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Uncovering latent profiles of ICT self-concept among adults in Germany and their relation with gender

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ABSTRACT
Self-concept related to the use of information and communication technology (ICT-SC) is reflected in how people feel and behave when confronted with digital technologies. Although evidence from variable-centered analyses suggests a hierarchical and multidimensional structure of ICT-SC in heterogeneous populations, it is not yet known whether different profiles of general ICT-SC and specific ICT-SC domains (communicate, process and store, generate content, safe application, solve problems) exist. This study aims to extend previous research using person-centered analyses and to examine whether different profiles of ICT-SC can be identified in a heterogeneous adult population (18–69 years) from Germany and how these profiles relate to gender. Results of a latent profile analysis (German quota sample, $N = 369$) indicate a reliable three-profile solution. Profile I ($n = 48$) is characterised by rather low ICT-SC with relative profile strengths in the verbal-interactive domains (communicate, process and store). Profile II ($n = 149$) is characterised by low to average ICT-SC across ICT-SC domains. Profile III ($n = 172$) is characterised by high ICT-SC with profile strengths in the technical-analytical domains (safe application, solve problems). Gender did not correlate significantly with profile membership. We discuss the practical implications of the results for ICT-SC interventions and suggest directions for future research.

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1. Introduction

In recent years, the use of information and communication technology (ICT) has become a daily practice in private, professional, and educational life. Individuals' interest in and acceptance and use of ICT, as well as their perception of technostrain and computer anxiety depend on their competence self-beliefs, in particular their ICT-related self-concept (ICT-SC; Janneck, Vincent-Höper, and Ehrhardt 2012; Rubach and Lazarides 2019; Schauffel et al. 2021b).

ICT-SC is a multidimensional and hierarchically structured set of ICT-related competence self-beliefs (Schauffel et al. 2021b) comprising general ICT-SC and domain-specific ICT-SCs (i.e. communicate, process and store, generate content, safe application, and solve problems). It represents a new self-concept field that has received increasing research attention in the last decade (see, e.g. Christoph et al. 2015; Langheinrich, Schönfelder, and Bogner 2016; Schauffel and Ellwart 2021; Zylka et al. 2015). To investigate the antecedents and consequences of ICT-SC in more detail, knowledge about prevailing ICT-SC profiles with different configurations in terms of the level (i.e. high vs. low general ICT-SC) and shape (i.e. verbal-interactive vs. technical-analytical ICT-SCs) of ICT-SC is essential.

Self-concept research has a long research tradition in educational science. A plethora of variable-centered studies in this field support a multidimensional structure of academic self-concept (i.e. individuals' perceptions of their own academic abilities in general or in specific domains; see Arens et al. 2021; Brunner et al. 2010) and also of the recently introduced construct of ICT-SC (Schauffel et al. 2021b). Advanced person-centered analyses (e.g. latent profile analysis, LPA) complement traditional self-concept research because

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they enable researchers to identify distinct profiles of self-concept characterised by differences in level and shape and thus to detect heterogeneity in and provide detailed insight into structures of self-concept in populations (Marsh et al. 2009; Meeusen et al. 2018). The few studies that have investigated heterogeneity in the structure of academic self-concept (Franzen et al. 2022; Marsh et al. 2009; Saß and Kampa 2019) point to the existence of subgroups with different self-concept profiles. An even smaller number of studies have investigated profiles of self-perceived ICT competence (Schulze Heuling and Wild 2021; Schulze Heuling, Wild, and Vest 2021). The herein-focused self-perceived ICT competence is a concept similar to ICT-SC. ICT-SC describes the own mental representations and evaluations of competences in using ICT (Schauffel et al. 2021b) and belongs to the group of competence self-beliefs (Marsh et al. 2017). However, ICT-SC is a broader concept, as it includes aside from self-assessed ICT competence ('I can'), also its evaluation ('I am good at'), and mental representations of temporal aspects ('I have always been good at', 'I quickly learn'). Also, ICT-SC is typically considered from a domain-specific perspective (i.e. competence domains), rather than focussing on single subcompetences. For an overview and in-depth comparison of different competence self-beliefs, including self-concept, we recommend Marsh et al. (2017) (no specific focus on ICT). ICT-related competence self-beliefs are discussed in Peiffer et al. (2020). These existing studies found different profiles of self-perceived ICT competence. However, the samples that they used were rather homogeneous (e.g. student teachers in the science, technology, engineering, and mathematics [STEM] fields). Hence, it is unclear if their findings regarding distinct profiles apply also to more heterogeneous samples, for example, adults with a broad range of ages and educational and professional backgrounds.

Investigating self-concept profiles in heterogeneous samples is highly relevant because self-concepts have the potential to influence vocational choices and thus professional career paths (see expectancy-value theory of achievement motivation; Eccles and Wigfield 2002). The fact that women are still underrepresented in degree programmes and jobs in the STEM fields worldwide (Blackburn 2017; World Economic Forum [WEF], 2021), especially in the IT sector, might be attributable to the fact that they have lower general ICT-SC than men (Janneck, Vincent-Höper, and Ehrhardt 2012). However, it might also be due to differences in domain-specific ICT-SCs or different configurations (i.e. ICT-SC profiles) of general and domain-specific ICT-SCs between women and men.

Thus, besides identifying different ICT-SC profiles, it is highly relevant to investigate whether gender differences in profile membership exist. Previous studies have indicated mean-level gender differences in general ICT-SC (Janneck, Vincent-Höper, and Ehrhardt 2012) and domain-specific ICT-SCs (Fraillon et al. 2014; Gómez-Trigueros and Yáñez de Aldecoa 2021). Furthermore, first evidence from academic self-concept research points to gender differences in profile membership (e.g. Franzen et al. 2022) corresponding to the math/language–gender stereotypes described in the literature (see, e.g. Morrissey et al. 2019), whereby women perceive themselves as more talented than men in verbal-like domains (e.g. native language) than in math-like domains (e.g. mathematics and physics), and vice versa. The math/verbal domains distinction of these gender stereotypes aligns well with ICT domains (i.e. verbal-interactive vs. technical-analytical). Hence, similar findings might be expected for ICT-SC as for academic self-concept, although research is still lacking.

To pave the way for a nuanced understanding of hierarchical and multidimensional ICT-SC in heterogeneous populations, this study uses LPA with gender as a covariate to examine whether different profiles of ICT-SC exist in the adult population in Germany and whether and to what extent gender correlates with profile membership.

With this study, we contribute theoretically and practically to existing research. By applying person-centered analyses that account for interindividual variation in the structure of ICT-SC, not accounted for in variable-centered analyses, we extend theoretical knowledge of the structure of ICT-SC in heterogeneous populations (Marsh et al. 2009) and provide insight into whether math/language–gender stereotypes in competence perceptions apply also to domain-specific ICT-SCs (i.e. verbal-interactive domains vs. technical-analytical domains).

Practically, identifying distinct ICT-SC profiles and investigating whether and to what extent they covary with gender allows for customised, profile-specific ICT-SC interventions that address the support needs of a given population.

2. Theoretical background

2.1. Multidimensional structure of (ICT)-SC

Self-concept represents a set of self-perceptions of an individual's abilities on a general level and in specific domains. Self-concept research is particularly prominent in educational science. A plethora of research in that field supports the hierarchical (e.g. students' overall school self-concept) and multidimensional (e.g. students' subject-specific self-concepts) structure of academic self-concept (Arens et al. 2021; Brunner et al. 2010) and its influence on performance, motivation, performance-related behaviour, and vocational choices (for a summary, see Marsh et al. 2017).

With increasing digitalisation, ICT-SC has entered scientific discussion (e.g. Christoph et al. 2015; Langheinrich, Schönfelder, and Bogner 2016; Schauffel and Ellwart 2021; Zylka et al. 2015). ICT-SC can be defined as individuals' own mental representations and evaluations of their competence in using ICT (Schauffel et al. 2021b). Previous research indicates that like academic self-concept (see Arens et al. 2021; Brunner et al. 2010), ICT-SC is also hierarchical and multidimensionally structured: A general self-concept related to the use of ICT is located on a global level, and five domain-specific self-concepts (e.g. ICT-SC related to communication or safe application) are located on a lower hierarchical level (Schauffel et al. 2021b). This structure has been modelled in a factor analytical approach as an incomplete bifactor model called the nested Marsh/Shavelson model (see Brunner et al. 2010). A special feature of this model is that it allows to clearly separate the level and shape of an individual's self-concept profile. This is achieved by including a direct measure of general ICT-SC in the model. General self-concept ('level') is comprised of items that measure general self-concept directly and is, in addition, also shaped by the shared variance of all domain-specific ICT-SC items (i.e. the variance that can be attributed to the 'level' of ICT-SC). Thus, the domain-specific ICT-SCs contain only variance unique to the respective domains and depict the shape of an individual's profile (see Figure 1, lower part).

The five domains of ICT-SC correspond to the five areas of digital competence described in the earliest version of the European Digital Competence Framework for Citizens (DigComp; Ferrari 2013) and in the updated versions, DigComp 2.0 (Vuorikari et al. 2016) and DigComp 2.1 (Carretero, Vuorikari, and Punie 2017). Following Schauffel et al. (2021b), the ICT-SC domain *communicate* refers to individuals' evaluations of their own competences 'related to communicating with relevant others through the use of ICT' (p. 4); the ICT-SC domain *process and store* represents individuals' evaluations of their own competences 'related to processing and storing digital data, information, and content' (p. 4); the ICT-SC domain *generate content* refers to individuals' evaluations of their own competences 'related to creating digital data, information, and content' (p. 4); and the ICT-SC domain *safe application* represents individuals' evaluations of their own competences 'related to protecting digital data, information, and content as well as an entire system' (p. 4). Schauffel et al. (2021b) noted that the domain *safe application* 'also refers to the responsible use of ICT' (p. 4). And finally, the ICT-SC domain *solve problems* represents individuals' evaluations of their own competences 'related to successfully solving emerging technical problems of ICT' and 'to solving content-related tasks, challenges, and problems using ICT' (Schauffel et al. 2021b, p. 4).

2.2. The role of dimensional comparisons in the development of (ICT)-SC profiles

Self-concepts are formed by experiences, interactions with the environment, feedback from significant others (Shavelson, Hubner, and Stanton 1976), and comparison processes within different frames of reference (see Marsh 1986; Wolff et al. 2019). For the development of the multidimensional structure of self-concept, comparison processes within an internal frame of reference (i.e. dimensional comparisons) are crucial (e.g. Marsh 1986). To explain the multidimensional structure of academic self-concept, dimensional comparison theory (DCT, Möller and Marsh 2013) was developed and validated for academic self-concept (Marsh et al. 2017). DCT posits that individuals use an internal frame of reference to compare their performance in one self-concept domain (e.g. math) with their performance in another self-concept domain (e.g. their native language). Dimensional comparisons can result in contrast or assimilation effects, depending on the perceived dissimilarity of, or distance between the target domains. In DCT, competence domains are arranged on a continuum ranging from verbal to math-like (Marsh, Byrne, and Shavelson 1988). In the academic context, the verbal–math continuum[1] refers to the self-concept related to school subjects ranging from native and foreign languages to STEM subjects. Contrast effects are more likely to occur between domains that are expected to be located at the endpoints of a competence continuum (i.e. native language and math). Contrast effects result in a lower self-concept in the competence domain in which the individual performs less well (e.g. in terms of grades) and in higher self-concept in the competence domain in which the individual performs better (Möller and Marsh 2013). By contrast, assimilation effects are more likely to occur between domains in which individuals are expected to have related or similar competences – that is, domains that are located adjacent to each other on a competence continuum (e.g. STEM subjects). Assimilation effects lead to positive correlations between domain-specific self-concepts.

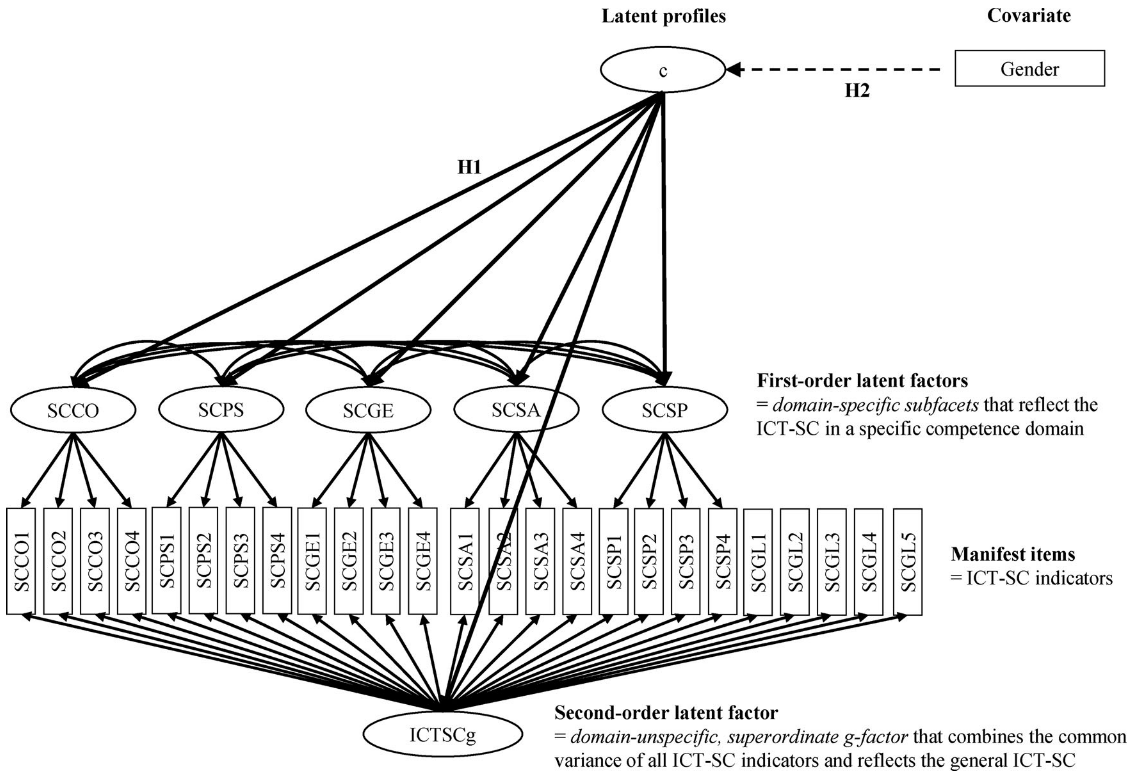

Figure 1. Latent profiles of ICT self-concept and gender as a covariate.

Notes: Factor scores of the five domain-specific ICT self-concept (ICT-SCs) and general ICT-SC based on the nested Marsh/Shavelson model provided the input for the latent profile analysis. ICT-SC = self-concept related to information and communication technology; H1 = hypothesis 1; H2 = hypothesis 2; SCCO = ICT-SC domain *communicate*; SCPS = ICT-SC domain *process and store*; SCGE = ICT-SC domain *generate content*; SCSA = ICT-SC domain *safe application*; SCSP = ICT-SC domain *solve problems*; SCGL1-5 = items measuring general ICT-SC; ICTSCg = g-factor general ICT-SC.

DCT thus offers a theoretical explanation of why individuals perceive strengths and weaknesses in their academic self-concept (i.e. perceiving themselves as more competent in the verbal domain than in the mathematical domain, or vice versa). Because the ICT-SC domains show substantive similarities with competence domains in the academic context, it can be expected that the continuum of verbal and mathematical competences in the academic context will be reflected in the ICT context and that DCT should therefore also be applicable to ICT-SC. The verbal-interactive ICT-SC facet *communicate* is similar to the verbal domains of academic self-concept, whereas the technical-analytical ICT-SC facets *solve problems* and *safe application* align with the mathematical academic competence domains. As the ICT-SC facets *process and store* and *generate content* integrate to some extent both verbal and technical-analytical abilities, they might fall near the middle of the competence continuum.

The complex pattern of dimensional comparison processes in self-concept development suggests an idiographic process of self-concept structure and thus implies distinct profiles of ICT-SC configurations. The idiosyncratic pattern of assimilation and contrast effects can contribute to explaining why some self-concept profiles are rather heterogeneous (i.e. differences between self-concept domains) and others homogeneous (i.e. uniform self-concept levels across domains, Marsh et al. 2009).

For example, a rather heterogeneous ICT-SC profile could be characterised by high general ICT-SC and high ICT-SC in the competence domain *communicate* but low ICT-SC in the competence domain *safe application*. Exemplarily, a homogeneous ICT-SC profile could be characterised by high or low levels of ICT-SC across the five competence domains. However, person-centered approaches to investigating self-concepts are still scarce. Most evidence stems from variable-centered approaches such as factor analysis, correlation, or regression analysis (see Arens et al. 2021). These methods focus on the relationship between variables and assume homogeneity across individuals (i.e. comparable variable relations across all individuals) but disregard potential individual differences in ICT-SC configurations.

To investigate self-concept profiles, person-centered analyses such as latent class analysis (LCA, for categorical variables), latent profile analysis (LPA, for continuous variables), or latent transition analysis (for longitudinal data) are necessary (Hickendorff et al. 2018). These person-centered approaches consider heterogeneity in variable interactions (i.e. distinct profiles) among individuals and can thus detect similar patterns of self-concept profiles clustering individuals into subgroups. Hence, person-centered analyses complement variable-centered ones (Marsh et al. 2009; Robins et al. 1996).

2.3. Research status of (ICT)-SC profiles

LPA is especially useful in ICT-SC research, as assumptions derived from DCT (Möller and Marsh 2013) suggest the existence of qualitatively distinct ICT-SC profiles. In line with these models, self-concept configuration should differ not only according to the general level of ICT-SC (i.e. quantitative differences such as high, medium, or low ICT-SC) but also regarding the shape of the five ICT-SC competence domains (i.e. qualitative differences such as high ICT-SC in the domain *communicate* but low ICT-SC in the domain *safe application*). Previous research investigating academic self-concept has revealed different profiles. For instance, applying LPA in a sample of upper secondary school students, Marsh et al. (2009) investigated profile levels (high vs. low) and profile shapes (mathematical vs. verbal self-concept profile) and found distinct self-concept profiles. Similarly, Saß and Kampa (2019) identified four distinct self-concept profiles characterised by high math self-concept, high verbal self-concept, low overall self-concept, and high overall self-concept, respectively. Marsh et al. (2009) and Saß and Kampa (2019) also included technical-analytical self-concept domains (e.g. math, computers, problem solving). They found distinct configurations across the profiles – for instance, a profile with either high self-concept in technical-analytical self-concept domains and low verbal self-concept, or vice versa. In a longitudinal study, Franzen et al. (2022) found evidence for similar distinct profiles in a student sample that were stable over time.

In the context of ICT use, two empirical studies (Schulze Heuling, Wild, and Vest 2021; Schulze Heuling and Wild 2021) examined profiles of self-perceived competence in the five areas of ICT competence proposed in DigComp (Ferrari 2013). Schulze Heuling and Wild (2021) used LPA in a sample of students in vocational education and training and found four profiles that differed mainly in the level of self-perceived ICT competence (i.e. high vs. low ICT competence). In particular, one profile showed a weak ICT competence profile across all five competence areas, with extremely low ICT competence in safety, a rather technical-analytical competence area.

In another study (Schulze Heuling, Wild, and Vest 2021), a similar pattern of results was described in a sample comprising engineering students and student science teachers. The authors found four ICT competence profiles (high, rather high, rather low, low), differing mainly in the level of ICT competence domains. The majority of the sample members were assigned to the profiles with high or rather high ICT competence (27% and 44%, respectively).

In sum, there is first evidence for the existence of distinct academic self-concept profiles and ICT-SC profiles in specific samples (i.e. engineering students and student science teachers; students in vocational education and training). Whether previous findings can be transferred to more heterogeneous populations remains an open question. Comparable latent profile analyses for heterogeneous populations do not exist, to our knowledge, but would be valuable since ICT use became an essential demand of individuals' private (e.g. e-government, e-health) and professional lives, across ages and beyond typically IT-related professions (e.g. nurses: Duffy 2012; digital farming: Shamshiri et al. 2018). Moreover, the studies by Schulze Heuling, Wild, and Vest (2021) and Schulze Heuling and Wild (2021) did not aim to assess ICT-SC specifically but rather self-reported ICT competence. Furthermore, they did not consider the hierarchical structure of self-concepts (see Figure 1) that implies a distinction between general ICT-SC and domain-specific ICT-SCs and thus allows to capture the level and shape of the profile in a manner consistent with the theory. To achieve this, it is necessary to include a measure of general ICT-SC alongside measures of domain-specific ICT-SCs and to use an incomplete bifactor model to model the structure of ICT-SC (see Section 2.1). Investigating the shape of an ICT-SC profile separately from its general level can lead to a clearer shape of the profile because domain-specific ICT-SCs otherwise contain shared variance that can be attributed to general ICT-SC (see Schmidt et al. 2017).

2.4. Gender as a covariate of (ICT-)SC profile membership

When assuming different profiles of ICT-SC, the question arises as to what factors might correspond to profile membership. Here, gender, as a person characteristic, should be carefully examined. Men typically report higher self-concepts than women in more technical-analytical domains (e.g. computers: Janneck, Vincent-Höper, and Ehrhardt 2012; mathematics: Mejía-Rodríguez, Luyten, and Meelissen 2021), whereas women typically report higher self-concepts than men in more verbal-interactive domains (e.g. Esnaola et al. 2020). Because self-concepts (profiles) have the power to impact both vocational choices and performance (e.g. Saß and Kampa 2019), and thus individuals' professional careers (see also expectancy-value theory; Eccles and Wigfield 2002), self-concept differences might explain why women are still underrepresented in more technical-analytical occupational fields (Blackburn 2017; Janneck, Vincent-Höper, and Ehrhardt 2012). Here, evidence from person-centered analyses would complement evidence from variable-centered analyses. Confirming – or refuting – the gender-specificity of ICT-SC profiles would allow conclusions to be drawn regarding the customised design and promotion of self-concept interventions by educators, institutions, and human resource developers.

Results from previous studies using variable-centered analyses point to gender differences in general ICT-SC and domain-specific ICT-SCs in favour of men (Janneck, Vincent-Höper, and Ehrhardt 2012; Marsh et al. 2009; Sáinz and Eccles 2012; Schauffel et al. 2021b) that correspond to career motivation (Janneck, Vincent-Höper, and Ehrhardt 2012). Further, longitudinal research in a secondary school context suggests that the more positive computer-related self-concept of male students increases over time, whereas the lower computer-related self-concept of female students decreases over time (Sáinz and Eccles 2012).

Previous studies investigating academic self-concept profiles using person-centered analyses have found evidence for gender differences in profile membership. Recent studies by Saß and Kampa (2019) and Franzen et al. (2022) revealed that males are overrepresented in high math profiles and high/moderate overall profiles, whereas females are overrepresented in high verbal profiles. Given the substantive similarity of ICT domains and academic self-concept domains (i.e. verbal vs. mathematical; verbal-interactive vs. technical-analytical), the findings for academic self-concept should be transferable to ICT-SC. However, research investigating this has been lacking to date.

3. Present research

In this study, we investigate latent ICT-SC profiles (see Figure 1, bold lines) and their covariation with gender. We aim to contribute to a better understanding of the structure of ICT-SC in heterogeneous adult populations.

Integrating and reflecting on previous research findings that revealed distinct profiles of academic self-concept (e.g. Franzen et al. 2022) and self-perceived ICT competence in homogeneous samples (e.g. Schulze Heuling and Wild 2021), and assuming the applicability of DCT (Marsh, Parker, and Craven 2015; Möller and Marsh 2013) to ICT-SC, we hypothesise:

> *Hypothesis 1 (H1)*: Latent ICT-SC profiles showing differences in shape (verbal-interactive vs. technical-analytical ICT-SC) and level (high vs. low general ICT-SC) exist within the adult population.

Further, transferring to the context of ICT use results from previous research in academic settings that point to gender differences in profile membership, we examine gender as a person-related covariate of profile membership (see Figure 1, dashed line). We hypothesise:

> *Hypothesis 2 (H2)*: Gender correlates with ICT-SC profile membership, with women being more likely than men to belong to profiles characterised by low general ICT-SC and by strengths in verbal-interactive ICT-SC domains, and men being more likely than women to belong to profiles characterised by high general ICT-SC and by strengths in technical-analytical ICT-SC domains.

4. Method

4.1. Sample and design

The data on which the present study is based were collected in August 2020 from a quota sample that reflected the heterogeneity of the adult population in Germany with regard to age, gender, and educational attainment. The quotas were based on the German Microcensus 2011. The data is publicly available in a data repository (see Schauffel et al. 2021a). Data were collected via computer-assisted self-administered interviewing (CASI) in the course of the quality investigation of several measures. The person in charge of the survey (Isabelle Schmidt) ensured that the study meets ethical and legal requirements. Participation was voluntary, anonymous, and informed consent was given. Informed consent was assured by for example explaining the aims, overall purpose, and methods of the study. No vulnerable participants (e.g. children) were surveyed. Research participants were not subjected to harm in any way; no harm in physical or psychological terms can be expected due to the content of the survey. The study follows the General Data Protection Regulation (GDPR). A planned missingness three-form design (Graham, Hofer, and Piccinin 1994) was used in which all respondents answered items within a common block (X), and each respondent answered only two of the three partial blocks (A, B, and C). Due to the planned missingness design and the placement of the items investigated in the present study in one of the partial blocks, the final research sample comprised $N = 369$[2,3] individuals aged between 18 and 69 years ($M = 43.11$, $SD = 14.88$), with 48.8% men, and heterogeneous educational attainment levels (low: 35.7%, medium: 31.2%, high: 33.1%).[4]

4.2. Measures

ICT-SC: We measured ICT-SC on a general and a domain-specific level using the original German-language version of the 25-item scale ICT-SC25g (Schauffel et al. 2021b). Because the ICT-SC25g contains both general and domain-specific items, it is suitable for adequately capturing the multidimensional and hierarchical structure of ICT-SC. Five items measure general ICT-SC (e.g. 'I am good at using digital systems'; $\omega = .95$), and four items each measure the five domain-specific ICT-SCs *communicate* (e.g. 'It is easy for me to spread information through digital systems'; $\omega = .94$), *process and store* (e.g. 'I quickly learn how and where digital data, information, and content have to be stored'; $\omega = .95$), *generate content* (e.g. 'I can create digital data, information, and content on my own'; $\omega = .94$), *safe application* (e.g. 'I can protect digital systems through safety measures'; $\omega = .92$), and *solve problems* (e.g. 'I can restore the functionality of digital systems in case of problems without the help of others'; $\omega = .95$). Item stems (e.g. 'I can', 'I quickly learn') are consistent across the five domain-specific ICT-SCs. Each item was rated on a six-point Likert-type scale ranging from *strongly disagree* (1) to *strongly agree* (6). The full item wording of the ICT-SC25g in German and in its English version (ICT-SC25e) is publicly available (see Schauffel et al. 2021b).

Gender: We assessed the hypothesised covariate, gender (0 = male; 1 = female), with a single item.

4.3. Data analysis

The data analyses were conducted in Mplus Version 8.4 (Muthén and Muthén 1998–2017). For all models, we used a maximum likelihood estimator with robust standard errors (MLR), which is robust to non-normality of data (Enders 2010).

In a first step, we used confirmatory factor analysis (CFA) to specify the incomplete bifactor model of ICT-SC (see Figure 1). We evaluated model fit using the following cut-off criteria for good model fit proposed by Hu and Bentler (1999): comparative fit index ($CFI \geq .95$), root-mean-square error of approximation ($RMSEA \leq .06$), and standardised root-mean-square residual ($SRMR \leq .08$). Ensuring comparability of the measure across our main covariate gender, we conducted measurement invariance analysis across gender (male vs. female). Following a step-up approach (Putnick and Bornstein 2016), we tested increasing levels of measurement invariance against each other (i.e. configural, metric, scalar, strict), using multigroup CFAs. We accept the higher level of measurement invariance if CFI decreases less than .010 and RMSEA increases less than .015 (Chen 2007).

In the next step, we saved the factor scores to run the LPA (Morin et al. 2016). The factor scores for the five domain-specific ICT-SCs and general ICT-SC provided the input for the LPA. This procedure represents an appropriate alternative to the use of fully latent mixture models, given the limited sample size ($N = 369$) and model complexity, as the factor scores preserve the nature of the underlying measurement structure (Gillet et al. 2021; Morin et al. 2016), here the incomplete bifactor model.

To conduct the LPA, we used the three-step BCH (Bolck-Croon-Hagenaars) approach (Asparouhov and Muthén 2014), which is one of the currently recommended methods for LPA with covariates (see Ferguson et al. 2020). First, we ran iterative LPA models for solutions in the range from $K = 1$ to $K = 4$. In the models, we constrained the variances across classes to equality (Ferguson et al. 2020; Tein, Coxe, and Cham 2013). To address potential local maxima issues, we followed the recommendation of Spurk et al. (2020) that 'the best log-likelihood value should be replicated in at least two final-stage solutions' (p. 10). To identify the optimal number of profiles, we used the following fit performance scores: the Akaike information criterion (AIC), the Bayesian information criterion (BIC), sample-size adjusted BIC (SABIC), and entropy. Entropy, a measure of classification uncertainty, can range from 0 to 1, with higher values indicating a higher degree of classification certainty (e.g. Tein, Coxe, and Cham 2013). Values > .80 indicate low entropy (Tein, Coxe, and Cham 2013). When comparing AIC, BIC, and SABIC values across models, the model with the lower values indicates the better model fit. Further, we used bootstrap likelihood ratio test (BLRT) scores, which provide p values indicating whether the fit of K classes is significantly better than that of $K - 1$ classes. We chose the BLRT because compared with other tests and indexes, it has been found to be the most consistent indicator for the correct number of classes in a population given the disadvantage of a multiplied computation time (Nylund, Asparouhov, and Muthén 2007). As latent profiles that comprise less than 5% of the total number of respondents are likely to be spurious (e.g. Masyn 2013), we checked these carefully. To identify the optimal number of profiles, we evaluated not only the meaningfulness of profile solutions in terms of statistical salience but also whether the profile solutions reflected theoretical assumptions (see Ferguson et al. 2020).

In the second step, we used the respondents' profile probabilities to specify their probability of membership of each latent profile. We describe the final profile solution by the profiles' levels and shapes. We determine profile separation by effect sizes of mean differences between profiles on the LPA indicators (Nylund, Asparouhov, and Muthén 2007), following the conventions by Cohen (1988, i.e. small: $|d| \geq 0.20$, medium: $|d| \geq 0.50$, large: $|d| \geq 0.80$). Following Marsh et al. (2009), we examine within-profile differences between ICT-SC in the verbal-interactive (i.e. communicate) and technical-analytical (i.e. solve problems) domains, as an indicator of profile shape.

In the third and final step, we included gender as a predictor variable in the model. In doing so, we fixed the profile memberships according to the previous step and used profile memberships in a multinomial logistic regression as dependent variables. The code for the conducted LPA is available as electronic supplementary material (see ESM 2).

5. Results

Descriptive statistics (i.e. means, standard deviations, range, skewness, and kurtosis) for all variables used in the analysis for the total sample, and separately by gender, are displayed in Table 1.

Results of the CFA showed a good model fit of the incomplete bifactor model, χ^2 (df) = 521.155 (245), $p < .001$; CFI = .957; RMSEA = .055; SRMR = .025. Factor correlations between domain-specific ICT-SCs are depicted in Table 2. The pattern of correlations showed that the correlations between the ICT-domains *communicate* (corresponding to the verbal-interactive pole of the ICT-SC continuum) and *safe application* and *solve problems* (corresponding to the technical-analytical pole of the ICT-SC continuum) were lowest (r = .405/.406). Results from the multigroup CFA (see Table 3) supported strict measurement invariance (i.e. equal pattern, factor loading, intercepts, residual variances) across gender (male vs. female). Thus, the ICT-SC25 measures ICT-SC comparably across gender.

Table 4 shows the results of the LPA. Fit summary of the best log-likelihood solutions was replicated at least twice. Results showed that AIC, BIC, and SABIC values continuously decreased with the increasing number of latent profiles (K). Entropy was lowest (i.e. the entropy value was highest) at $K = 4$. According to the BLRT test, models with a higher number of profiles fit the data significantly better. However, the model with $K = 4$, which had the best performance indices, included one latent group that comprised less than 5% of the cases ($n = 1$, which is not reliable). Therefore, we excluded that model and accepted the $K = 3$ solution because it showed low entropy (.843) and the three ICT-SC profiles lend themselves very well to theoretical interpretation.

Model results of the final three-class solution are depicted in Table 5. Profile I, which we called the

Table 1. Descriptive statistics for the ICT self-concept items for the whole sample and separately by gender.

	Total (n = 369)			Men (n = 180)			Women (n = 189)		
Item	*M (SD)*	Skew/Kurtosis	Min/Max	*M (SD)*	Skew/Kurtosis	Min/Max	*M (SD)*	Skew/Kurtosis	Min/Max
SCGL1	4.59 (1.22)	−0.92/0.84	1.00/6.00	4.57 (1.31)	−0.95/0.50	1.00/6.00	4.60 (1.12)	−0.85/1.17	1.00/6.00
SCGL2	4.44 (1.22)	−0.89/0.63	1.00/6.00	4.45 (1.30)	−0.86/0.32	1.00/6.00	4.42 (1.15)	−0.92/0.99	1.00/6.00
SCGL3	4.46 (1.18)	−0.74/0.37	1.00/6.00	4.46 (1.24)	−0.65/−0.16	1.00/6.00	4.47 (1.13)	−0.84/1.02	1.00/6.00
SCGL4	4.41 (1.19)	−0.68/0.18	1.00/6.00	4.46 (1.25)	−0.64/−0.22	1.00/6.00	4.37 (1.12)	−0.75/0.70	1.00/6.00
SCGL5	4.27 (1.23)	−0.57/0.04	1.00/6.00	4.35 (1.24)	−0.62/0.07	1.00/6.00	4.19 (1.22)	−0.55/0.04	1.00/6.00
SCCO1	4.45 (1.25)	−0.75/0.36	1.00/6.00	4.41 (1.32)	−0.70/0.09	1.00/6.00	4.49 (1.19)	−0.80/0.63	1.00/6.00
SCCO2	4.36 (1.24)	−0.69/0.22	1.00/6.00	4.38 (1.30)	−0.78/0.21	1.00/6.00	4.34 (1.17)	−0.57/0.18	1.00/6.00
SCCO3	4.36 (1.20)	−0.76/0.47	1.00/6.00	4.36 (1.27)	−0.80/0.36	1.00/6.00	4.35 (1.13)	−0.71/0.54	1.00/6.00
SCCO4	4.32 (1.22)	−0.66/0.21	1.00/6.00	4.32 (1.30)	−0.72/0.06	1.00/6.00	4.32 (1.14)	−0.58/0.31	1.00/6.00
SCPS1	4.27 (1.19)	−0.65/0.39	1.00/6.00	4.30 (1.24)	−0.76/0.41	1.00/6.00	4.24 (1.14)	−0.54/0.34	1.00/6.00
SCPS2	4.26 (1.19)	−0.59/0.29	1.00/6.00	4.31 (1.23)	−0.67/0.37	1.00/6.00	4.21 (1.15)	−0.52/0.22	1.00/6.00
SCPS3	4.38 (1.17)	−0.71/0.50	1.00/6.00	4.37 (1.26)	−0.81/0.42	1.00/6.00	4.39 (1.08)	−0.52/0.38	1.00/6.00
SCPS4	4.30 (1.19)	−0.72/0.46	1.00/6.00	4.31 (1.29)	−0.72/0.11	1.00/6.00	4.29 (1.09)	−0.71/0.84	1.00/6.00
SCGE1	4.03 (1.36)	−0.63/−0.04	1.00/6.00	4.07 (1.37)	−0.67/0.00	1.00/6.00	4.00 (1.35)	−0.59/−0.07	1.00/6.00
SCGE2	3.65 (1.33)	−0.40/−0.44	1.00/6.00	3.73 (1.34)	−0.37/−0.53	1.00/6.00	3.58 (1.32)	−0.44/−0.38	1.00/6.00
SCGE3	4.06 (1.29)	−0.62/0.08	1.00/6.00	4.06 (1.36)	−0.62/−0.10	1.00/6.00	4.06 (1.23)	−0.61/0.27	1.00/6.00
SCGE4	3.86 (1.35)	−0.48/−0.38	1.00/6.00	3.86 (1.33)	−0.46/−0.38	1.00/6.00	3.86 (1.37)	−0.49/−0.38	1.00/6.00
SCSA1	3.71 (1.39)	−0.30/−0.56	1.00/6.00	3.83 (1.41)	−0.38/−0.50	1.00/6.00	3.60 (1.36)	−0.25/−0.59	1.00/6.00
SCSA2	3.84 (1.33)	−0.43/−0.30	1.00/6.00	3.93 (1.36)	−0.52/−0.21	1.00/6.00	3.76 (1.28)	−0.35/−0.37	1.00/6.00
SCSA3	3.98 (1.30)	−0.60/−0.06	1.00/6.00	3.97 (1.39)	−0.56/−0.28	1.00/6.00	3.98 (1.20)	−0.64/0.13	1.00/6.00
SCSA4	4.30 (1.28)	−0.75/0.30	1.00/6.00	4.21 (1.39)	−0.68/−0.10	1.00/6.00	4.38 (1.17)	−0.77/0.70	1.00/6.00
SCSP1	3.69 (1.33)	−0.38/−0.44	1.00/6.00	3.79 (1.42)	−0.40/−0.55	1.00/6.00	3.60 (1.22)	−0.43/−0.35	1.00/6.00
SCSP2	3.81 (1.29)	−0.43/−0.23	1.00/6.00	3.93 (1.37)	−0.45/−0.32	1.00/6.00	3.70 (1.20)	−0.49/−0.16	1.00/6.00
SCSP3	3.91 (1.28)	−0.55/−0.02	1.00/6.00	4.01 (1.36)	−0.60/−0.09	1.00/6.00	3.81 (1.19)	−0.55/0.04	1.00/6.00
SCSP4	3.80 (1.29)	−0.47/−0.08	1.00/6.00	3.92 (1.37)	−0.60/−0.17	1.00/6.00	3.68 (1.18)	−0.38/0.12	1.00/6.00

Notes: SCGL1–5 = items measuring general ICT self-concept (ICT-SC); SCCO1–4 = items measuring the ICT-SC domain *communicate*; SCPS1–4 = items measuring the ICT-SC domain *process and store*; SCGE1–4 = items measuring the ICT-SC domain *generate content*; SCSA1–4 = items measuring the ICT-SC domain *safe application*; SCSP1–4 = items measuring the ICT-SC domain *solve problems*.

Table 2. Latent intercorrelations of the ICT self-concept domains.

	ICTSCg	SCCO	SCPS	SCGE	SCSA	SCSP
ICTSCg	.00[a]	.00[a]	.00[a]	.00[a]	.00[a]	.00[a]
SCCO			.739	.534	.405	.406
SCPS				.543	.526	.452
SCGE					.861	.751
SCSA						.823
SCSP						

Notes: All correlations are significant ($p < .001$). ICTSCg = general ICT self-concept (ICT-SC); SCCO = ICT-SC domain *communicate*; SCPS = ICT-SC domain *process and store*; SCGE = ICT-SC domain *generate content*; SCSA = ICT-SC domain *safe application*; SCSP = ICT-SC domain *solve problems*.
[a]The correlations between ICTSCg and the domain-specific ICT-SCs were fixed to zero.

'shallow users' ($n = 48$), is characterised by low ICT-SC, with the expected profile strengths in the verbal-interactive ICT-SC domains. Profile II, the 'hesitant users' ($n = 149$), is characterised by rather low/below average to average ICT-SC across domains. Profile III, the 'reflective users' ($n = 172$), is characterised by high ICT-SC across domains and strengths in the technical-analytical domains. Between- and within-profile differences indicate both level and shape differences between the ICT-SC profiles.

While between-profile differences in the general ICT-SC are negligible to small ($|d| = 0.126$ to $|d| = 0.320$), profile differences related to the verbal-interactive ICT-SC *communicate* need to be considered as small to large ($|d| = 0.459$ to $|d| = 1.352$). In technical-analytical competence domains, the three profiles show large differences ($|d| \geq 1.659$). Varying effect sizes indicate profile level and shape differences.

Within-profile differences between ICT-SCs at the end-poles of the verbal-interactive–technical-analytical continuum further underline the existence of shape differences in ICT-SC profiles. Profile I shows the most pronounced shape with relative strengths in the verbal-interactive ICT-SC and weaknesses in the technical-analytical ICT-SC domains ($\Delta M_{SCCO\text{-}SCSP} = 1.066$). Profile III shows slight strengths in technical-analytical ICT-SC ($\Delta M_{SCCO\text{-}SCSP} = -0.270$). The shape of Profile II is homogeneous with uniform ICT-SC levels across domains ($\Delta M_{SCCO\text{-}SCSP} = -0.024$). Profiles of the final solution LPA model are visualised in Figure 2.

The probability of being classified into a particular profile did not significantly depend on gender. However, the pattern of results is descriptively in line with our hypothesis (H2). Results of the covariate analysis with changing reference groups are shown in Table 6. Descriptively, these results show that women were less likely to belong to Profile III (the 'reflective users': high ICT-SC across domains and strengths in technical-analytical ICT-SC domains) or Profile II (the 'hesitant users': below average to average ICT-SC across domains) than to Profile I (the 'shallow users': low ICT-SC with relative strengths in verbal-interactive ICT-SC domains). Further, women were descriptively more likely to belong to Profile I than to Profiles II or III.[5]

6. Discussion

In this study, we examined whether different profiles of ICT-SC existed in a heterogeneous population of adults in Germany and whether gender correlated with ICT-SC profile membership. Drawing on findings from academic self-concept research and first evidence from self-concept research in the context of ICT, we hypothesised,

Table 3. Measurement invariance testing of the ICT-SC25g across gender (male vs. female) based on the NMS model.

M	χ^2	*df*	MC	ΔSBχ2	Δdf	CFI	ΔCFI	RMSEA	ΔRMSEA
c	968.550***	490	–	–	–	.936	–	.073	–
m	1007.341***	529	m−c	32.639	39	.936	.000	.070	−.003
s	1043.502***	548	s−m	36.151*	19	.934	−.002	.070	.000
st	1063.588***	573	st−s	30.016	25	.935	.001	.068	−.002

Notes: $N = 369$, $n_{male} = 180$, $n_{female} = 189$. NMS model = nested Marsh/Shavelson model (incomplete bifactor model); M = model; MC = model comparison; SBχ2 = Satorra-Bentler scaled chi-square difference test; CFI = comparative fit index; RMSEA = root-mean-square-error-of-approximation; ΔCFI ≥ │.010│ and ΔRMSEA ≥ │.015│ signal lack of invariance between nested models; c = configural (equal pattern); m = metric (equal pattern and factor loading); s = scalar (equal pattern, factor loading, and item-intercepts); st = strict (equal pattern, factor loading, item-intercepts, and residual variances).
*$p < .05$. **$p < .01$. ***$p < .001$.

Table 4. Results of the latent profile analysis.

No.	LL	No. param.	AIC	BIC	SABIC	Entropy	*p* BLRT	LT5%
1	−2942.399	12	5908.798	5955.728	5917.656	–	–	0
2	−2635.334	19	5308.667	5382.973	5322.692	.906	.000	0
3	−2497.717	26	5047.434	5149.115	5066.626	.843	.000	0
4	−2364.781	33	4795.562	4924.618	4819.921	.915	.000	1

Notes: No. = number of the model with 1–4 classes; LL = log likelihood; No. param. = number of free parameters; AIC = the Akaike information criterion; BIC = the Bayesian information criterion; SABIC = sample-size adjusted BIC; *p* BLRT = bootstrap likelihood ratio test for *K* versus *K* − 1 classes; LT5% = number of latent groups with less than 5% of the cases.

Table 5. Three-class solution: Profile descriptions and model results including within-profile differences and between-profile effect sizes.

	Profile I ($n = 48$) 'Shallow users'	Profile II ($n = 149$) 'Hesitant users'	Profile III ($n = 172$) 'Reflective users'	Profile I vs. II	Profile II vs. III	Profile I vs. III
	M (S.E.)	*M (S.E.)*	*M (S.E.)*	$\|d\|$	$\|d\|$	$\|d\|$
ICTSCg	−0.041 (0.157)	−0.163 (0.096)$^{+}$	0.147 (0.079)$^{+}$	0.126	0.320	0.194
SCCO	−0.614 (0.326)$^{+}$	−0.272 (0.074)***	0.393 (0.145)**	0.459	0.893	1.352
SCPS	−0.755 (0.349)*	−0.327 (0.097)**	0.477 (0.147)**	0.587	1.103	1.690
SCGE	−1.632 (0.544)**	−0.259 (0.293)	0.658 (0.109)***	2.571	1.717	4.288
SCSA	−1.686 (0.459)***	−0.256 (0.344)	0.670 (0.100)***	2.843	1.841	4.684
SCSP	−1.680 (0.441)***	−0.248 (0.323)	0.663 (0.116)***	2.608	1.659	4.268
$\Delta M_{SCCO\text{-}SCSP}$ [a]	1.066	−0.024	−0.270			

Notes: Profile I = rather low ICT self-concept (ICT-SC) with relative strengths in verbal-interactive ICT-SC domains; Profile II = rather low/below average to average ICT-SC across domains; Profile III = high ICT-SC across domains, with strengths in technical-analytical ICT-SC domains; ICTSCg = general ICT-SC; SCCO = ICT-SC domain *communicate*; SCPS = ICT-SC domain *process and store*; SCGE = ICT-SC domain *generate content*; SCSA = ICT-SC domain *safe application*; SCSP = ICT-SC domain *solve problems*. As variances are set to equal across classes, *SD* are as follows: $SD_{ICTSCg} = 0.970$; $SD_{SCCO} = 0.745$; $SD_{SCPS} = 0.729$; $SD_{SCGE} = 0.534$; $SD_{SCSA} = 0.503$; $SD_{SCSP} = 0.549$.

[a]Mean difference between ICT-SC domain *communicate* and ICT-SC domain *solve problems* representing ICT-SC at the end-poles of the proposed verbal-interactive–technical-analytical competence continuum; an indicator of the profile shape, according to Marsh et al. (2009).

$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

first (H1), that distinct latent ICT-SC profiles showing differences in level (i.e. high vs. low ICT-SC) and shape (i.e. verbal-interactive vs. technical-analytical strengths) existed in the adult population. We hypothesised, second (H2), that women would be more likely than men to belong to profiles characterised by low general ICT-SC and strengths in verbal-interactive domains, and that men would be more likely than women to belong to profiles characterised by high general ICT-SC and strengths in technical-analytical domains.

The results are partly in line with our hypotheses. As expected (H1), we found distinct profiles of ICT-SC characterised by level and shape differences: Profile I, the 'shallow users' ($n = 48$), characterised by low ICT-SC and strengths in the verbal-interactive domains; Profile II, the 'hesitant users' ($n = 149$), characterised by rather low/below average to average ICT-SC across domains; Profile III, the 'reflective users' ($n = 172$), characterised by high ICT-SC across domains and particular strengths in the technical-analytical domains. Contrary to our expectations (H2), gender did not significantly covary with profile membership.

6.1. Profile solutions

Although our results are partly consistent with those of previous studies investigating ICT-SC profiles

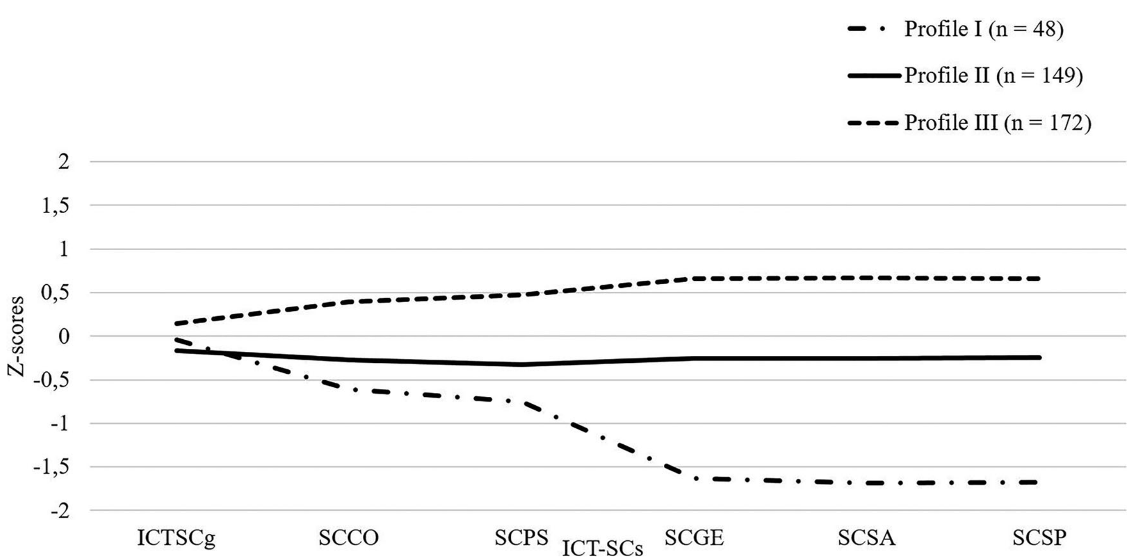

Figure 2. Profiles of ICT self-concept according to the three-profile model.

Notes: The depicted values are z-scores. Profile I ($n = 48$) = the 'shallow users', with rather low ICT self-concept (ICT-SC) and relative strengths in the verbal-interactive ICT-SC domains; Profile II ($n = 149$) = the 'hesitant users', with rather low/below average to average ICT-SC across domains; Profile III ($n = 172$) = the 'reflective users', with high ICT-SC across domains and strengths in the technical-analytical ICT-SC domains; ICTSCg = general ICT-SC; SCCO = ICT-SC domain *communicate*; SCPS = ICT-SC domain *process and store*; SCGE = ICT-SC domain *generate content*; SCSA = ICT-SC domain *safe application*; SCSP = ICT-SC domain *solve problems*.

Table 6. Results of the covariate analysis with gender for the three-profile model.

	Profile I 'Shallow users'		Profile II 'Hesitant users'		Profile III 'Reflective users'	
	b	*SE*	*b*	*SE*	*b*	*SE*
Profile I[a]			−.180	.379	−.481	.354
Profile II[b]	.180	.379			−.300	.262
Profile III[c]	.481	.354	.300	.262		

Notes: Gender (0 = male; 1 = female). $N = 369$. All parameter estimates are non-significant ($p > .05$). Profile I ($n = 48$) = the 'shallow users', with rather low general ICT self-concept (ICT-SC) and relative strengths in the verbal-interactive ICT-SC domains; Profile II ($n = 149$) = the 'hesitant users', with rather low/below average to average ICT-SC across domains. Profile III ($n = 172$) = the 'reflective users', with high ICT-SC across domains, and strengths in technical-analytical ICT-SC domains. Profile I represents latent class 3, Profile II represents latent class 1, and Profile III represents latent class 2 of the Mplus output.
[a]Parameterization using Reference Profile I.
[b]Parameterization using Reference Profile II.
[c]Parameterization using Reference Profile III.

(e.g. Schulze Heuling, Wild, and Vest 2021), we found a different number of profiles and slightly different profile configurations. Whereas we identified three ICT-SC profiles, previous studies have proposed four profiles of ICT-SC (e.g. Schulze Heuling and Wild 2021) or academic self-concept (e.g. Franzen et al. 2022; Saß and Kampa 2019). Similar to the findings of Schulze Heuling, Wild, and Vest (2021) and Schulze Heuling and Wild (2021), we found that a large proportion of our sample belonged to a profile characterised by rather high ICT-SC (Profile III: the 'reflective users', $n = 172$). However, in contrast to Schulze Heuling, Wild, and Vest (2021), we did not find a profile with strengths in the domain *generate content*. Instead, we found a profile characterised by rather low ICT-SC with relative strengths in the expected verbal-interactive ICT-SC domains (i.e. the 'shallow users'). Further, in contrast to our findings, Schulze Heuling, Wild, and Vest (2021) did not identify a profile with rather low/below average to average ICT-SC across domains.

The divergence between the present results and those of previous studies might be due mainly to two reasons. First, we included both general ICT-SC and domain-specific ICT-SCs in our analysis, whereas previous studies used only domain-specific ICT-SC measures (e.g. Schulze Heuling and Wild 2021). More specifically, we used factor scores from an incomplete bifactor model (the nested Marsh/Shavelson model, Brunner et al. 2010), a special feature of which is that it allows the level (high vs. low general ICT-SC) and shape (verbal-interactive vs. technical-analytical ICT-SCs) of an individual's ICT-SC profile to be clearly separated. This might have contributed to the more pronounced shapes of the profiles identified in our study.

The second possible reason for the divergence between our results and those of previous profile analysis studies of ICT-SC might be that those studies used more homogeneous (i.e. student) samples (e.g. Schulze Heuling, Wild, and Vest 2021), whose members typically have above-average ICT competences across domains – in contrast to the members of the heterogeneous sample used in our study.

Furthermore, Schulze Heuling, Wild, and Vest (2021) found a profile with strengths in the ICT-SC domain *generate content*, which is plausible because 58% of the members of their study sample were student science teachers, and the generation of digital content (e.g. teaching material) is a typical task for teachers, who frequently use ICT.

Regarding the separation of ICT-SC profiles, our results show that Profile I to Profile III are (rather) close to each other regarding general ICT-SC and the ICT-SC domain *communicate* while the profiles are clearly separated from each other regarding ICT-SC in *process and store*, *generate content*, and especially regarding the technical-analytical ICT-SC domains (i.e. *safe application*, *solve problems*). Contentwise, this is an interesting and new insight into the structure and distribution of ICT-SC (profiles) alongside the verbal-interactive–technical-analytical competence continuum in the German adult population, which was the central goal of the present study. Methodwise, it should be taken into account that besides the sample size and the number of LPA indicators also class separation influences LPA performance (Tein, Coxe, and Cham 2013). Tein, Coxe, and Cham (2013) argue that '[i]ndicators should have a certain degree of distance between latent classes' (p. 3) to detect the correct number of latent classes with sufficient power and to 'consider discarding indicators that have small inter-class distances' (p. 12). However, such an approach would have been contrary to the main goal of our study, which explicitly focused on the examination of ICT-SC profiles including general ICT-SC and domain-specific ICT-SCs along the entire ICT competence continuum (Carretero, Vuorikari, and Punie 2017), ranging from verbal-interactive to technical-analytical ICT-SC domains. Further, Tein, Coxe, and Cham (2013) also stated that '[i]n real world situations, the indicators are not likely to be so uniform in nature. Some indicators will be very good at distinguishing between classes and others will not' (p. 12). As the vast majority of inter-class separation is large, varying class separation should not have interfered with the correct number of class extraction. Methodological articles dealing exclusively with this aspect, however, do not yet exist to the authors' knowledge as '[LPA] is an active area of research and continues to evolve' (Weller, Bowen, and Faubert 2020, p. 287).

In conclusion, the distinct ICT-SC profiles characterised by level and shape differences found in our study support previous findings and extend them to a heterogeneous sample of the adult population in Germany.

6.2. Gender as a covariate of profile membership

Based on previous research on academic self-concept showing that gender correlates with profile membership (see Franzen et al. 2022; Marsh et al. 2009; Saß and Kampa 2019), we expected that gender would covary with ICT-SC profile membership. In particular, we hypothesised that women would be more likely than men to belong to profiles characterised by low general ICT-SC and strengths in verbal-interactive ICT-SC domains and that men would be more likely than women to belong to profiles characterised by high general ICT-SC and strengths in technical-analytical ICT-SC domains.

Contrary to our expectations, gender did not significantly covary with profile membership in our study, although the values pointed descriptively in the assumed direction. Thus, although in most previous variable-centered analyses, females have reported on average lower general ICT-SC (e.g. Janneck, Vincent-Höper, and Ehrhardt 2012) and lower domain-specific ICT-SC (e.g. Fraillon et al. 2014), profile membership of women and men did not vary significantly in our study.

There are two likely explanations for the latter finding. First, we based our hypothesis on results from studies investigating academic self-concept and the application of assumptions of the DCT to ICT-SC. In particular, we assumed that the verbal–math continuum in the context of academic self-concept would correspond to the verbal-interactive–technical-analytical continuum in the context of ICT-SC. However, our results suggest a less pronounced continuum with domains being more closely related compared with those in the context of academic self-concept. We found larger correlations between ICT-SC domains compared with those found between verbal and mathematical domains in studies on academic self-concept (e.g. Brunner et al. 2010; Schmidt et al. 2017). For instance, using an incomplete bifactor model in a student sample, Brunner et al. (2010) found smaller and also negative correlations between verbal and mathematical academic self-concept domains. Hence, further investigations are needed to clarify the applicability of DCT to ICT-SC.

Second, the data for the present study were collected in August 2020, almost six months after the outbreak of the COVID-19 pandemic. Due to the pandemic-related lockdown and a nationwide obligation to work from home (Maurer, Bach, and Oertel 2022), social activities (e.g. gatherings, sports, or concerts) and work activities had shifted online. Thus, more ICT functions (corresponding to the five ICT-SC competence domains) had to be used than before the crisis. With this externally driven increase in ICT use, gender-specific interests and gender-specific preferences for specific functions of ICT may have faded into the background, thereby resulting in our finding of no gender differences in profile membership.

Theoretically, the absence of an association between ICT-SC profile membership and gender helps to challenge gender stereotypes in competence perception patterns (i.e. verbal-interactive vs. technical-analytical) in ICT use (e.g. Comunello et al. 2017; Janneck, Vincent-Höper, and Ehrhardt 2012; Sáinz and Eccles 2012). Our results suggest that women do not perceive themselves to be generally more competent than men in verbal-interactive ICT domains compared with technical-analytical ICT domains, and vice versa.

At this point, it must be pointed out that the identified profiles and gender-related findings cannot be transferred to other samples without further ado. Especially in less digitised countries (for digital competitiveness ranking see Institute for Management Development 2021), gender might play a crucial role in ICT-SC profile membership, displaying a gender-related digital divide (i.e. inequalities in ICT access, use, and outcomes, Scheerder, van Deursen, and van Dijk 2017). However, recent results from variable-centered analyses comprising university teachers from different Latin American countries (e.g. Argentina, Peru, Venezuela) show that at least among this highly educated sample no gender difference in teachers' self-concept related to the use of digital content creation tools was found (e.g. Antón-Sancho et al. 2021).

6.3. Practical implications

The empirical evidence of three distinct ICT-SC profiles within the adult population in Germany found in the present study has important implications for decision-makers in politics, adult education, and human resource management.

Previous research has shown that ICT-SC is related to other motivational variables (e.g. Schauffel et al. 2021b), therefore high ICT-SC is a desirable developmental goal.

It is, thus, first of all, positive feedback that there was no significant effect of gender on profile membership, however, future research should examine the role of occupational activities (e.g. care work, occupational sector). ICT-SC has an important role in bridging the digital divide, as ICT-related competence self-beliefs are antecedents of ICT acceptance and use motivation (e.g. Rizun and Strzelecki 2020; Schauffel and Ellwart 2021; Venkatesh 2000). Furthermore, it is positive feedback that although there seem to exist different ICT-SC profiles, only approximately 13% of the study participants belonged to Profile I, characterised by rather low ICT-SC. Across profiles, similar ICT-SCs in the general use of ICT and communication with others via ICT speak for the ability of the adult population in Germany to participate in everyday life via digital systems. However, the profiles also differed significantly, especially concerning technical-analytical ICT competences and the generation of digital content. This is where practical interventions should start.

ICT-SC is not static, but rather it changes depending on individual experiences and ICT-related interactions (see Shavelson, Hubner, and Stanton 1976). From self-concept research, it is well known that self-concepts can be strengthened by interventions. A meta-analysis conducted by O'Mara et al. (2006) confirmed the effectiveness of self-concept interventions. The identified ICT-SC profiles showing differences in level and shape suggest a modular conception of ICT-SC interventions. Individuals differ in the configurations of their ICT-SC profiles. Thus, to address a broad range of people, ICT-SC interventions should enable individuals to choose single modules, based on their individual needs. Concerning the structure of the intervention modules, our results suggest that differentiation between verbal-interactive and technical-analytical training elements would be helpful. The shape of the profile of individuals with low ICT-SC (i.e. the 'shallow users') – who are most likely to require an ICT-SC intervention – is characterised by a fracture between the verbal-interactive and technical-analytical competence domains. Because competence beliefs regarding ICT (e.g. ICT-SC) and performance-based ICT competence are positively correlated (e.g. Gnambs 2021; Siddiq et al. 2016), the level differences across the three ICT-SC profiles underline the need for ICT-SC interventions starting at different ICT competence levels.

For providers of interventions (e.g. educational institutions), our results offer two practical implications. First, because gender is not a significant determinant of profile membership, the gender-specific design and promotion of ICT-SC interventions are neither advisable nor necessary. Second, to ensure the fit of the intervention to the needs of individuals, advertisements for ICT-SC interventions should use keywords that address profile characteristics (e.g. focus on ICT-mediated communication, build on technical-analytical strengths, basic competence across topics) and directly name the modules and competence domains that will be focused on.

For the communication and justification of ICT-SC intervention needs, the identified profiles are more easily to articulate to human resource managers and decision makers than findings from variable-centered analyses, being cognitively more easily understood (Morin et al. 2011).

6.4. Limitations and future research

Our study has some limitations. First, due to the rather small sample size, we did not implement a fully latent modelling approach but used factor scores based on the NMS model as the input of the LPA. Although this approach is frequently used in applied LPA research (e.g. Morin et al. 2016), future research using a substantially larger sample size could enhance the methodological approach by modelling the NMS directly in the LPA and thus control for measurement errors more sufficiently.

Second, the present results were discussed against the background of existing literature (e.g. Schulze Heuling and Wild 2021). However, no multigroup analyses of profile similarity across samples and also countries were included in the present study.[6] Here, Morin et al. (2016) provide a rigorous guideline on how to compare the similarity/generalizability of profile solutions across samples with six steps (i.e. number of profiles, means, variability, profile size, relations with predictors and outcomes). Nevertheless, the results provide a first step to increasing the attention on ICT-SC profiles alongside a verbal-interactive–technical-analytical competence continuum on which future research can be based.

Third, we did not include a multidimensional ICT competence test in our study, because no such test is available to our knowledge. Thus, we were unable to directly examine the effect of dimensional comparisons on domain-specific ICT-SCs. Usually, the effect of dimensional comparisons is reflected in higher correlations between domain-specific performance indicators of distal domains (i.e. verbal vs. mathematical or verbal-interactive vs. technical-analytical) than those between the self-concepts in the corresponding domains (see Möller and Marsh 2013). Future research is needed to investigate the applicability of DCT to ICT-SC.

Fourth, our study investigated only one variable – gender – as a covariate of profile membership. Other interesting covariates are the occupational sector in which individuals are employed or the vocational track to which they belong. One would expect different types of ICT-SC profiles depending on the degree of digitalisation of and the ICT functions required in the respective occupational sectors or vocational tracks. A nuanced understanding of whether and to what extent individuals' ICT-SC profiles match with the ICT competences that are needed to succeed in a particular sector (i.e. person–environment fit; see Pasca 2014) might help student advisors or human resource developers to identify training needs and understand individuals' career decisions (e.g. job preferences: Ribaud and Saliou 2015, virtual leadership: Roy 2012), and thus might help to predict individuals' career paths.

Furthermore, the stability of ICT-SC profiles over time, especially if the ICT-related context changes, remains an open question. Focusing on the work context, it would be beneficial to examine how professional experiences (e.g. digitalisation of work processes, switching to a job in a different sector) impact membership of ICT-SC profiles. Future longitudinal studies applying latent transition analysis are needed here.

7. Conclusion

The present study contributes to the understanding of the structure of ICT-SC in heterogeneous adult populations. We found evidence for different profiles of ICT-SC characterised by shape and level differences. Our finding that profile membership was independent of gender challenges gender stereotypes that women perceive themselves to be more competent than men in verbal domains (e.g. verbal-interactive ICT-SC) than in math-like domains (e.g. technical-analytical ICT-SC), and vice versa. Practically, this finding implies that interventions to promote general and domain-specific ICT-SC do not have to be gender-specific, but rather should focus on individuals' ICT-SC profiles.

Notes

1. In existing research, the term 'math-verbal continuum' instead of 'verbal-math continuum' is predominant (e.g., Arens et al. 2020). However, to increase the readability of our article, we use the term verbal-math continuum, in concordance with the verbal-interactive–technical-analytical continuum presented in this article.
2. The final research sample refers to screened data only. Data screening (e.g., Mahalanobis distance, ipsative variance, implausible response time) led to the exclusion of 36 participants with potentially invalid cases ($N_{initial} = 405$). Electronic supplemental material 1 (ESM 1) displays how the final sample conforms to the quotas.
3. Supplementary a posteriori power analysis (i.e. Monte Carlo simulation) supported that the sample size is sufficient to identify multiple classes.
4. Education levels (from low to high) are defined as follows: ohne Bildungsabschluss/Hauptschule [no educational qualification/ lower secondary leaving certificate], mittlerer Schulabschluss [intermediate school leaving certificate], (Fach-)Hochschulreife [higher education entrance qualification].
5. We performed a supplementary analysis with a retested sample ($n = 177$, age: 18–69 years, $M = 44.40$, $SD = 15.36$; educational attainment: 34.5 % low, 33.3% medium, 32.2% high) which was assessed two to three weeks after the initial survey ($Mdn = 14$ days), to provide some initial form of robustness evidence (see ESM 3). LPA with the retest sample resulted in a descriptively similar three-profile solution as with the study sample concerning the percentage of profile membership as well as the level and shape characteristics. Again, gender did not significantly predict profile membership.
6. In supplementary analysis, initital empirical robustness analysis using a retest sample were included (see footnote 5).

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Availability of data and materials

The dataset of the article is available in the GESIS Sowi-DataNet | datorium repository. https://doi.org/10.7802/2343.

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