Students' Profiles of ICT Use: Identification, Determinants, and Relations to Achievement in a Computer and Information Literacy Test

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Abstract

Current debates on students' use of information and communication technology (ICT) have brought to attention profiles and purposes of ICT use in either school-related or recreational contexts. Examining these two contexts at the same time, the present study seeks to identify student profiles of ICT use on the basis of the Norwegian International Computer and Information Literacy Study (ICILS) 2013 data (N = 2,426). In order to explore profiles of ICT use in schools *and* at home for different purposes such as recreation, study purposes, exchanging information, and social communication, we take a person-centered approach and apply latent profile analysis. These analyses revealed two independent user profiles and showed that background characteristics (i.e., gender, immigration status) and motivational constructs (i.e., self-efficacy, interest, and enjoyment in ICT) play a significant role in determining profile membership. Significant differences between the user profiles in students' computer and information literacy test performance did not exist. Given that the coverage of ICT at home and in schools has increased substantially over the last decades, the identification of user profiles informs teachers and parents about whether or not students exploit these opportunities to the same extent. Implications for future research and practice are discussed.

Keywords: Computer and information literacy; ICILS 2013; ICT use; latent profile analysis; user profiles

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Introduction

Research on students' use of information and communication technology (ICT) has examined its effects on educational outcomes, well-being, and health (Cotten, 2008; Cox & Marshall, 2007); OECD (2015b); (Spiezia, 2010). In a parallel, yet almost distinct line of research, the antecedents and institutional determinants of ICT use were studied at different levels of educational systems (Bozionelos, 2004; Fraillon, Ainley, Schulz, Friedman, & Gebhardt, 2014; Teo & Noyes, 2011; Van Braak & Kavadias, 2005). These research traditions have revealed findings on the relations between the use of ICT and academic achievement, and have pointed to the importance of students' background and cultural capital for exploiting the available technologies. Most of the studies contributing to these traditions have taken a general view on students' use of ICT by simply examining the relations among the above mentioned constructs for an entire sample or population. This *variable-centered* approach represents "a synthesis (or averaged estimate) of the relationships observed in every individual from the sample under study, without systematically considering the possibility that these relationships may meaningfully differ in subgroups of participants" (Morin, Morizot, Boudrias, & Madore, 2011, p. 59). Yet, as Tondeur, Sinnaeve, van Houtte, and van Braak (2010) pointed out, the availability of information and communication technology may not be equally exploited, because specific profiles of ICT use may exist depending on students' background characteristics. Along the same lines, Vicente and López (2006), Chinn and Fairlie (2010), and Rohatgi and Throndsen (2015) found evidence that, although ICT has been widely made available in many countries, the actual use of ICT depends on the contexts and cultures, in which it takes place, and the specific purposes it is used for. It therefore seems necessary to become more specific in studying ICT use by distinguishing between subgroups of students that represent potentially different user profiles (Cotten, 2008). In fact, taking a more differentiated, *person-centered* perspective allows researchers to describe how specific groups of students use ICT for different purposes and in different contexts. At the same time it becomes possible to investigate the profile-specific effects on educational outcomes, well-being, and health on the one hand, and the antecedents and institutional determinants of ICT use on the other hand.

As a consequence, the present study seeks to examine whether or not different user profiles of students' ICT use exist. On the basis of a representative, large-scale sample of Norwegian ninth-grade students, a person-centered approach is taken in order to (a) examine the existence of latent user profiles; (b) investigate factors that determine students' profile membership; and (c) estimate the relation between profile membership and performance on a computer and information literacy test.

Theoretical Framework

Computer and information literacy as an educational goal

With the rapid development of digital technology in today's society, the concept of digital literacy includes more than just basic technical knowledge; it encompasses a wider framework that includes the use of computers and the internet "as a fundamental learning tool" (H.-S. Kim, Kil, & Shin, 2014; Lennon, Kirsch, Von Davier, Wagner, & Yamamoto, 1993). The International Computer and Information Literacy Study (ICILS) 2013 conceptualized computer and information literacy (CIL) as a transversal competence in different contexts of learning with ICT both in and outside of school. It is defined as "individual's ability to use computers to investigate, create, and communicate in order to participate effectively at home, at school, in the workplace, and in society" (Fraillon, Schulz, & Ainley, 2013), p. 17), and comprises two strands with seven aspects: The first strand refers to "Collecting and managing information" and contains three aspects: 1.1) Knowing about and understanding computer use, 1.2) Accessing and evaluating information, and 1.3) Managing information. The second strand refers to "Producing and exchanging information" and contains four aspects: 2.1) Transforming information, 2.2) Creating information, 2.3) Sharing information; and 2.4) Using information safely and securely. In the context of ICILS 2013, computers comprise desktop computers, laptops, and tablets (Fraillon et al., 2014).

Computer and information literacy is clearly emerging as an essential part of school curricula in many countries in order to help students to become proficient and reflective users of ICT (Bai, Mo, Zhang, Boswell, & Rozelle, 2016; Fraillon et al., 2014; Vanderlinde, van Braak, & Dexter, 2012). Researchers, educators, and other stakeholders are unanimous in the opinion that integrating ICT in teaching and learning is an essential element of 21st century instruction (Binkley et al., 2012; Siddiq, Scherer, & Tondeur, 2016; Teo, 2014). In fact, not only does the use of ICT contribute to varying learning activities for students, it also assists teachers in preparing and developing learning material (Donnelly, McGarr, & O'Reilly, 2011; Wang, 2008). Prior research has shown that the integration of ICT depends, to a large extent, on student and teachers attitudes towards their ICT use (Hatlevik, Ottestad, & Throndsen, 2015; Mama & Hennessy, 2013; Prestridge, 2012; Sang, Valcke, Braak, & Tondeur, 2010; Teo, 2011). Nevertheless, it has also been pointed out that the successful integration of ICT requires fundamental shifts in the core activities of schools (Hayes, 2007; Tondeur, van Keer, van Braak, & Valcke, 2008). For instance, in 2006, the Norwegian Ministry of Education and Research identified the development in ICT-related competences in schools as a primary educational goal. Emphasis was put on understanding the role of ICT in learning and teaching processes along with the practical use of technology in developing learning outcomes.

As students are presented with new ways to participate in social activities and civic life digitally on the one hand (Hague & Williamson, 2010), and face the demand of developing competences that are required for their future work situations on the other hand (OECD, 2015a), it is important to provide them with opportunities to learn how to deal with

ICT in various settings and for multiple purposes. Hence, schools and educators have the mission to develop environments that allow for meaningful learning with ICT (Hew & Brush, 2006; John & Sutherland, 2004; Nivala, 2009). Moreover, since generous amounts of funds have been invested in ICT technology, it has become important to understand the ways in which students make use of these technologies (Erdogdu & Erdogdu, 2015). This knowledge may inform both parents and educators about potential needs for intervention and ways to foster the development of CIL. The data obtained from the ICILS 2013 study provide an opportunity to understand the contexts and outcomes of appropriate ICT use in various settings and for different purposes.

ICT use at home and in schools

As mentioned earlier, the use of ICT is subject to different purposes and contexts. Indeed, prior research has shown that students use ICT more frequently at home than in schools (Kent & Facer, 2004; Murphy & Beggs, 2003; Rohatgi & Throndsen, 2015; Selwyn, Potter, & Cranmer, 2009). The ICILS 2013 data confirmed this finding on the differences between home use and school use internationally (Fraillon et al., 2014). Specifically, about 87% of the students participating in ICILS 2013 reported that they use ICT at home at least once a week, whereas 54% reported the same frequency of ICT use at school and 13% at other places (Fraillon et al., 2014, p. 140). Rohatgi and Throndsen (2015) identified the same tendencies for the Norwegian sample. They extended these findings by showing that students, by and large, used ICT at home for recreational purposes rather than school-related activities. At school, significant differences across subjects could be identified with higher frequencies of ICT use in the social sciences and humanities than in mathematics and science. Furthermore, Fraillon et al. (2014) pointed out that students used specific ICT applications outside of school primarily for creating and editing documents; the Internet was mostly used for communicating with others or engaging in social networks. On the basis of PISA 2006 data, Tømte and Hatlevik (2011) took this research even further and were able to distinguish between students' user behavior during leisure time and at school, and related these two profiles to their self-efficacy and gender. These findings support the assumption that the use of ICT outside of school is more frequent than at school (Fraillon et al., 2014). At the same time, this is merely a descriptive observation and does not point to potential explanations for the differences in ICT use frequencies. Nevertheless, the less frequent use of ICT in schools may be attributed to teachers' acceptance of technology, their willingness to integrate ICT in teaching and learning, their sense of preparedness, and beliefs about their digital competences in classrooms (e.g., Graham, Borup, & Smith, 2012; Scherer & Siddiq, 2015; Teo, 2014; Tondeur, van Braak, Siddiq, & Scherer, 2016). Pelgrum (2001), for instance, argued that one of the main obstacles for the integration of computers in schools refers to the relatively limited professional development of teachers with respect to technology. This argument has been supported in the Norwegian context in that teacher training in the educational use of technology is largely missing (Tømte, Kårstein, & Sutherland Olsen, 2013), and teachers are in fact not required to use technology in their lessons (Guðmundsdóttir & Throndsen, 2015). Besides these potential barriers that may explain the less frequent use of ICT in schools, a number of large-scale studies revealed that even younger children use computers or other digital devices at an early age (Jacobsen, Loftsgarden, & Lundh, 2013). In light of the ICILS 2013 findings, this use outside of school seems to continue until at least grade level 9 (Fraillon et al., 2014). Overall, the current research on students' use of information and communication technologies revealed differences in the frequencies of ICT use at home and at school. These differences might be partly due to students' background and motivation, but also the availability of ICT resources and instruction at school.

The role of students' background and motivation in the use of ICT

In order to understand the contexts and determinants of students' use of ICT, researchers have studied potential covariates of ICT use. A number of studies have revealed that students' socioeconomic and home background, gender, their motivation toward using

ICT, and their self-efficacy play essential roles in this respect (Bozionelos, 2004; Fraillon et al., 2014; Livingstone & Helsper, 2007; Looker & Thiessen, 2003; Sutherland-Smith, Snyder, & Angus, 2003; Tondeur et al., 2010; Tømte & Hatlevik, 2011).

Background variables. Although students' background variables have been studied extensively in the context of educational technology, the evidence provided from these studies does not draw a clear picture about the actual effects of these variables. For instance, although Tondeur et al. (2010) identified significant relations between students' socioeconomic background and computer use, Van Braak and Kavadias (2005) could not. This diversity of research findings may be due to the differences in ICT access across the samples under investigation (Livingstone & Helsper, 2007). Alternatively, the diversity in parental support may provide another explanation; parents with higher education are found to be involved in their children's' education, facilitate learning and motivate them to do well in school. Research on the factors affecting academic achievement has shown that parents who accomplished a higher education are both interested in and familiar with learning at school, and lend more support to their children regarding school work and out-of-school activities (Houtenville & Conway, 2008; Jeynes, 2005). Along the same lines, mixed evidence on gender differences in the use of ICT for different purposes and in different contexts exists (Imhof, Vollmeyer, & Beierlein, 2007). For instance, in ICILS 2013, gender differences could not be found for Norwegian students' use of ICT for specific applications outside of school, whereas boys tended to use ICT more frequently for recreational purposes (Fraillon et al., 2014).

Another finding of existing research is that students' academic aspirations are positively correlated with their parents' education and occupation (Jodl, Michael, Malanchuk, Eccles, & Sameroff, 2001). It is not uncommon that teenagers have expectations about their future careers. In addition, the attitudes of parents and peers toward education and careers could be a source of potential influence in shaping educational aspirations (Hill & Wang, 2015; Nagengast & Marsh, 2012). These attitudes could, for instance, manifest in the provision of educational resources such as information and communication technology.

Besides students' gender and home background, the availability of ICT both at home and at school determine their use of ICT (Imhof et al., 2007; Sutherland-Smith et al., 2003; Vekiri & Chronaki, 2008). Looking at the school context, researchers identified a number of factors determining the use and integration of ICT in teaching. Among others, the availability of ICT, teachers' acceptance of digital technologies, teachers' education to integrate ICT, and school's curricular autonomy to integrate ICT were constraining factors that limited the use of ICT in schools in contrast to students' home resources (Donnelly et al., 2011; Hadjithoma & Karagiorgi, 2009; Røkenes & Krumsvik, 2016). Nevertheless, Kent and Facer (2004) argued that "boundaries between home and school are less distinct in terms of young people's ICT use than has previously been proposed" (p. 440).

Motivational variables. Tømte and Hatlevik (2011) pointed out that students' ICT self-efficacy, that is, the degree to which they believe they can master specific, ICT-related tasks (Compeau & Higgins, 1995), plays an essential role in the use of ICT. This relation can be interpreted in at least two ways: First, students who frequently use ICT may experience mastery in working on ICT-related tasks, which in turn helps them to strengthen the beliefs in their competencies (Usher & Pajares, 2008). This is in line with Bandura's (1982) original understanding of self-efficacy beliefs as beliefs about one's ability that are influenced by the environment and situations students engage in. Second, the more confident students are in using ICT the lower the barriers of using these technologies later on (Compeau & Higgins, 1995). Along the same lines do students' general attitudes toward ICT (i.e., their interest and enjoyment in it) influence the actual ICT use (Tondeur et al., 2010).

Taken together, researchers have recognized that students' home background and motivation correlate with the use of ICT to some extent; furthermore, these relations may be subject to gender differences.

The relation between ICT use and CIL

Reviewing existing literature with respect to the relation between the use of ICT and students' achievement in general, researchers have come to realize that there is mixed evidence: For instance, Kulik and Kulik (1991) conducted a meta-analysis and found that the longer students use ICT, the more experience and confidence they gain. Nevertheless, this positive finding did not automatically imply that there was a positive impact on students' learning. Tamim, Bernard, Borokhovski, Abrami, and Schmid (2011) identified a positive and moderate effect on the basis of more than 20 meta-analyses; thus providing evidence for the positive impact of ICT use on student learning. At this point, it has to be noticed that both meta-analyses focused on student learning in well-defined school subjects other than ICT education. Focusing on achievement in the context of ICT specifically, some studies identified significantly positive achievement – use relations (Berge, Hatlevik, Kløvstad, Ottestad, & Skaug, 2009; Hatlevik, Egeberg, Guðmundsdóttir, Loftsgarden, & Loi, 2013; Luu & Freeman, 2011), whereas others failed to identify any achievement gains in ICT-related competences (Angrist & Lavy, 2002; Appel, 2012). Interestingly, the use of ICT in schools correlated even negatively with achievement in a digital literacy test for a Norwegian sample of ninth graders (Hatlevik, Ottestad, et al., 2015).

Knowing that the use of ICT is rather complex to measure and to conceptualize, the achievement–use relation may further depend on the specific purpose for which ICT is used in different contexts. Indeed, using computers for recreation can be positively correlated with student achievement (Appel, 2012). This finding may be due to the focus of recreational computer use on participating in online discussions or using virtual environments – systems that require higher-order thinking and visual-spatial skills (Biagi & Loi, 2012; Steinkuehler & Duncan, 2008). In contrast to this positive finding, some researchers claimed that the use of ICT at home or in informal settings does not guarantee fostering CIL; hence, it is the mission of formal education to help students to develop digital literacy by providing meaningful opportunities to use ICT (Aesaert, van Braak, van Nijlen, & Vanderlinde, 2015; Aesaert, van Nijlen, et al., 2015).

The present study

Given that students' use ICT for different purposes in multiple rather than single areas in life, their profiles may not necessarily show equal frequencies in the use of ICT across the different types of ICT use. Based on this expectation, our assumption is that unobservable subgroups of students exist which represent distinct profiles of their ICT use. In order to test this assumption, we use a person-centered approach and identify latent (unobservable) profiles. These profiles are disentangled based on the means of the ICT use variables; this latent profile analysis groups students such that the resultant profiles comprise individuals that are similar to each other within the profile group, but different from individuals from another profile group (Lubke & Muthén, 2005). The ICILS 2013 data form the basis for our approach, and comprise six variables of ICT use in multiple settings (i.e., at school or at home) and for various purposes (i.e., recreation, study purposes, learning at school, information exchange, and social communication). These variables serve as indicators of the latent profiles in the first step of our analyses. In the second step, we investigate how profile membership relates to students' background and motivational variables. This step basically aims at identifying factors that may determine different user profiles. In a third and final step, we examine whether students' profile membership is associated with their achievement in a computer and information literacy test (distal outcome). Knowledge about this association provides insights into the nature of the different profiles, as it characterizes students within a profile with respect to their CIL. Against this background, the present study seeks to answer the following three research questions:

- *Do different latent user profiles of students' ICT use exist, and, if they exist, what characterizes them? (Research Question 1)*

- *To what extent do students' background and motivational characteristics differentiate the latent profiles of ICT use? (Research Question 2)*
- *To what extent can the latent profiles of ICT use be differentiated by students' achievement in the ICILS 2013 computer and information literacy test? (Research Question 3)*

Method

Sample and procedure

The Norwegian ICILS 2013 data set formed the basis for the present study. This data set comprised 2,436 ninth-grade students who were enrolled in 138 schools (50.2% girls). Students' average age was 14.8 years (*SD* = 0.3 years) and ranged between 14 and 16 years; one student did not report on his or her age and another student indicated that he was 19 years old. The latter student enrolled in grade level 9 at a later age, probably due to his immigration background. In total, the data obtained from 10 students had to be excluded from the data set, because they showed missing values on all variables under consideration in the present study. Hence, a final sample of *N* = 2,426 students was included in the analyses.

The ICILS achievement test and the student questionnaire were administered in a single test session with a short break between the two assessments. The questionnaire consisted of two parts which focused on background information such as gender, age, home resources, and parents' education, and ICT-related constructs such as ICT use for different purposes, ICT self-efficacy, and interest and enjoyment (Fraillon et al., 2014). All assessment instruments were delivered in a computer-based format. The processes of collecting and coding data were conducted by the International Association for the Evaluation of Educational Achievement (IEA) according to pre-defined quality standards (for details, please refer to Fraillon et al., 2014; Fraillon, Schulz, Friedman, Ainley, & Gebhardt, 2015).

Measures

In order to address our research questions, we used the ICILS 2013 measures of students' ICT use, ICT self-efficacy, interest and enjoyment, and their achievement in the CIL test along with background variables. In this context, ICILS 2013 specifically refers ICT to computers and thereby includes desktop computers, notebooks, laptops, netbooks, and tablets such as iPads (Fraillon et al., 2014, p. 125). Except for students' immigration status, gender, and educational aspirations, these measures resulted from an item response theory scaling procedure (Fraillon et al., 2015); specifically, Warm's weighted likelihood estimates (WLE) served as indicators for these constructs (Warm, 1989). In order to facilitate the interpretation of these scores, the scaling procedure was conducted in such a way that high scores on the scale reflect a stronger presence of the underlying construct and high levels thereof; responses were reversed to achieve this. For instance, high WLE scores on the ICT self-efficacy scale reflect on high self-efficacy. Details on the scaling procedures can be found in the ICILS 2013 technical report in chapters 11 and 12 (Fraillon et al., 2015).

ICT use for different purposes. We used the following six scales of students' ICT use for different purposes and in various settings: Use of specific ICT applications, use of ICT during lessons in school, use of ICT for recreation, use of ICT for study purposes, use of ICT for social communication, and the use of ICT for exchanging information. These scales implicitly reflected on the opportunities of ICT use that are presented both in and outside of school. Please find a more detailed description and the reported reliabilities for the Norwegian sample in Table 1. Students were asked to indicate the frequency of their ICT use; the resultant responses were scaled (WLE) and transformed to a mean of 50 and a standard deviation of 10 for equally weighted countries (Jung & Carstens, 2015).

Socioeconomic and immigration background. There are different measures such as economic wealth, cultural capital, education levels, and occupation of the parents that are used to capture socioeconomic background (Hauser, 1994). In ICILS 2013, students' socioeconomic status is indicated by the highest education of parent(s), parent(s) occupation, and home literacy (number of books at home) resources in the family. These three variables have been reported by students, and ISCO coding has been used for coding the occupation for comparisons between countries. In the questionnaire, students were required to identify their parents' level of education on predefined categories based on the ISCED definitions (UNESCO, 2006). In Norway, almost 66 percent of the students reported having at least one parent with a university degree. The highest occupational status was estimated as the maximum of the mother's and the father's status (HISEI). On average, Norwegian students' HISEI was 54.3 points (*SD* = 15.4)[1].

Students' home literacy index (HOMLIT) was derived from their estimations of the number books at home. The resultant categorical codes ranged from 0 (*0-10 books*) to 4 (*more than 200 books*). Please find more details on this index in Fraillon et al. (2015).

Finally, students' indicated their immigration background by choosing among the following options (IMMIG): 0 (*Student and/or at least one parent/guardian born in country of test*), 1 (*Student born in country of test but both parents/guardians or only one parent/guardian born* abroad), and 2 (*Student and both parents/guardians or only one parent/guardian born abroad*). In the analysis of latent profiles, this variable was dichotomized and indicated whether or not at least one parent or guardian was born abroad (0 = Native background [previous code 0], 1 = Immigration background [previous codes 1 and 2]).

Educational aspirations. One of the questions put to the students was to state the level of education they expected to attain for themselves. In this respect, ISCED definitions were used (UNESCO, 2006). A high percentage (64%) of students in Norway reported that they expected to complete tertiary university education. Students' ISCED was categorically

[1] In ICILS 2013, the HISEI points were categorized as follows: < 40 points: low HISEI (e.g., letter carriers, hairdressers); 40-59 points: medium HISEI (e.g., police officers, nurses); > 59 points: high HISEI (e.g., journalists, teachers, and lawyers).

scored and ranged from 0 (*I do not expect to complete ISCED 2*) to 4 (*ISCED 5a or 6*). Further details can be found in Jung and Carstens (2015).

ICT self-efficacy, interest, and enjoyment. In general, self-efficacy is understood as students' beliefs in their competence to solve specific tasks (Bandura, 1997). Specifically, ICT self-efficacy refers to students' confidence in solving basic and advanced computer- and Internet-related tasks (Fraillon et al., 2014). ICILS uses the terms "ICT self-efficacy basic" and "ICT self-efficacy advanced" to indicate two types of self-efficacy. Students were asked to rate the degree to which they believed how well they can perform thirteen computer- and Internet-related tasks on a 3-point scale (*1 = I know how to do this, 2 = I could work out how to do this, 3 = I do not think I can do this*). Six tasks were assigned to self-efficacy in basic ICT skills (e.g., "*Search for and find information you need on the Internet*"); seven tasks were assigned to self-efficacy in advanced ICT skills (e.g., "*Build or edit a webpage*").

The measurement of students' ICT-related interest and enjoyment comprised seven items (e.g., "*It is more fun to do my work using a computer than without a computer*", "*I use a computer because I am very interested in the technology*", "*I enjoy using the internet to find out information*") that students had to rate on a 4-point agreement scale (*1 = strongly agree, 4 = strongly disagree*). For both the self-efficacy and the interest and enjoyment scales, WLE scores with a mean of 50 and a standard deviation of 10 were obtained for equally weighted countries (Jung & Carstens, 2015). The reliabilities of these scales were sufficient (Self-efficacy in advanced ICT skills: $\alpha = .83$, Self-efficacy in basic ICT skills: $\alpha = .69$, Interest and enjoyment: $\alpha = .83$).

Achievement in the CIL test. The Computer and Information Literacy (CIL) test administered in ICILS 2013 comprised 62 items (Fraillon et al., 2014). This assessment was delivered in four test modules, two of which students had to solve within 60 minutes. By means of item response theory (IRT), students' responses were scaled, and an overall CIL achievement score (WLE) was obtained with a mean of 150 and a standard deviation of 10

(Fraillon et al., 2015). The resultant scores can be interpreted in the same way as sum scores, meaning that high values indicate high levels of CIL. The reported reliability of the CIL test on an international scale was .89 (Fraillon et al., 2015).

Data analysis

Estimator, missing data, and the clustered sample structure. All analyses that were aimed at examining the existence of latent profiles of ICT use (Research Question 1), the relations between profile membership, students' background, and motivational variables (Research Question 2), and the degree to which CIL achievement differentiates between the latent profiles (Research Question 3) were employed in the statistical package M*Plus* 7.3 (Muthén & Muthén, 1998-2015). Please find the corresponding samples code in Appendix A. In all models, robust maximum likelihood estimation was applied in order to correct for potential bias due to non-normality of variables (MLR estimator). Moreover, since students' responses and the resultant continuous indicators were subject to the clustering of students in schools, the current data implied a hierarchical structure. This structure was due to the sampling procedure conducted in ICILS 2013, in which two stages of sampling occurred: Schools were sampled at the first stage, and students within schools were sampled in the second stage (Fraillon et al., 2015). As a consequence, differences in the probabilities of being selected as a study participant occurred (Asparouhov, 2005). In order to adjust for these differences in all analyses, we used students' final weights (MPlus option WEIGHT = TOTWGTS; Fraillon et al., 2015), and the design-based correction of standard errors and the χ^2 statistic (MPlus option TYPE = COMPLEX; Satorra & Bentler, 2010). In this approach, the full-information-maximum-likelihood (FIML) procedures handles missing data under the assumption that they are missing at random (Enders, 2010). In the current data, only 0.4% of the variables were missing.

Latent profile analysis. We applied cross-sectional latent profile analysis (LPA), a method that identifies distinct groups of students on the basis of selected, continuous indicator variables of students' ICT use. This approach is of probabilistic nature and therefore results in probabilities of profile membership for individual students (Morin et al., 2011). It is also *person-centered*, because it attempts to group students that are similar to each other within specific ICT user profiles but different from students of other profiles (Lubke & Muthén, 2005; Marsh, Lüdtke, Trautwein, & Morin, 2009). In other words, LPA clusters individual students by creating, a categorical latent variable, which represents the unobservable (probabilistic) membership in a profile (Berlin, Williams, & Parra, 2014; Masyn, 2013). As Marsh et al. (2009) noticed, LPA has advantages in comparison to cluster analysis in that LPA allows for a more flexible, yet model-based approach to group students in homogeneous profiles, and provides fit indices that allow researchers to compare competing LPA models (p. 194).

Commonly, LPA is conducted by specifying a series of models with varying numbers of latent profiles; changes in relative fit statistics such as information criteria are examined subsequently (Nylund, Asparouhov, & Muthén, 2007). The LPA model with the lowest information criteria (i.e., Akaike's Information Criterion [AIC], Bayesian Information Criterion [BIC], and the sample-size adjusted BIC [aBIC]) is generally preferred (Marsh et al., 2009; Masyn, 2013). Moreover, the LPA model with *k* profiles can be accepted as the better-fitting model if the Vuong-Lo-Mendell-Rubin (VLMR) and Lo-Mendell-Rubin (LMR) likelihood ratio tests (LRT) indicate significant differences in the log-likelihood values in comparison to the LPA model with *k-1* profiles (Lo, Mendell, & Rubin, 2001; Nylund et al., 2007; Tein, Coxe, & Cham, 2013). Another criterion refers to the model's entropy, that is, the classification uncertainty. In the statistical package M*Plus*, the relative entropy is obtained as the degree of classification *certainty*; hence, the higher the relative entropy, the better the classification of students in latent profiles (Morin et al., 2011; Ramaswamy, Desarbo, Reibstein, & Robinson, 1993). Reinecke (2006) and Flunger et al. (2015) argue that entropies larger than .70 still indicate a good classification accuracy, whereas Pastor, Barron, Miller, and Davis (2007) claim that values larger than 0.60 may already be sufficient. The extent to which these guidelines apply to complex data sets such as the one obtained from ICILS 2013 in which data are clustered due to a two-step random sampling procedure (i.e., randomly sampled students clustered in randomly sampled schools) is however unclear.

At this point, it must be noted that the described tools and criteria to compare competing LPA models with the aim of deciding on the number of latent profiles have limitations. More specifically, Tein et al. (2013) showed that the AIC and the entropy obtained from an LPA model “poorly selected the correct number of classes, regardless of degree of separation, number of indicators, or sample size” (p. 640). Morin, Meyer, Creusier, and Biétry (2016) argued even further and suggested not to use entropy as a criterion for deciding on the number of profiles in LPA. Still, this index provides information on the accuracy of the classification. Furthermore, Schwinger, Steinmayr, and Spinath (2012), Marsh et al. (2009), and Morin et al. (2011) argued that the decision on the number of profiles must also be based on their interpretability; if they do not differentiate well, therefore complicating their interpretability, a solution with less profiles is preferred. As a consequence, we will not base our decision on the number of latent ICT user profiles solely on these statistics, yet on their interpretability.

Latent profile analysis with regression and a distal outcome. Addressing Research Question 2 on the relations between profile membership and students’ background and motivational variables, we introduced predictors of the latent profile variable to the LPA (Figure 1). This procedure estimates the probability of profile membership and the regression coefficients of the covariates simultaneously, thereby overcoming the potential bias that is caused by poor entropies in directly using the most likely profile membership as a grouping variable (Masyn, 2013). Since the outcome variable (i.e., the latent profile) is categorical, this procedure conducts a (multinomial) logistic regression with one profile as the reference group (Bulotsky-Shearer, Bell, & Dominguez, 2012). We finally added students’ CIL achievement as a distal outcome to the LPA regression model (Figure 1). In this model, the relations between profile membership and the outcome can be estimated directly; these relations are informed by the covariates (Lanza, Tan, & Bray, 2013; Muthén et al., 2002). We note that all latent profile analyses have been performed by constraining the variances of the ICT use variables to equality across the latent profiles, whereas means were freely estimated. In fact, alternative models with freely estimated variances converged on improper solutions (e.g., negative variance estimates), showed substantially lower entropies for all models that could be estimated (range: .65-.72), worse model fit, and lower classification accuracies. Moreover, the three- and five-profile solutions did not converge. Morin et al. (2016) as well as Eynon and Malmberg (2012) reported similar issues and consequently recommended constraining variances across latent profiles. We are aware that this constraint reflects on the substantive assumption that the variation in ICT use variables is equal across the profiles. Although this might not necessarily be the case from a theoretical perspective, we had to impose this constraint to the model for methodological reasons.

Results

Descriptive statistics and correlations of the ICT use variables

Before identifying potential user profiles, we examined the distributions of the ICT use variables. Table 2 details the resultant descriptive statistics, ranges, and moments, and shows that the use of ICT for the purpose of exchanging information was the least, whereas the use for study purposes and during lessons at school was the variable with the highest mean. Regarding the correlations among the different kinds of ICT use, low to moderate figures occurred (Table 3). Specifically, the highest correlations were found among the variables associated with using specific applications and the ICT use for study purposes (r = .42), the use of ICT for recreation and social communication (r = .46), and the use for social communication and exchanging information (r = .48).

Latent profile analysis

Decision on the number of profiles. We performed latent profile analyses with covariates, the distal outcome, and varying numbers of profiles to address our research questions (see the model in Figure 1). Table 4 details the model fit statistics and the results of the likelihood ratio tests. Clearly, the increasing numbers of latent profiles in the LPA models are associated with a decrease in the log-likelihood value (LL) and the information criteria, consistently across the different types of information criteria (i.e., AIC, BIC, and aBIC). This finding indicates that the more profiles are distinguished, the better the fit of the underlying categorical model. It also suggests that different profiles of ICT use exist, therefore contrasting the null hypothesis that there is only one latent profile. At the same time, the decrease in information criteria with larger numbers of profiles is natural as model complexity increases (Yi & Lee, 2016). Against this background, Morin and Marsh (2015) proposed using an “elbow plot” in order to present the changes in information criteria with increasing numbers of profiles. The point after which the changes flatten indicates the number of profiles in the data. Figure 2 shows the elbow plot for the current data and identifies the two-profile solution as such a point.

The model entropies systematically increased between the two- and five-profile solutions, and showed a slight decrease when adding a sixth profile. Although higher values of entropy indicate better classification accuracies, we did not accept the model with the highest entropy (five-profile solution, entropy = .821) as the final model for a number of reasons: First, referring back to our considerations of entropy as a criterion to decide on the number of profiles, we decided to base our decision not only on this statistic but on the likelihood ratio tests, the information criteria, and the elbow plot. Second, the solution with five profiles did not indicate a clear substantive differentiation between the suggested profiles and only small group sizes for some of their profiles (see Appendix B). Hence, the interpretability of this solution was compromised. The same reasoning applied to the solutions with three, four, and six profiles (see Appendix B). The entropy of .707 was sufficient, and the average classification probabilities for profiles 1 and 2 were reasonably high (Profile 1: 94.0%; Profile 2: 85.7%).

Regarding the likelihood ratio tests, the results suggested that there was no significant improvement in model fit when adding a third profile to the two-profile solution (Table 4), pointing to the preference of two latent profiles. In order to test the robustness and replicability of this finding, we randomly drew ten samples of n = 1,500[2] students from the current data set and performed the latent profile analyses again. For each of the ten random samples, the two-profile solution was preferred according to the above mentioned criteria and the results could be replicated by 98.3% (see Appendix C). This finding supported our decision for the two-profile solution. As a response to the first part of RQ1, we consequently state that two latent profiles of ICT use could be identified in the Norwegian ICILS 2013 data.

Description of the latent profiles. The second part of RQ1 was aimed at describing the two profiles. Table 5 details the corresponding figures, and Figure 3 depicts them in a diagram. Examining the means across the different types of ICT use, we found that profile 2 described students who use ICT for the different purposes and in the various contexts almost equally often. Their profile indicated a more frequent ICT use than that of profile 1 students. In fact, a comparison of the mean differences between the two profiles for each of the types of ICT use indicated significantly lower means for profile 1 with moderate to high effect sizes (Table 5). The lowest average score within profile 2 was identified for the use of ICT for exchanging information. In contrast to this profile, profile 1 showed a less consistent profile, and the lowest means could be identified for the use of ICT for recreation, social communication, and exchanging information. The mean differences between the two profiles in these types of ICT use were substantially larger than those in the school- and study-related

[2] The choice of this sample size was motivated by recent findings on the performance of the split-half method in large-scale data sets, which showed that random samples comprising 50% or more of the entire sample could be used to replicate LPA findings (Kampa, Neumann, Heitmann, & Kremer, 2016).

use variables; this is indicated by the lower effect sizes for the latter (Table 5). In addition to these descriptions, students in profile 1 use ICT for exchanging information less frequently than for other purposes. It is also noteworthy that students in profile 1 scored significantly lower than students in profile 2 in the specific use of ICT applications, which had the highest correlation with the use of ICT for study purposes.

Taken together, profile 2 can be characterized by a consistent and frequent use of ICT for different purposes and in various settings, whereas profile 1 describes students who frequently use ICT for school- and study-related purposes but a less frequent use of the Internet outside of school. The two profiles differed significantly in the frequencies of using ICT for recreation, social communication, and exchanging information.

Results of the latent regression. In order address our second research question, we examined the effects of students' background and motivational variables as covariates in the LPA model. Table 6 shows the resultant coefficients. Since profile membership was a categorical variable, the relations to covariates have to be interpreted in the context of logistic regression. The variance inflation factors (VIF) for each covariate ranged between 1.08 and 1.39 and indicated that the correlations among the selected covariates did not cause any substantial multicollinearity which may have led to biases in the reported regression coefficients. Hence, the positive relation to students' educational aspirations suggested that the *probability* of being a member of profile 1 increased if educational aspirations increased, respectively, the probability of being a member of profile 2 decreased. Along the same lines, the negative effect of immigration status revealed that the probability of being a member of profile 1 was significantly lower for students with an immigration background than for natives; hence, it was more likely for immigrant students to be a member of profile 2. Furthermore, self-efficacy in both basic and advanced ICT skills and ICT interest and enjoyment mattered for membership in profile 2; Girls were more likely to belong to profile 2 than boys. The unadjusted overall effect size (OOR) of the corresponding regression model was OOR = 3.32 and can be considered to be indicative of a large covariate effect (for details on this effect size, please refer to Allen & Le, 2008).

Finally, we addressed RQ3 on the extent to which the two latent profiles could be differentiated by CIL achievement by adding the CIL score as a continuous outcome variable to the simultaneous LPA regression model (see RQ2). The CIL score mean difference was insignificant, $\Delta M = 0.11$, $SE = 0.55$, $p = .84$; Profile 1: $M = 150.08$, $SD = 10.03$; Profile 2: $M = 149.97$, $SD = 10.03$. The same conclusion could be drawn from the R3STEP approach with CIL as the outcome variable, $\Delta M = 0.41$, $SE = 0.56$, $p = .47$; Profile 1: $M = 150.18$, $SD = 9.99$; Profile 2: $M = 149.77$, $SD = 9.99$.

In response to RQ2, we point out that students' immigration background, gender, self-efficacy in basic and advanced ICT skills, and their interest and enjoyment in ICT differentiated between the two latent profiles; in response to RQ3, we point out that CIL achievement was not related to profile membership; thus, this variable did not contribute to profile differentiation.

Discussion

This study was aimed at identifying latent profiles of students' ICT use in different settings. It also sought to examine the extent to which students' background and motivational characteristics contributed to the distinction between profiles. Finally, the relation between profile membership and students' CIL achievement was disentangled.

Reflections on the methodological approach

Before engaging in a discussion about the ICT user profiles, we would like to point out that the research approach taken in the present study can be best described as *exploratory*, *probabilistic*, and *person-centered*. More specifically, it was exploratory because we did not have any a-priori assumptions on neither the number nor the characteristics of the latent profiles. In fact, LPA is per se an exploratory method to identify unobservable profiles, and so are alternative methods such as cluster analysis (Morin et al., 2011). Our approach was probabilistic, because we did not assign students to a specific profile with perfect accuracy; yet, the assignment was based on the most probable profile membership (Masyn, 2013). Finally, we chose a person-centered methodology – an approach rarely taken in the context of ICT user behavior – in order to describe subgroups of students rather than an entire sample. Taking this perspective provided more differentiated insights into the characteristics of ICT use across contexts and purposes. To our knowledge, the identification of ICT user profiles by means of LPA has not yet been employed with a representative large-scale sample of students. The present study consequently adds to the substantive literature and provides an example of applied LPA in an educational context. At the same time, it brings up methodological challenges that are associated with LPA. For instance, the performance of commonly used statistics and tests such as the entropy or the bootstrapping parametric likelihood ratio test (BLRT) – an alternative test of LPA models with different numbers of profiles – has not yet been examined in detail for large-scale samples with complex (i.e., nested) data structures. Even further, although the BLRT is said to be a more reliable test than its alternatives (i.e., LMR- and VLMR-LRT; Nylund et al., 2007), it has not yet been extended to the kind of data we have used in the current study. Moreover, it is unclear to what extent the commonly applied guidelines for entropies to be sufficiently large (i.e., usually above 0.7) actually apply to complex data sets. In the Programme for International Student Assessment (PISA) in 2009, latent profile analysis was used to disentangle different reader profiles. The corresponding entropies for all countries ranged between .68 and .69 (OECD, 2010). Hence, the performance of entropy as a measure of classification accuracy in complex data sets is still to be examined. As a consequence, we did not base our decision on the number of profiles identified by LPA solely on entropy. In fact, we aligned our approach with Marsh et al.'s (2009) plea for taking into account both empirical and theoretical considerations when deciding for a final LPA model and thus the number of profiles.

Existence of latent ICT user profiles (RQ 1)

Overall, we found evidence on the existence of two latent profiles that describe students' use of ICT at school and outside of school. The mere existence of such profiles suggests that students – although given almost the same opportunities to access digital technology in Norway – do not equally exploit these opportunities (Chinn & Fairlie, 2010; Rohatgi & Throndsen, 2015). This leads to different patterns of ICT use, in which specific contexts and purposes are more pronounced than others. Specifically, the main differences between the two profiles identified in the present study were found in the use of ICT outside of school. Interestingly, Tømte and Hatlevik (2011) identified a similar distinguishing feature and consequently classified the profiles according to the use of ICT for "leisure purposes" and "school-related purposes". The finding that only small differences in the school-related use of ICT existed in our study can be explained by the fact that students in the same classroom are provided with the same opportunities to use ICT for learning; moreover, the differences in ICT availability in Norwegian schools were comparably small (Rohatgi & Throndsen, 2015). It therefore seems as if the profiles describe different ways how individual students make use of digital technologies rather than differences in ICT availability. Hence, our approach is, indeed, person- rather than variable-centered (Marsh et al., 2009).

Students in the two profiles differed largely in the extent to which they used ICT outside of school and for leisure-related activities that require an Internet connection. More specifically, latent profile 1 showed a less consistent use of ICT such that the lowest frequencies were identified for the leisure-related Internet activities. As Livingstone (2012) put it, digital technologies "are not yet so embedded in the social practices of everyday life as to be taken for granted" (p. 9). Indeed, there is evidence on differences in the use of computers and the Internet that was obtained from further studies (Cotten, 2008; Kent & Facer, 2004; D. Kim, Nam, Oh, & Kang, 2016). Watkins, Engel, and Hastedt (2015, p. 1) noted that one should not assume that "young people (…) naturally acquire CIL skills" inside and outside of school. For at least 2/3 of the students, the observation of less frequent leisure-related Internet activities outside of school contrasts what has been mutually argued about adolescents' ICT use in Norway: The ICILS 2013 descriptive data of the Norwegian sample suggested that the use of ICT at home was more frequent than at school (Fraillon et al., 2014; Rohatgi & Throndsen, 2015). However, it must be noted that this finding applied to the *entire sample*, thereby neglecting the potential existence of *subgroups of students*. The identification of such subgroups is, in fact, one of the strengths of the latent profile analysis conducted in the present study (Masyn, 2013; Tein et al., 2013). Against this background, we argue that distinguishing between latent profiles provides a more differentiated view on students' ICT use and its relations to further constructs.

This differentiated view on students' use of ICT will help teachers to understand and acknowledge its diversity, yet not to enforce a uniform and ideal type of user profile during instruction (Eynon & Malmberg, 2012). Even further, identifying differences and similarities between students in the use of ICT provides teachers with valuable information about students' potential needs for support, be it in order to strengthen their confidence in using ICT for school-related purposes or enhance their knowledge and skills to critically reflect on the use of ICT for social purposes. In fact, the latter might be practically relevant for teachers who would like to support students who use ICT for these purposes more frequently than others (i.e., members of profile 2); the awareness of such a user profile helps teachers to identify potential risks they might want to prevent (Chen, 2012).

In light of existing findings on different types of ICT users (Brandtzæg, 2010), profile 2, for instance, can be described as the "advanced users' profile", because both the frequency and variety of ICT use are high for its members. On the one hand, students who are likely to belong to this profile might be users who make use of digital technologies in various contexts; they may be reflective users who acknowledge the potential and possibilities of these technologies in many situations. On the other hand, this profile may represent a group of students that is at risk, potentially because they report a high frequency of ICT use for different purposes outside of school. For instance, according to the OECD (2015b), students who spend more than six hours online per weekday in an outside-of-school context, are more likely to feel lonely at school. These interpretations may both seem reasonable and therefore complicate the process of thinking about potential consequences for teaching and learning. We therefore argue that the practical importance of the identified profiles needs to be supplemented with further information on students' motives to use ICT and examined in specific contexts of teaching and learning. Indeed, the latter is critical because the interpretation of any profile that includes the use of ICT in schools cannot be separated from the classroom or school context (Hatlevik, Guðmundsdóttir, & Loi, 2015; Tømte & Hatlevik, 2011).

Influences of students' background and motivational characteristics (RQ 2)

As mentioned earlier, it is important to note that the interpretation of the relations among students' background, motivational characteristics, and profile membership is probabilistic. In this sense, positive and significant relations indicate that the higher the scores on the student variables, the higher the probability of being a member of latent profile 1, and therefore the lower the probability of being a member of profile 2; along the same lines, negative relations suggest that higher scores of student variables are associated with a lower probability.

Interestingly, the results obtained from the two different methods, which were applied to estimate the relations to covariates, by and large, concurred. Only the effect of students' educational aspirations was insignificant in the R3STEP approach due to a larger standard error, whereas this effect was significant in the simultaneous approach. Apart from that, the congruence between the findings points to their robustness across estimation procedures, and therefore provides stronger evidence on the relations to covariates (Popper Shaffer, 2006).

The LPA regression showed that the probability of being a member of latent profile 2 is related to students' immigration status, being a female student, and high levels of interest and self-efficacy in ICT. In fact, the positive relations between high levels of ICT use and motivation in this profile are somehow natural, given that a number of studies have already identified positive use–motivation relations (e.g., Tondeur et al., 2010; Tømte & Hatlevik, 2011). Students' interest in ICT and their self-efficacy can be regarded as variables that discriminate between the two profiles. Again, the fact that self-efficacy is considered to be such a variable is in line with Tømte and Hatlevik (2011), who were able to distinguish between ICT user profiles on the basis of students' self-efficacy.

Students' gender and their immigration background were further significant covariates of profile membership. As the probability of being a member of profile 2 was associated with being a girl, it seems as if girls tended to use ICT across different contexts and for different purposes consistently frequent in this group. It is interesting that gender determined profile membership in this study, because gender differences did rarely exist in the ICT use variables for the Norwegian ICILS 2013 sample (Fraillon et al., 2014). We interpret this result as indicative of the existence of potential gender-specific user profiles. Along the same lines, immigrant students were more likely to enter profile 2, showing high levels of ICT use at school and outside of school. Given that the differences in the school-related use of ICT were rather small, yet differences in the use of ICT outside of school occurred, immigration status seems to be sensitive toward these profile differences.

Our approach to examine the relations between profile membership and covariates extended existing research, such that determinants of the occurrence of different user profiles could be identified.

Differences in CIL achievement across profiles (RQ 3)

In our study, profile membership was not significantly related to students' achievement on the CIL test. This finding may have different explanations: From a substantive point of view, it suggests that a relation between CIL and user profiles does not exist for the current sample, although they differed largely in the use of ICT outside of school. It therefore seems as if these differences in ICT user profiles do not necessarily lead to differences in CIL achievement. This result sheds light on the often controversially discussed relation between ICT use outside of school and student achievement (Rosén & Gustafsson, 2016; Tamim et al., 2011). In fact, the ICILS 2013 study did not reveal substantial relations among students' ICT use and their CIL achievement in Norway (Fraillon et al., 2014); hence, it seems somehow expected that the profiles, which are identified on the basis of ICT use variables, do not differentiate by CIL achievement. From a measurement point of view, the CIL national achievement score may not necessarily provide a differentiated picture of students' CIL, such that specific competencies can be disentangled. Finally, the insignificant differences in CIL achievement also show that the two latent profiles cannot be interpreted as performance-based subgroups of students; rather, they only describe patterns of ICT use. Practically, this finding might also indicate that the acquisition of computer and information literacy is almost independent of where students get in touch with digital technology; situations inside as well as outside of school provide them with learning opportunities. Moreover, the intensity with which students use ICT for various purposes did not to play a significant role for the CIL achievement.

Limitations and future directions

The present study entails some limitations which point to opportunities for further research. First, this study provided insights into the Norwegian context of students' ICT user profiles. This context is characterized by a high degree of ICT availability in both families and schools with an almost complete access to the Internet and digital resources across the country (EuropeanSchoolnet, 2012, 2013). It may therefore be worthwhile comparing the occurrence of the latent profiles identified for the Norwegian ICILS 2013 data set with those resulting from countries that have only limited availability of ICT; the hypothesis is that ICT user profiles may represent country-specific entities (Erdogdu & Erdogdu, 2015).

Second, it is desirable to draw from an even larger pool of ICT use variables, which focus especially on the use of ICT in classrooms and schools. More specific information on how and for which purposes digital technology is implemented to support instruction and enhance students' learning may shed light on teaching effectiveness with ICT for specific user profiles. In order to achieve this, we encourage research that directly links student data on reported classroom instruction, school achievement, and computer and information literacy with teacher data on their ICT use in the very classrooms students were enrolled in. In this context, specific profiles of ICT use in school and for the purpose of learning could be disentangled in more depth.

Conclusion

This study has shown that different profiles of students' ICT use exist, therefore pointing to the fact that students do not equally exploit the opportunities offered by the almost complete availability of digital resources. Besides, as students' use of ICT varies across contexts (i.e., school-related vs. outside-of-school activities) and purposes (i.e., social communication, information exchange, study purposes, recreation), an overall high use of ICT across almost all areas of life cannot be assumed for all students. We also point out that it cannot be taken for granted that all students use ICT inside and outside of schools to the same extent, thereby acquiring digital competences similarly. In light of these results, we further conclude that it is important for researchers to consider distinguishing between subgroups of students in describing the use of ICT rather than reporting on the average ICT use for an entire sample. The findings in the current study point to the need for further research on the consequences different user profiles might have for student learning, behavior, and well-being inside and outside of school. From a teacher's perspectives, it also needs to be disentangled how knowledge about these profiles influences teaching practices in specific subjects.

We believe that by acknowledging the different patterns in students' ICT use, the teachers can rightly incorporate ICT in their pedagogical practice. Teachers will be able to identify the opportunities students could avail in order to enhance their digital competences. At the same time teachers will also be able to map the potential risks (e.g., extremely frequent ICT use outside of school without any guidance or purpose, potential risk of social isolation) thereby creating an awareness around the specific needs of students in these subgroups.

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Tables

Table 1

Description and reliabilities of ICT use scales

Scale	*#Items*	*Item stimulus*	*Item example*	*Response categories*	α
Use of specific ICT applications	7	How often do you use a computer outside of school for each of the following activities?	Using a spreadsheet to do calculations, store data or plot graphs (Excel)/ using drawing, painting, or graphics software	5-point scale ranging from 1 (Never) to 5 (Every day)	.80
Use of ICT during lessons in school	5	At school, how often do you use computers during lessons in the following subjects or subject areas?	At school, how often do you use computers during lessons in the following subjects or subject areas? Mathematics, Language arts: foreign and other national languages	4-point scale ranging from 1 (Never) to 4 (In every or almost every lesson); I don't study this subject/these subjects.	.71
ICT use for recreation	5	How often do you use the internet outside of school for each of the following activities?	Accessing the internet to find out about places to go or activities to do	5-point scale ranging from 1 (Never) to 5 (Every day)	.70
ICT use for study purposes	8	How often do you use computers for the following school-related purposes?	Working with other students from your own school, Completing worksheets or exercise	4-point scale ranging from 1 (Never) to 4 (At least once a week)	.81
ICT use for social communication	4	How often do you use the internet outside of school for each of the following activities?	Use the internet for posting comments to online profiles or blogs	5-point scale ranging from 1 (Never) to 5 (Every day)	.71
ICT use for exchanging information	4	How often do you use the internet outside of school for each of the following activities?	Use the internet for answering other people's questions on forums or websites	5-point scale ranging from 1 (Never) to 5 (Every day)	.64

Note. The reliabilities presented in this table refer to Cronbach's α and are those reported in the ICILS 2013 Technical Report (Fraillon et al., 2015).

Table 2

Descriptive statistics, skewness, and kurtosis of the ICT use variables

	M	*SD*	*Min*	*Max*	*Skewness*	*Kurtosis*
1. Use of specific ICT applications	49.09	8.84	22.82	95.64	-0.53	2.95
2. Use of ICT during lessons at school	52.67	5.93	35.53	76.62	-0.23	2.34
3. Use of ICT for recreation	51.12	7.71	20.88	80.21	0.67	2.75
4. Use of ICT for study purposes	52.65	6.89	23.92	83.46	-0.15	4.66
5. Use of ICT for social communication	49.92	6.80	27.04	75.27	0.36	3.31
6. Use of ICT for exchanging information	45.62	8.52	36.79	88.39	0.74	0.90

Note. ** p < .01

Table 3

Correlations among all variables under investigation

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
1. USEAPP														
2. USELRN	.21**													
3. USEREC	.34**	.12**												
4. USESTD	.42**	.27**	.34**											
5. USECOM	.27**	.11**	.46**	.26**										
6. USEINF	.32**	.11**	.35**	.23**	.48**									
7. ISCED	.03	-.01	-.00	.07**	-.04	-.09**								
8. HISEI	.03	-.02	.02	.03	-.08**	-.06**	.24**							
9. HOMLIT	.04	.01	.05*	.01	-.05*	-.02	.21**	.32**						
10. ADVEFF	.21**	.11**	.27**	.12**	.24**	.31**	-.07**	-.07**	-.03					
11. BASEFF	.17**	.07**	.24**	.12**	.25**	.18**	.06**	.05*	.10**	.52**				
12. INTRST	.19**	.08**	.35**	.14**	.26**	.22**	-.02	.02	-.03	.44**	.35**			
13. CIL	-.00	-.01	.00	.00	-.01	-.04	.01	.00	.01	-.02	-.01	.02		
14. GENDER	-.03	-.08**	-.10**	-.02	.03	-.05*	.16**	-.04*	.08**	-.31**	-.03	-.26**	.05*	
15. IMMIG	.08**	.02	.02	.09**	.03	.03	.02	-.17**	-.22**	.06**	-.01	-.00	.03	.02

Note. USEAPP = Use of specific ICT applications, USELRN = Use of ICT during lessons at school, USEREC = Use of ICT for recreation, USESTD = Use of ICT for study purposes, USECOM = Use of ICT for social communication, USEINF = Use of ICT for exchanging information, HOMLIT = Home literacy index, ADVEFF = Self-efficacy in advanced ICT tasks, BASEFF = Self-efficacy in basic ICT tasks, INTRST = Interest and enjoyment in ICT, CIL = Computer and Information Literacy , IMMIG = Immigration status (0 = native background, 1 = immigration background), GENDER = Students' gender (0 = boy, 1 = girl).

* $p < .05$, ** $p < .01$

Table 4

Comparisons of relative model fit indices between latent profile analysis models with up to six profiles

Number of latent profiles	*LL (Npar)*	*SCF*	*AIC*	*BIC*	*aBIC*	*Entropy*	*VLMR-LRT*	*LMR-LRT*	*Smallest group frequency*	*Interpretability*
1	-49,632.3 (12)	2.7785	99,288.5	99,358.1	99,319.9	1.000	–	–	100%	
2	**-46,682.8 (27)**	**2.1338**	**93,419.5**	**93,574.9**	**93,489.1**	**.707**	$\boldsymbol{p < 0.001}$	$\boldsymbol{p < 0.001}$	**32.1%**	**Good**
3	-46,374.7 (42)	2.3996	92,833.3	93,074.9	92,941.5	.763	$p = 0.348$	$p = 0.351$	2.49%	Difficult
4	-46,154.3 (57)	2.2418	92,422.5	92,750.4	92,569.3	.800	$p = 0.372$	$p = 0.374$	1.93%	Difficult
5	-45,981.2 (72)	2.0035	92,106.3	92,520.5	92,291.8	.821	$p = 0.207$	$p = 0.208$	2.19%	Difficult
6	-45,922.1 (87)	2.0051	92,018.1	92,518.6	92,242.2	.796	$p = 0.681$	$p = 0.689$	1.42%	Difficult

Note. LL = Loglikehood, Npar = Number of parameters, SCF = Scaling correction factor (Satorra & Bentler, 2010), VLMR-LRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio test, LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio test.

Table 5

Means of the ICT use variables for the two identified profiles (standard errors of means in parentheses)

Variable *M (SE)*	*Latent profile 1 (N = 1,580)*	*Latent profile 2 (N = 748)*	*t*	*d [95% C.I.]*
Use of specific ICT applications	46.47 (0.37)	54.60 (0.57)	18.01**	0.54 [0.45, 0.63]
Use of ICT during lessons at school	51.82 (0.28)	54.44 (0.35)	7.86**	0.25 [0.16, 0.33]
Use of ICT for recreation	48.51 (0.29)	56.75 (0.60)	17.84**	0.62 [0.53, 0.71]
Use of ICT for study purposes	50.93 (0.30)	56.19 (0.45)	14.66**	0.44 [0.35, 0.52]
Use of ICT for social communication	47.77 (0.23)	54.65 (0.55)	16.43**	0.61 [0.52, 0.69]
Use of ICT for exchanging information	42.00 (0.38)	52.87 (0.71)	18.25**	0.65 [0.57, 0.74]

Note. d = Effect size Cohen's *d*. ** $p < .01$

Table 6

Unstandardized regression coefficients of membership to latent profile 1 on predictors following the simultaneous modelling approach (based on the two-profile solution)

Predictor variables	*B (SE)*	*OR = Exp(B)*
Highest occupational status of parents (HISEI)	.00 (.01)	1.00
Educational aspirations (ISCED)	.18 (.08)*	1.20
Home literacy index (HOMLIT)	–.09 (.06)	0.92
Immigration status (0 = Norwegian, 1 = Immigration background)	–.50 (.21)*	0.60
Gender (0 = Boy, 1 = Girl)	–.45 (.18)*	0.64
Self-efficacy in advanced ICT skills	–.07 (.01)**	0.94
Self-efficacy in basic ICT skills	–.03 (.01)**	0.97
Interest and enjoyment in ICT	–.06 (.01)**	0.94
Overall effect size *OOR*	3.32	

Note. N = 2,328. Due to missing values in all covariates, the data of 98 students had to be excluded from these analyses. OR = Odds ratio; OOR = Unadjusted overall odds ratio for the entire set of predictors. * $p < .05$, ** $p < .01$

Figures

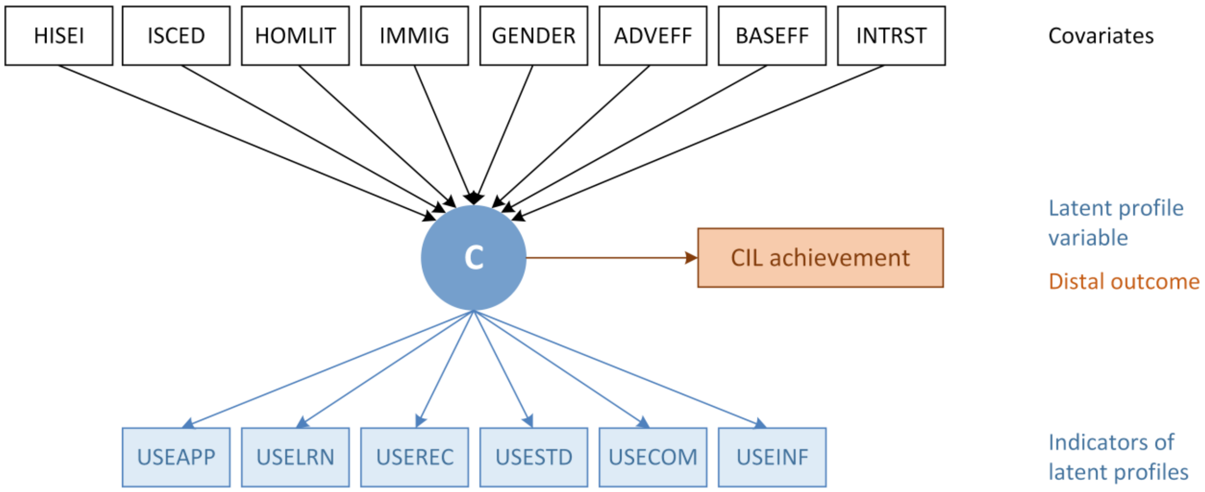

Figure 1. Full model of latent profile regression with CIL achievement as the distal outcome.

Note. C indicates the categorical latent variable describing the latent profiles. CIL = Computer and Information Literacy, USEAPP = Use of specific ICT applications, USELRN = Use of ICT during lessons at school, USEREC = Use of ICT for recreation, USESTD = Use of ICT for study purposes, USECOM = Use of ICT for social communication, USEINF = Use of ICT for exchanging information, HOMLIT = Home literacy index, IMMIG = Immigration status, ADVEFF = Self-efficacy in advanced ICT tasks, BASEFF = Self-efficacy in basic ICT tasks, INTRST = Interest and enjoyment in ICT.

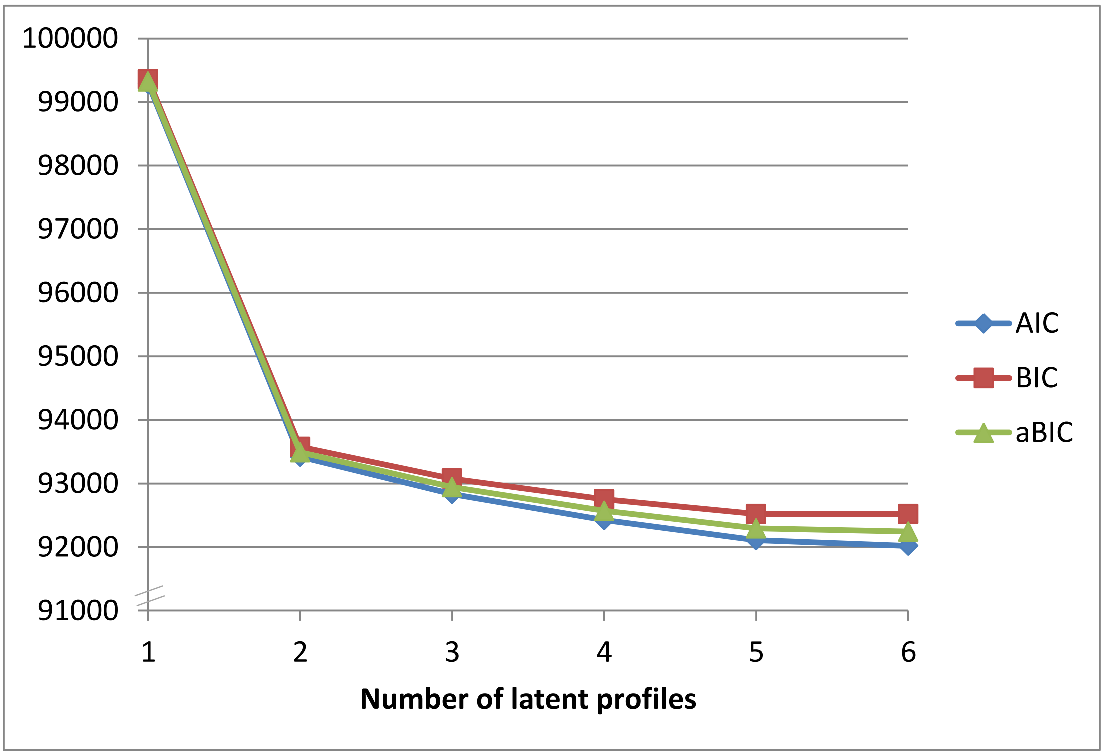

Figure 2. Elbow plot of the latent profile analyses with varying numbers of profiles.

Notes. AIC = Akaike's Information Criterion, BIC = Bayesian Information Criterion, aBIC = sample size adjusted Bayesian Information Criterion.

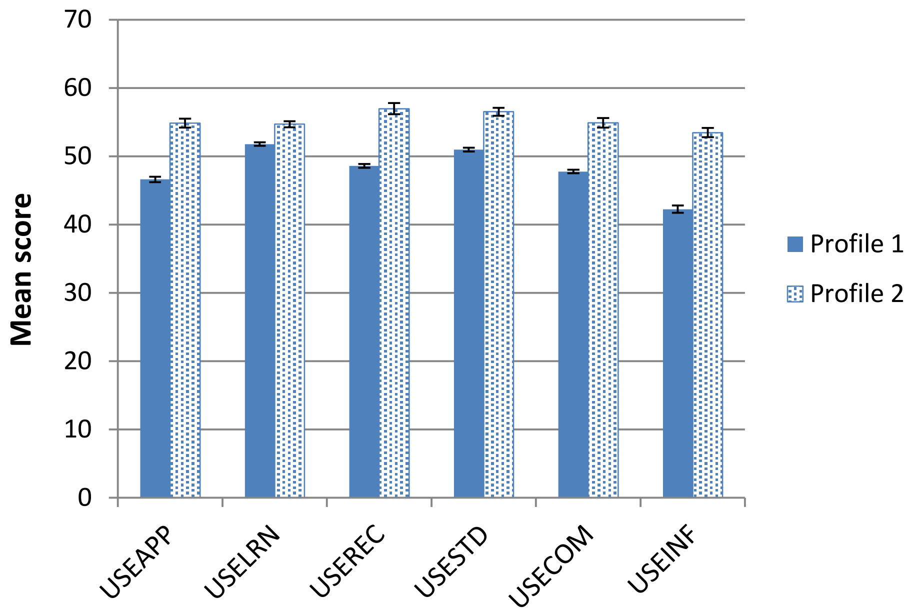

Figure 3. Means and their standard errors of means for the two-profile solution.

Note. USEAPP = Use of specific ICT applications, USELRN = Use of ICT during lessons at school, USEREC = Use of ICT for recreation, USESTD = Use of ICT for study purposes, USECOM = Use of ICT for social communication, USEINF = Use of ICT for exchanging information. The error bars indicate the standard errors of the means.

Highlights

- Two latent profiles of students' ICT use were identified.
- Profile 1 describes students who stay low on leisure-related Internet activities.
- Profile 2 describes students who frequently use ICT for almost all purposes.
- Profile membership was related to immigration status, gender, and motivation.
- The profiles did not differ in students' communication and information literacy.

Appendices

Students' Profiles of ICT Use: Identification, Determinants, and Relations to Achievement in a Computer and Information Literacy Test

A) M*plus* sample code of the Latent Profile Analysis (LPA) with covariates and the CIL score as the distal outcome

```
TITLE:    LPA of ICT use with predictors and a distal outcome
          Variable (CIL score)

DATA:     FILE IS icils2013nor.dat;

VARIABLE: NAMES ARE IDSCHOOL IDSTUD HISEI HOMLIT IMMIG
                    ISCED GENDER ADVEFF BASEFF INTRST CIL
                    USEAPP USELRN USEREC USESTD USECOM
                    USEINF TOTWGTS;
          ! ICT use variables are labelled as "USE"

          USEVARIABLES ARE HISEI-USEINF;

          CLUSTER = IDSCHOOL;
          ! School ID as the cluster variable to adjust
          ! standard errors and chi-square statistics

          IDVARIABLE = IDSTUD;
          ! Identify students' ID variable

          WEIGHT = TOTWGTS;
          ! Total weights to account for sampling bias

          MISSING ARE ALL(-99);
          ! Missing values are specified as -99

          CLASSES = c(2);
          ! Specify the number of profiles (in this case: 2)

ANALYSIS: TYPE = MIXTURE COMPLEX;
          ! Choose the type of analysis: mixture modeling
          ! The complex option is used to address the sampling
          ! and the clustering in schools.

          ESTIMATOR = MLR;
          ! Due to the complex sample design, the robust
          ! maximum likelihood estimation is chosen. It also
          ! accounts for deviations from normality.

          STARTS = 800 40;
```

```
          STITERATIONS = 40;
          LRTBOOTSTRAP = 100;
          LRTSTARTS = 10 5 80 20;
          ! Settings for the analyses
          ! (Morin, Morizot, Boudrias, & Madore, 2011)

          PROCESSORS = 3;
          ! Choose a number of processors to be used

MODEL:    %OVERALL%
          c#1 ON HISEI-INTRST;
          ! Multinomial logistic regression
          ! Use one profile as the reference (here: c#2)

          %c#1%
          ! Latent profile 1

          [USEAPP USELRN USEREC USESTD USECOM USEINF];
          ! Request means of ICT use variables in profile 1
          ! Notice that the variances of these variables are
          ! constrained to equality across profiles by default.

          [CIL](m1);
          ! Estimate the mean of the CIL score in profile 1
          ! CIL score is the distal outcome here.

          %c#2%
          ! Latent profile 2

          [USEAPP USELRN USEREC USESTD USECOM USEINF];
          ! Request means of ICT use variables in profile 2

          [CIL](m2);
          ! Estimate the mean of the CIL score in profile 2
          ! CIL score is the distal outcome here.

MODEL CONSTRAINT:

          new(diff);
          diff = m1-m2;
          ! Estimate the mean difference in the CIL score
          ! between the two latent profiles.
          ! This will give us the effect of profile membership
          ! on the distal outcome (i.e., the CIL score).

OUTPUT:   SAMP; STAND; CINTERVAL;
          ! Sample statistics, standardized coefficients, and
          ! confidence intervals

          TECH1; TECH7; TECH11; TECH14;
          ! Technical outputs
```

B) Means and standard errors of the means for the 3-, 4-, 5-, and 6-profile solutions

Table B1. Solution with 3 latent profiles

M (SE)	*Profile 1 (N = 1,033)*	*Profile 2 (N = 1,236)*	*Profile 3 (N = 58)*
USEAPP	52.73 (0.72)	45.51 (0.63)	61.03 (2.96)
USELRN	53.99 (0.32)	51.44 (0.38)	55.17 (1.45)
USEREC	54.60 (0.93)	47.57 (0.54)	66.60 (2.75)
USESTD	54.83 (0.47)	50.30 (0.49)	62.97 (3.33)
USECOM	52.54 (0.74)	46.94 (0.46)	69.07 (5.31)
USEINF	49.90 (1.40)	41.02 (0.36)	63.11 (4.84)

Table B2. Solution with 4 latent profiles

M (SE)	*Profile 1 (N = 1,304)*	*Profile 2 (N = 848)*	*Profile 3 (N = 132)*	*Profile 4 (N = 45)*
USEAPP	47.85 (0.36)	53.77 (0.46)	29.13 (1.18)	62.50 (3.60)
USELRN	51.80 (0.30)	54.15 (0.31)	50.61 (0.91)	55.67 (2.22)
USEREC	48.26 (0.37)	55.28 (0.61)	47.19 (1.15)	67.89 (3.84)
USESTD	51.37 (0.33)	55.26 (0.40)	44.85 (1.50)	64.13 (3.35)
USECOM	47.53 (0.31)	53.08 (0.63)	46.93 (1.25)	70.22 (3.27)
USEINF	41.41 (0.40)	51.16 (0.94)	42.06 (0.86)	64.75 (5.27)

Table B3. Solution with 5 latent profiles

M (SE)	*Profile 1 (N = 119)*	*Profile 2 (N = 1,336)*	*Profile 3 (N = 83)*	*Profile 4 (N = 738)*	*Profile 5 (N = 51)*
USEAPP	28.90 (1.18)	48.40 (0.35)	41.84 (1.41)	54.15 (0.42)	61.14 (2.70)
USELRN	50.96 (1.10)	51.99 (0.30)	50.57 (0.86)	54.29 (0.33)	54.80 (1.09)
USEREC	49.05 (0.91)	48.95 (0.30)	40.62 (1.34)	55.79 (0.54)	65.65 (3.15)
USESTD	45.74 (1.73)	51.78 (0.29)	46.74 (0.78)	55.45 (0.35)	62.64 (2.98)
USECOM	49.35 (0.75)	48.31 (0.26)	35.61 (2.27)	53.40 (0.47)	71.15 (1.82)
USEINF	43.17 (0.78)	42.00 (0.42)	37.93 (0.39)	51.80 (0.67)	63.75 (3.44)

Table B4. Solution with 6 latent profiles

M (SE)	*Profile 1 (N = 33)*	*Profile 2 (N = 43)*	*Profile 3 (N = 1,371)*	*Profile 4 (N = 209)*	*Profile 5 (N = 624)*	*Profile 6 (N = 48)*
USEAPP	41.64 (3.67)	42.83 (1.95)	48.55 (0.63)	39.97 (6.05)	53.93 (0.74)	60.96 (2.26)
USELRN	49.24 (1.74)	51.67 (0.80)	52.59 (0.38)	49.38 (1.98)	54.27 (0.42)	54.87 (1.10)
USEREC	49.80 (1.89)	41.79 (1.70)	49.87 (0.98)	44.40 (1.14)	56.24 (1.09)	65.74 (2.56)
USESTD	29.11 (2.38)	46.80 (1.31)	52.52 (0.52)	47.70 (2.04)	55.81 (0.60)	63.11 (2.73)
USECOM	52.75 (1.81)	30.46 (3.36)	48.87 (0.81)	44.81 (1.18)	53.94 (0.81)	71.83 (1.86)
USEINF	46.66 (1.57)	37.79 (0.48)	42.65 (1.21)	39.97 (0.75)	52.72 (0.97)	63.72 (3.07)

Note. USEAPP = Use of specific ICT applications, USELRN = Use of ICT during lessons at school, USEREC = Use of ICT for recreation, USESTD = Use of ICT for study purposes, USECOM = Use of ICT for social communication, USEINF = Use of ICT for exchanging information. Standard errors of means are shown in parentheses.

C) Replication of the LPA models for 10 randomly drawn samples (n_i = 1,500 students)

Comparisons of relative model fit indices between latent profile analysis models with up to six profiles

Number of latent profiles	*Random sample*	*Loglikelihood*	*SCF*	*Npar*	*AIC*	*BIC*	*aBIC*	*Entropy*	*p(VLMR-LRT)*	*p(LMR-LRT)*
1	1	-30583.3	2.1882	12	61190.5	61254.2	61216.1	1.000	–	–
	2	-30601.2	2.6808	12	61226.3	61290.1	61251.9	1.000	–	–
	3	-30575.2	2.3555	12	61174.4	61238.1	61200.0	1.000	–	–
	4	-30618.9	2.3885	12	61261.8	61325.5	61287.4	1.000	–	–
	5	-30639.3	2.3673	12	61302.7	61366.4	61328.3	1.000	–	–
	6	-30563.5	2.2291	12	61151.0	61214.8	61176.6	1.000	–	–
	7	-30547.9	2.6427	12	61119.9	61183.6	61145.4	1.000	–	–
	8	-30417.7	2.2156	12	60859.5	60923.1	60885.0	1.000	–	–
	9	-30520.9	2.4159	12	61065.8	61129.5	61091.4	1.000	–	–
	10	-30705.7	2.4514	12	61435.5	61499.2	61461.1	1.000	–	–
2	1	-28776.4	2.0024	27	57606.8	57749.0	57663.2	0.709	0.0108	0.0112
	2	-28792.8	2.1624	27	57639.7	57781.9	57696.1	0.717	0.0047	0.0049
	3	-28770.3	1.8845	27	57594.6	57736.9	57651.1	0.743	0.0000	0.0000
	4	-28831.3	1.9365	27	57716.7	57858.9	57773.1	0.709	0.0002	0.0002
	5	-28843.0	1.9212	27	57740.1	57882.4	57796.6	0.714	0.0001	0.0001
	6	-28721.9	1.8596	27	57497.9	57640.2	57554.4	0.708	0.0004	0.0004
	7	-28760.1	2.1684	27	57574.2	57716.5	57630.7	0.736	0.0059	0.0062
	8	-28695.3	1.7931	27	57444.5	57586.9	57501.1	0.732	0.0000	0.0000
	9	-28681.8	1.9548	27	57417.5	57559.7	57474.0	0.702	0.0000	0.0000
	10	-28878.8	2.0512	27	57811.6	57953.8	57868.1	0.716	0.0102	0.0106
3	1	-28563.5	2.2384	42	57211.1	57432.3	57298.8	0.743	0.3714	0.3746
	2	-28597.7	3.3440	42	57279.3	57500.6	57367.2	0.739	0.8025	0.8038
	3	-28571.0	2.2562	42	57226.0	57447.4	57313.9	0.796	0.4512	0.4547
	4	-28646.9	2.8761	42	57377.9	57599.1	57465.7	0.767	0.7790	0.7808
	5	-28636.8	2.5130	42	57357.5	57578.9	57445.5	0.770	0.5925	0.5948

	6	-28510.4	2.3016	42	57104.8	57326.1	57192.7	0.737	0.5255	0.5277
	7	-28563.4	3.4455	42	57210.8	57432.1	57298.7	0.792	0.7788	0.7796
	8	-28516.0	1.9283	42	57116.0	57337.4	57204.0	0.718	0.3153	0.3180
	9	-28496.3	3.1780	42	57076.7	57297.9	57164.5	0.748	0.8098	0.8112
	10	-28662.4	2.4371	42	57408.9	57630.1	57496.7	0.765	0.5145	0.5174
4	1	-28442.6	3.6156	57	56999.2	57299.4	57118.3	0.801	0.7804	0.7805
	2	-28435.0	1.8333	57	56984.0	57284.2	57103.1	0.835	0.3939	0.3973
	3	-28414.6	2.0004	57	56943.1	57243.5	57062.4	0.825	0.2962	0.2983
	4	-28496.7	1.9843	57	57107.5	57407.7	57226.6	0.816	0.2371	0.2375
	5	-28481.1	2.2483	57	57076.3	57376.7	57195.6	0.812	0.3444	0.3452
	6	-28334.3	1.8636	57	56782.6	57082.9	56901.8	0.784	0.2142	0.2150
	7	-28438.9	2.0593	57	56991.9	57292.3	57111.2	0.806	0.0937	0.0942
	8	-28399.0	2.0296	57	56912.1	57212.6	57031.5	0.803	0.0491	0.0496
	9	-28383.1	4.3594	57	56880.2	57180.4	56999.3	0.766	0.7232	0.7233
	10	-28525.0	2.0611	57	57163.9	57464.2	57283.1	0.804	0.2657	0.2670
5	1	-28315.2	2.0631	72	56774.4	57153.6	56924.9	0.802	0.2398	0.2398
	2	-28292.5	1.9503	72	56729.0	57108.3	56879.6	0.859	0.3867	0.3880
	3	-28307.3	1.7886	72	56758.6	57138.0	56909.3	0.853	0.1849	0.1874
	4	-28364.3	1.7987	72	56872.7	57251.9	57023.2	0.842	0.2950	0.2965
	5	-28383.6	1.8909	72	56911.2	57290.7	57062.0	0.832	0.1997	0.2004
	6	-28249.0	1.7378	72	56642.0	57021.4	56792.6	0.790	0.3707	0.3727
	7	-28339.3	1.9752	72	56822.6	57202.0	56973.3	0.798	0.5026	0.5041
	8	-28287.5	1.9084	72	56718.9	57098.5	56869.7	0.836	0.3878	0.3890
	9	-28279.9	1.9029	72	56703.9	57083.1	56854.3	0.817	0.3893	0.3932
	10	-28421.8	2.0403	72	56987.6	57366.9	57138.2	0.781	0.5156	0.5167
6	1	-28160.6	1.9038	87	56495.1	56953.4	56677.0	0.821	0.2398	0.2398
	2	-28233.2	2.2126	87	56640.3	57098.6	56822.2	0.806	0.7634	0.7635
	3	-28215.3	1.6948	87	56604.6	57063.0	56786.7	0.863	0.4210	0.4230
	4	-28221.8	1.6548	87	56617.6	57075.8	56799.4	0.880	0.2398	0.2398
	5	-28305.9	1.9539	87	56785.7	57244.3	56967.9	0.829	0.5206	0.5217
	6	-28143.2	2.2234	87	56460.4	56918.8	56642.4	0.814	0.7322	0.7324
	7	-28263.1	1.8452	87	56700.2	57158.6	56882.3	0.840	0.2398	0.2398

8	-28218.9	1.7050	87	56611.9	57070.5	56794.2	0.805	0.4017	0.4055
9	-28194.6	2.0314	87	56563.2	57021.4	56745.0	0.823	0.6922	0.6928
10	-28278.3	1.8965	87	56730.5	57188.8	56912.5	0.826	0.7029	0.7035

Note. Npar = Number of parameters, SCF = Scaling correction factor (Satorra & Bentler, 2010), VLMR-LRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio test, LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio test.

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