996) An entropy criterion for assessing the number of clusters in a mixture model. J Classif 13:195–212. https://doi.org/10.1007/BF01246098

de Witt C (2012) Neue Lernformen für die berufliche Bildung: Mobile Learning – Social Learning—Game Based Learning. Z Bundesinstituts Für Berufsbildung 41:6–9

Dunn OJ (1964) Multiple comparisons using rank sums. Technometrics 6:241–252

Evangelinos G, Holley D (2014) A qualitative exploration of the EU Digital Competence (DIGCOMP) Framework: a case study within healthcare education. In: Vincenti G, Bucciero A, VazdeCarvalho C (eds) E-learning, E-education, and online training. Springer, Cham, vol. 138, pp 85–92

Evangelinos G, Holley D (2015) A qualitative exploration of the DIGCOMP Digital Competence Framework: attitudes of students, academics and administrative staff in the health faculty of a UK HEI. EAI Endors Trans e-Learn 2:1–8. https://doi.org/10.4108/el.2.6.e1

Ferrari A (2013) DIGCOMP: A framework for developing and understanding digital competence in Europe. European Union, Luxembourg

Fraillon J, Ainley J, Schulz W, Friedman T, Duckworth D (2020) Preparing for life in a digital world: IEA International Computer and Information Literacy Study 2018 International Report. Springer, Cham

Frey CB, Osborne MA (2017) The future of employment: how susceptible are jobs to computerisation? Technol Forecast Soc Chang 114:254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gerick J, Massek C, Eickelmann B, Labusch A (2019) Computer- und informationsbezogene Kompetenzen von Mädchen und Jungen im zweiten internationalen Vergleich. In: Eickelmann B, Bos W, Gerick J, Goldhammer F, Schaumburg H, Schwippert K, Senkbeil M, Vahrenhold J (eds) ICILS 2018 Deutschland: Computer- und informationsbezogene Kompetenzen von Schülerinnen und Schülern im zweiten internationalen Vergleich und Kompetenzen im Bereich Computational Thinking. Waxmann, Münster, New York, pp 271–300

Goldhammer F, Naumann J, Keßel Y (2013) Assessing individual differences in basic computer skills. Eur J Psychol Assess 29:263–275. https://doi.org/10.1027/1015-5759/a000153

Härtel M, Averbeck I, Brüggemann M, Breiter A, Howe F, Sander M (2018) Medien- und IT-Kompetenz als Eingangsvoraussetzung für die berufliche Ausbildung—Synopse. BIBB, Bonn

Hatlevik OE (2010) Examining 'digital divide' in upper secondary school: a multilevel analysis of factors with an influence on digital competence. Int J Technol Knowl Soc 6:151–164. https://doi.org/10.18848/d1832-3669/CGP/v06i03/56081

Hatlevik OE, Christophersen K-A (2013) Digital competence at the beginning of upper secondary school: identifying factors explaining digital inclusion. Comput Educ 63:240–247. https://doi.org/10.1016/j.compedu.2012.11.015

Hatlevik OE, Ottestad G, Throndsen I (2015a) Predictors of digital competence in 7th grade: a multilevel analysis. J Comput Assist Learn 31:220–231. https://doi.org/10.1111/jcal.12065

Hatlevik OE, Guðmundsdóttir GB, Loi M (2015b) Examining factors predicting students' digital competence. J Inform Technol Educ Res 14:123–137

Hatlevik OE, Throndsen I, Loi M, Gudmundsdottir GB (2018) Students' ICT self-efficacy and computer and information literacy: determinants and relationships. Comput Educ 118:107–119. https://doi.org/10.1016/j.compedu.2017.11.011

Heldt M, Massek C, Drossel K, Eickelmann B (2020) The relationship between differences in students' computer and information literacy and response times: an analysis of IEA-ICILS data. Large Scale Assess Educ 8. https://doi.org/10.1186/s40536-020-00090-1

Holz C, Leppert S (2019) Kaufmännische Klassiker im digitalen Wandel II – Die Ausbildung von Kaufleuten im Einzelhandel in der Berufsschule. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. Epubli, Berlin, pp 239–266

Hosmer DW, Lemeshow S, Sturdivant RX (2013) Applied logistic regression, 3rd edn. Wiley, Hoboken

Ilomäki L, Paavola S, Lakkala M, Kantosalo A (2016) Digital competence—an emergent boundary concept for policy and educational research. Educ Inf Technol 21:655–679. https://doi.org/10.1007/s10639-014-9346-4
Jordanski G (2019) Kompetenzen für die digitalisierte Arbeit von morgen—Industriekaufleute. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. Epubli, Berlin, pp 119–146
Jung T, Wickrama KAS (2008) An introduction to latent class growth analysis and growth mixture modeling. Soc Pers Psychol Compass 2:302–317. https://doi.org/10.1111/j.1751-9004.2007.00054.x
Kirschner PA, De Bruyckere P (2017) The myths of the digital native and the multitasker. Teach Teach Educ 67:135–142. https://doi.org/10.1016/j.tate.2017.06.001
Kupfer U, Jaich R (2019) Zukünftige Kompetenzanforderungen in der Ausbildung „Kaufmann/-frau im Einzelhandel" bzw. „Verkäufer/Verkäuferin": Die Sicht der Gewerkschaft. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. Epubli, Berlin, pp 227–238
Löfgren S, Ilomäki L, Toom A (2019) Employer views on upper-secondary vocational graduate competences. J Vocat Educ Train 117:1–26. https://doi.org/10.1080/13636820.2019.1635633
Müller L-S, Stecher B, Dathe R, Boberach M, Exel S, Baethge CB (2018) D21: Digital Index 2017/2018: Jährliches Lagebild zur Digitalen Gesellschaft. Stoba-Druck GmbH
Oberski D (2016) Mixture models: latent profile and latent class analysis. In: Robertson J, Kaptein M (eds) Modern statistical methods for HCI. Springer, Cham, pp 275–287
Rost J (2006) Latent-Class-Analyse. In: Petermann F, Eid M (eds) Handbuch der Psychologischen Diagnostik. Hogrefe, Göttingen, pp 275–287
Schmelter M (2019) Shift happens—Wie die Digitale Transformation die Anforderungen an das Personal verändert. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. Epubli, Berlin, pp 219–226
Seeber S (2016) Economic competencies and situation-specific commercial competencies: reflections on conceptualization and measurement. Citizenship Soc Econ Educ 15:162–182. https://doi.org/10.1177/2047173417695275
Seeber S, Weber S, Geiser P, Zarnow S, Hackneberg T, Hiller F (2019) Effekte der Digitalisierung auf kaufmännische Tätigkeiten und Sichtweisen ausgewählter Akteure. berufsbildung:4–9
Seifried J, Brandt S, Kögler K, Rausch A (2020) The computer-based assessment of domain-specific problem-solving competence—a three-step scoring procedure. Cogent Educ 7:29. https://doi.org/10.1080/2331186X.2020.1719571
Seufert S, Jenert T, Kuhn-Senn A (2012) Didaktische Potenziale des Mobile Learning für die Berufsbildung. Z Bundesinstituts Für Berufsbildung 41:10–13
Siddiq F, Scherer R (2019) Is there a gender gap? A meta-analysis of the gender differences in students' ICT literacy. Educ Res Rev 27:205–217. https://doi.org/10.1016/j.edurev.2019.03.007
Tabachnick BG, Fidell LS (2013) Using multivariate statistics, 6th edn. Pearson, Boston
Traub C, Leppert S (2019) Kaufmännische Klassiker im digitalen Wandel I—Die Ausbildung von Industriekaufleuten in der Berufsschule. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. Epubli, Berlin, pp 177–194
Utecht A (2019) Zukünftige Herausforderungen in der Ausbildung von Industriekaufleuten. Die Forderungen und Herausforderungen aus Sicht der Gewerkschaft IG Metall. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. Epubli, Berlin, pp 159–176
van Laar E, van Deursen AJ, van Dijk JA, de Haan J (2017) The relation between 21st-century skills and digital skills: a systematic literature review. Comput Hum Behav 72:577–588. https://doi.org/10.1016/j.chb.2017.03.010
Vermunt JK, Magidson J (2002) Latent class cluster analysis. In: Hagenaars JA, McCutcheon AL (eds) Applied latent class analysis. Cambridge University Press, Cambridge, pp 89–106
Voogt J, Roblin NP (2012) A comparative analysis of international frameworks for 21st century competences: implications for national curriculum policies. J Curric Stud 44:299–321. https://doi.org/10.1080/00220272.2012.668938
Wilbers K (2012) Entwicklung der Kompetenzen von Lehrkräften berufsbildender Schulen für digitale Medien. Berufsbildung in Wissenschaft Und Praxis 41:38–41
Wilbers K (2019) Kaufmännische Digitalkompetenzen als Ausgangspunkt der digitalen Transformation beruflicher Bildung. In: Wilbers K (ed) Digitale Transformation kaufmännischer Bildung: Ausbildung in Industrie und Handel hinterfragt. Epubli, Berlin, pp 11–72
Wild S, Schulze Heuling L (2020) How do the digital competences of students in vocational schools differ from those of students in cooperative higher education institutions in Germany? Emp Res Vocat Educ Train 12:1. https://doi.org/10.1186/s40461-020-00091-y
Wild S, Schulze Heuling L (2021) Re-evaluation of the D21-digital-index assessment instrument for measuring higher-level digital competences. Stud Educ Eval 68:100981. https://doi.org/10.1016/j.stueduc.2021.100981
Winther E, Achtenhagen F (2009) Measurement of vocational competencies—a contribution to an international large-scale assessment on vocational education and training. Emp Res Vocat Educ Train 1:85–102. https://doi.org/10.1007/BF03546481
Yen WM (1993) Scaling performance assessments: strategies for managing local item dependence. J Educ Meas 30:187–213. https://doi.org/10.1111/j.1745-3984.1993.tb00423.x
Zhong Z-J (2011) From access to usage: the divide of self-reported digital skills among adolescents. Comput Educ 56:736–746. https://doi.org/10.1016/j.compedu.2010.10.016

Publisher's Note