Beyond the Results: Identifying Students’ Problem Solving Processes on A Problem Solving Task

Jayeong Song

Master’s Programme
Assessment, Measurement and Evaluation
30 Credits

Centre for Educational Measurement (CEMO)
Faculty of Educational Sciences, University of Oslo

Spring, 2021

Contents

Popular Abstract

Through paper-based assessment, it is not possible to infer why some successful students are good at solving problems while others are not. However, with computer-based assessment, all students' interaction with a problem task is recorded in a log file with time stamps. Through a computer-generated log file, it is available to discover students' different problem solving processes and possible relation to their performance in problem solving. This paper focuses on identifying students' different problem solving processes based on a single task. The main finding is that four qualitatively distinct profiles were identified based on students' exploration strategic behaviors and time. Providing information on subgroups of similar problem-solving patterns and backgrounds can support teachers to adapt their instruction to specific students' needs and develop automated feedback teaching tools that can provide instant feedback.

Acknowledgements

I am really grateful to my supervisor, Ronny Scherer who has left an indelible mark on my research, thinking and writing. Words cannot adequately express how thankful I am for all your dedicated support, specifically, for responding instantly to my questions regarding my thesis, guiding me into the steep learning of Mplus and LPA, and encouraging me during this whole journey.

My gratitude is extended to CEMO faculty and teaching staff, with special thanks to Alexandra Niculescu and Stefan Schauber for pushing me into preparing thesis writing, giving feedback on my writings and presentation. I am also particularly grateful to Bryan Maddox for providing insights on process data.

I am also thankful for my academic friends for going through the whole master's program together, with special thanks to Daniel Sanchez for the attention to my thesis and for saving me from the quagmire of coding. I also thank my friends, with special thanks to Martin Jernslett and Daniel Won for proofreading of my thesis paper.

The master thesis is dedicated with the deepest love to my wonderful parents Sunhun Jeong and Changyong Song, and to my beloved grandparents, Myeongsuk Choi and Dongyeok Jeong. Your dedication led me to higher education, and you have all been inspirations to me during this journey and beyond.

Abstract

Complex problem solving (CPS), one of the most prominent 21st century skills, is an important educational goal. Previous studies have demonstrated that varying levels of proficiency in students' problem solving processes exist through computer-based assessments. This present study aimed to identify students' problem solving processes by focusing on a single item based on the Norwegian PISA 2012 logfile data (*N* = 353). To specifically identify distinct profiles of students' problem solving processes, this study derived fine-grained indicators that jointly considered several exploration strategies and time related to problem solving. Using latent profile analysis, this study identified four qualitatively distinct profiles of students' problem solving processes: inactive, struggling, proficient, and adaptive. Further analysis demonstrated that students' demographic characteristics (i.e., gender, SES) and motivational characteristics (i.e., openness) differentiated profile membership. In addition, students' profile membership differentiated their performance not only on a specific item but also on overall problem solving to some extent. Providing information about different profiles can support teachers to adapt instructions to specific students' needs and develop automated feedback teaching tools that can provide instant feedback. Limitations and future research are discussed.

Keywords: Complex problem solving, latent profile analysis, VOTAT (vary-one-thing-at-a-time), NOTAT (vary-no-thing-at-a-time), time-on-task, log file, PISA2012

Introduction

Today's students grow up in a rapidly changing and developing world with computers and technology (OECD, 2014a). In response to this situation, new types of skills appeared as central educational objectives within educational programmes. Complex problem solving (CPS) is the most prominent skill among 21st century skills (OECD, 2017). CPS is defined as individual competency to understand and solve problems that change dynamically and where no immediate solution is available (Frensch & Funke, 1995).

The Programme for International Student Assessment (PISA) has implemented a computer-based assessment of CPS in 2012 (OECD, 2013). With such an assessment, all students' interactions with a problem space are recorded in log files with time stamps. Based on the log file, identifying students' varying levels of proficiency in problem solving processes is possible beyond students' correctness of response (Goldhammer et al., 2017). All of these contribute to deeper understanding of the students problem solving processes underlying CPS; and therefore provide insights to educators and researchers in terms of targeted instruction and developing CPS skills for students (Zoanetti, 2010).

In the past few years, researchers have investigated identifying different patterns of students' problem solving based on cognitive or behavioral indicators to gain a better understanding of students' problem-solving performance (Eichmann, Greiff, et al., 2020; Gnaldi et al., 2020; Greiff et al., 2018; Stadler et al., 2019; Wu & Molnár, 2021; Xu et al., 2018). It is because previous research has demonstrated that varying levels of students' problem solving processes exist. For example, a successful problem-solver has shown to apply relevant exploration strategies on a task within a moderate time, while an unsuccessful problem solver showed a too low frequency of interaction within too little or too much time (Greiff, Wüstenberg, et al., 2015; Greiff et al., 2016; Kröner et al., 2005; Lotz et al., 2017; Wüstenberg et al., 2012).

Although the different levels of the problem solving processes among students cannot be identified solely based on a single indicator, only a few researchers have considered employing multiple meaningful indicators to identify subgroups of a similar pattern (Teig et al., 2020; Tóth et al., 2014; Ulitzsch et al., 2021). Therefore, this study aimed to identify students' problem solving processes based on more fine-grained indicators that jointly considered domain-general exploration strategies and time related to problem solving. For this purpose, latent profile analysis was conducted as it could identify initially unobserved (hidden) groups of students based on their process data and shed light on the existence of subgroups (Morin et al., 2011).

Overall, this study tried to identify several subgroups of similar problem solving patterns based on the response processes from the PISA 2012 log files of Norwegian students, especially focusing on a single CPS item, 'Climate Control.' Furthermore, to validate extracted profiles, this study investigated whether these extracted profiles could be predicted by students' characteristics (i.e., gender, openness, perseverance, SES) and whether there was possible relationship between these profiles and problem solving performance.

Theoretical Framework

Complex Problem Solving as an Educational Goal

According to PISA 2012 framework, complex problem solving (CPS) is defined as:

"An individual's capacity to engage in cognitive processing to understand and resolve problem situations where a method of solution is not immediately obvious. It includes the willingness to engage with such situations to achieve one's potential as a constructive and reflective citizen" (OECD, 2014, p.30).

This definition describes the key features of CPS. First, from a cognitive and behavioral perspective, CPS requires a multistep process such as exploring and understanding a problem to be solved, representing and formulating a hypothesis, planning and executing a solution, and then monitoring and evaluating the progress to resolve the complex problem (OECD, 2013, 2017). Another main feature of CPS is that a test-taker should actively interact with the problem to generate relevant knowledge to solve an unfamiliar or non-routine problem. This characteristic resembles Buchner's definition of CPS in which the regularities of task environments can only be revealed by interacting with the task environment and combining gained knowledge in the problem solving process (Frensch & Funke, 1995, p.14). The last feature of CPS is that not only cognitive and behavioral processes but also motivational and affective characteristics (e.g., willingness to engage in CPS) influence students' use of knowledge and skills in unfamiliar problem situations. (Funke, 2010; Mayer, 1998).

CPS has been named differently in prior literature depending on which aspect is in focus: dynamic (Greiff et al., 2012), interactive (Fischer et al., 2015), creative (OECD, 2014a). Although PISA 2012 CPS assessment used the term 'creative problem solving', this study employed the most established term in prior studies, 'complex problem solving.'

In addition, CPS consists of two conceptual facets: knowledge acquisition and knowledge application. While knowledge acquisition represents generating the knowledge based on one's understanding of a problem structure (Mayer & Wittrock, 2006), knowledge application refers to applying this gained knowledge for achieving a targeted goal of problem situations (Novick &

Bassok, 2005). These two facets of CPS are separated for assessment purposes although they are related and do not occur sequentially in the real world (Wüstenberg et al., 2012).

As computers and technology rapidly develop, the demand for people who are capable of resolving non-routine problems is increasing, while the demand for routine jobs decreases. (OECD, 2014a). In addition, other researchers have found that domain-general problem solving competency is strongly associated with students' academic success, and it is distinct from other cognitive abilities such as reasoning, intelligence, domain-specific problem solving (Funke & Frensch, 2007; Greiff et al., 2013; Molnár et al., 2013; Wüstenberg et al., 2012).

In this context, researchers, teachers, and other stakeholders are in agreement that CPS, one of the most prominent 21st century skills, is an important educational goal that should be included in school curricula. This opinion has been supported by prior studies that students' problem solving skills can be developed in a regular school curriculum (Csapó & Funke, 2017).

Specifically, log files from computer-based assessment provide great detail of students' problem solving processes during CPS beyond the correctness of students' responses. Moreover, based on these observed behaviors, inferring the cognitive processes underlying CPS is possible (Goldhammer et al., 2017). All of these will provide insights in terms of targeted instruction and developing CPS skills for educators and researchers (Zoanetti, 2010).

The Role of Exploration Strategies and Time Underlying CPS

To describe students' problem solving processes and explain the possible relationship to their successful CPS performance, researchers have studied several theory-driven behavior indicators (e.g., exploration strategies, time on task). A number of existing studies have focused on specific exploration strategies that students employ during CPS as a behavior indicator

(Greiff, Wüstenberg, et al., 2015; Lotz et al., 2017). This is because applying efficient exploration strategies (i.e., systematically interacting with the problem situation) is essential to generate relevant information regarding the problem structure in a CPS environment, in which not all relevant information is provided (Kröner et al., 2005).

The Exploration Strategies: VOTAT, NOTAT

Among possible exploration strategies, the most optimal exploration strategy in CPS is the VOTAT strategy, which refers to Vary-One-Thing-At-A-Time while keeping all other input variables constant (Chen & Klahr, 1999; Tschirgi, 1980). The use of VOTAT enables students to discover which independent variable is responsible for the direct effect on a dependent variable.

Several studies have argued that applying the VOTAT strategy is positively related to both knowledge acquisition and knowledge application (Greiff, Wüstenberg, et al., 2015; Greiff et al., 2016; Kröner et al., 2005). Moreover, existing studies have found that different levels of applying exploration strategies exist, which is relevant for successful CPS (Greiff, Wüstenberg, et al., 2015; Greiff et al., 2016; Molnár & Csapó, 2018; Wüstenberg et al., 2012). For example, Greiff et al. (2015) investigated whether students applied VOTAT for all input variables based on one specific task ‘Climate Control’ and found that varying levels of proficiency in the use of VOTAT exist: unable to use VOTAT strategy, partially applied, fully applied. In addition, they found that the application of VOTAT was positively related to not only item performance but also overall performance in problem solving. They argued that students who showed to apply the VOTAT strategy were able to apply successful exploration strategies in other CPS tasks, thus leading to better performance in overall CPS.

Meanwhile, when the changes occur by themselves in the dependent variables without test-taker's manipulation, VOTAT is not an optimal strategy anymore (Funke, 2001). Instead, NOTAT is a more relevant strategy to detect such indirect effects in that problem scenario. NOTAT is an abbreviation for varying No-Thing-At-A-Time (Greiff et al., 2016; Lotz et al., 2017).

Few existing studies regarding NOTAT indicated that NOTAT is significantly related to students' performance in CPS as well, and successful problem solvers are characterized by applying both VOTAT and NOTAT when relevant along with actively exploring the problem. For example, Greiff et al. (2016) investigated Finnish students (N = 1476) and found that students who occasionally used the NOTAT strategy in addition to actively exploring the problem, showed better performance in CPS than students who randomly manipulated variables. This finding was also confirmed by that the intelligent students applied NOTAT in addition to VOTAT when those strategies were effective across nine CPS tasks (Lotz et al., 2017).

The VOTAT strategy, in general, has been operationalized as dichotomous in previous studies while NOTAT has been operationalized as constraining all variables at zero in prior studies (Greiff et al., 2016; Lotz et al., 2017). Above this operationalized definition, the current study attempts to use more fine-grained indicators to understand how students explore the problem space. More details will be discussed in the method section.

Time Variables: Time-on-task and Time Before First Action

Time-on-task can be an indicator of test-taking effort or engagement on a task. For example, the total time that a test-taker spent on a specific task could indicate whether a test-taker has spent substantial effort to solve a problem or not. In addition, time-on-task can also be considered an indicator of cognitive and behavioral processes on solving a task. (Goldhammer et al., 2017, 2020; Wise & Gao, 2017).

Under the assumption that time-on-task can be an indicator of the difference in cognitive, behavioral process, a vast study has studied time-on-task in CPS. Previous studies have found that time-on-task had a positive relation with CPS performance (Goldhammer et al., 2014, 2020; Scherer et al., 2015), indicating that the more time students spend on an unfamiliar task, the better they perform in CPS. In contrast, Greiff et al., (2016) found an inverted-U-shaped relation with problem solving performance, indicating that too much or too little time on a CPS task is related to poor CPS performance. However, Naumann & Goldhammer (2017) argued that the relation between time-on-task and performance could vary across domains, constructs, individual ability, and levels of task difficulty.

Beyond the total time on a specific task, several studies pointed out the importance of planning before execution and found that the time taken before a first action was related to successful performance in problem solving (Albert & Steinberg, 2011; Eichmann et al., 2019; Unterrainer & Owen, 2006). For example, Albert & Steinberg (2011) found that individuals with a longer average amount of time before the initial action showed great performance with fewer actions in non-complex problem tasks. Along with the same line, Greiff et al. (2016) showed a negative relationship between the number of interactions and CPS performance, indicating that few interactions are preferred for successful CPS; thereby, highlighting the importance of planning. Similarly, Eichmann et al. (2019) indicated that planning before action is more beneficial in CPS, but the extent of relevance differs depending on the task.

Taken together, researchers have recognized that varying levels of students' problem solving processes exist, especially in the exploration strategies that students employ and time variables. Also, these varying level in students' problem solving processes were significantly related to students' CPS performance.

The Role of Noncognitive Factors Underlying CPS

Several studies have found that students' demographic and motivational characteristics may play essential roles in how students explore CPS environment.

Demographic Characteristics: Gender and SES

Concerning gender, several researchers have found gender differences in students' problem solving behaviors. For example, Wittmann & Hattrup (2004) argued that boys were likely to be engaged in risky behavior when facing unfamiliar problems, thus taking advantage of finding more information about the problem system, resulting in better CPS performance. Similarly, this finding was also supported by the meta-analysis result where boys showed more risk-taking behaviors than girls in general (Cross et al., 2011). Along the same lines, a recent study by Eichmann et al. (2020) argued that a gender difference in CPS performance could be fully explained by gender-specific interaction with the problem space. Moreover, several findings indicated that boys were more likely to use optimal strategies more often than girls, resulting in better CPS performance (Gnaldi et al., 2020; He et al., 2021; Wüstenberg et al., 2014; Wu & Molnár, 2021). This finding was also confirmed by the PISA 2012 report in which boys performed 7-score higher than girls in overall problem solving performance. However, it was noted that boys were specifically better in representing and formulating tasks while girls were better in planning and executing tasks (OECD, 2013).

Generally, existing research has revealed that students' educational performance is positively correlated with their SES, such as the education and occupation of parents (Dubow et al., 2009; Sewell & Shah, 1968). Specifically, students with high SES were found more likely to enjoy educational support from their parents, show more interest, and have high self-confidence in school subjects. It was argued that all of these advantages might facilitate their learning (Artelt & Programme for International Student Assessment, 2003).

There were few studies on the relationship between students' SES and problem solving processes, but only some studies related to students' CPS performance exist. For example, SES was related positively to CPS performance (OECD, 2014c), and the variation in SES explained about 11 % of students' CPS performance. In parallel, Csapó & Molnár (2017) showed that the education level of students' mother was significantly related to students' performance in the knowledge acquisition (r = .18). Given that SES predicts CPS performance (Csapó & Molnár, 2017; OECD, 2014c) and students' problem solving process (e.g., students' varying level of exploration strategy use) predicts CPS performance (Greiff, Wüstenberg, et al., 2015), it is reasonable to assume that students' SES might explain the variation in students' difference problem solving processes as well.

Motivational Characteristics: Students' Willingness to Engage in CPS

Besides students' demographic characteristics, their motivational characteristics determine the variability in how students explore the problem. Frensch & Funke (1995) pointed out that one's willingness to engage with novel situations is an integral part of problem-solving competence, indicating that the use of cognitive skills to solve a problem relies on motivational and affective constructs as well. In the same vein, PISA 2012 measured students' motivation as student's willingness to engage in problem solving via their openness and perseverance (OECD, 2014a). The underlying assumption was that motivational constructs could predict students' behavior and their performance in CPS (Dörner, 2013). PISA data indicated that a high level of students' willingness to solve the problem might guide a high level of proficiency in CPS, differentiating top-quality students (OECD, 2014a).

Existing research has also found that one's motivation predicted cognitive achievement. They explained that motivation may facilitate the effective use of knowledge and skills, thus leading to better achievement, even when facing difficulties (Hautamäki et al., 2002). In addition, Rudolph et al. (2017) showed that one's perception of being capable to solve a complex problem was related to CPS performance. Similarly, on the basis of PISA data, Scherer & Gustafsson (2015) found a positive relationship between students' openness and perseverance ($p = .47$), and these two constructs were positively correlated with CPS performance across countries ($r = .25$-$.36$). This was confirmed by several longitudinal studies as well in which learning-related motivation predicted CPS performance (Mustafić et al., 2019; Vainikainen et al., 2015). Specifically, Mustafić et al. (2019) pointed out that students with positive learning motivational beliefs gradually improved strategy use during CPS assessment.

Taken together, researchers have recognized that students' demographic characteristics (i.e., gender, SES) and motivational characteristics (e.g., openness, perseverance) are associated with how students explore problem space to some extent.

The Present Study

Given that varying levels of proficiency exists in students' exploration strategies and time, it is reasonable to consider that several latent (i.e., unobserved) subgroups of students may exist. To test this assumption, the present study employs latent profile analysis with the Norwegian PISA 2012 log file. To provide more detail of students' proficiency in how students explore one specific task, 'Climate Control', this study jointly considers the frequency of students' exploration strategies and time variables. In addition, this study investigates how students' demographic and motivational characteristics are related to their profile membership. It is aimed at finding variables that may determine different profile membership. Lastly, this study examines whether student's profile membership is associated with their performance in CPS. The current study investigates the following three research questions:

- RQ1 : Which profiles can be identified based on students' exploration strategies and time variables?
- RQ2 : Which variables (i.e., gender, SES, openness, perseverance) differentiate students' profile membership?
- RQ3 : How do the profiles differ in terms of item performance on climate control and overall problem-solving performance?

Method

Sample and Procedure

The present study used the Norwegian PISA 2012 CBA problem-solving data set. Out of 4686 students, 410 students were assigned to the climate control task. Seven students had to be excluded due to a recorded error (i.e., the student ID was missing for five students, time value was negative for two students). In addition, 45 students had to be excluded as they only submitted answers without any interaction with the simulated problem interface. Lastly, five students were dropped as identified outliers. Hence, the final sample was N = 353 students in 161 schools. The average age of the students was 14.9 years (SD = 0.3 years, 45% of girls in the student sample).

The computer-based assessment of problem solving was administered in 40 minutes after the major domain of cognitive assessment administration such as reading, math, and science. In addition, the PISA background questionnaire was given to students for 30 mins to collect information about students' demographic characteristics, family and home resources, classroom and school climate, math learning experiences, and problem solving experiences (OECD, 2013).

Measures

The Climate Control Task

The present study used a specific task unit called "Climate Control" (see Figure 1). This unit consisted of two items that correspond to knowledge acquisition and knowledge application of CPS. This study only focused on one item CP025Q01, the knowledge acquisition stage of the climate control unit. At this stage, students were expected to apply appropriate strategies to obtain the knowledge related to the problem structure (i.e., what constitutes the problem and how important factors are related and interact with one another) (OECD, 2013).

In the computer-based assessment, all the interactions students performed to solve the given problem were recorded, along with timestamps, in a log file (OECD, 2013). Based on all students' actions in the knowledge acquisition stage of the climate control unit, six pre-defined problem-solving process indicators were extracted: familiar time (i.e., time taken before any execution performed by a student), total action time (i.e., time taken until the last action of the students), NOTAT (i.e., the number of non-interfering observation strategy), effective VOTAT (i.e., the number of applied VOTAT strategy for input variables such as top, center and bottom; VOTAT indicated changing one variable at a time; note that redundant VOTAT was not counted so the range was from 0 to 3). Redundant VOTAT (i.e., the number of repeated VOTAT strategy after the VOTAT strategy was already applied for one input variable) and action (i.e., the number of exploration behavior not overlapped with any other strategy; changing multiple inputs at a time). Students' latent profiles were identified based on these six manifest indicators (RQ1).

Demographic and Motivational Characteristics

To address which predictors may differentiate the latent profiles of the problem-solving process (RQ2), students' demographic characteristics (i.e., gender, SES: social and economic status) and their motivational characteristics related to general problem solving (i.e., openness, perseverance) were used in this study. To capture the students' SES, the index of economic, social and cultural status (ESCS) was used. This index was assessed based on the highest parental education level, literacy resources in the family, and parental profession (OECD, 2013). The reliability using Cronbach's alpha for this scale was 0.56 (OECD, 2014b). Furthermore, to measure how much students were willing to engage in problem situations, five items related to their openness to problem solving were administered (e.g., *I like to solve complex problems*; OECD, 2013). The openness measure consisted of students' intrinsic motivation and self-belief in one's problem-solving ability (Scherer & Gustafsson, 2015). These response options ranged from *1 (Very much like me)* to 5 (*Not at all like me*). The reliability using Cronbach's alpha for this scale was 0.88 (OECD, 2014b).

Furthermore, to measure students' willingness to engage in problem solving when being confronted with difficult problems, five items related to perseverance were given to the students (e.g., *When confronted with a problem, I give up easily*; OECD, 2013). A five-point scale was used for this measure (from *1 = Very much like me* to *5 = Not at all like me*). The reliability using Cronbach's alpha for this scale was 0.83 (OECD, 2014b). The score of openness, perseverance and SES were estimated using Warm's weighted likelihood estimates (WLE) and rescaled to a mean of 0 and a standard deviation of 1. Positive values of these scores implied high levels of the corresponding constructs (OECD, 2014b).

Problem Solving Performance

The PISA 2012 CPS assessment contained 16 test units with a total of 42 items, with 15 static and 27 interactive items. While all necessary information was given to students from the start in static problems, students were required to interact with problem situations to acquire necessary knowledge to solve interactive problems. The cognitive processes involved in CPS comprised exploring and understanding, representing and formulating, planning and executing, monitoring and reflecting (OECD, 2013). For example, climate control corresponded to the representing and formulation cognitive process.

The current study used both item performance on climate control and overall problem solving performance. For the item performance on climate control, full credit was given if the correct diagram was drawn for all output variables at the knowledge phase of this unit (coded as *1 = Full credit*); otherwise, no credit was given (coded as *0 = No credit*; see Figure 1). For the overall problem-solving performance, the five plausible scores were generated based on students’ responses on the static and interactive items. These five plausible scores were combined following Rubin’s rules (Campion & Rubin, 1989), and the overall problem-solving performance was rescaled with a mean of 500 and a standard deviation of 100. The positive value of this score can be interpreted as a high level of problem-solving competence, and the reliability using Cronbach’s alpha for this scale was 0.86 (OECD, 2014b)

Data Analysis

Data Cleaning and Preparation

In order to clean and prepare the data, R version 4.0.1 was employed (R Team et al., 2014). For the CP025Q01 item, five event types were available in the downloaded log file. (i.e., start, end, apply, reset, diagram). Since the diagram of event type mainly indicated drawing a line to represent the relation between two input variables and three output variables in the item space, this log event was deleted. Furthermore, the log events generated by the system (i.e., start, event) had to be deleted. While the end of event type was deleted from the beginning, the start of event type was kept until extracting specific exploration strategies was completed and deleted later (see Figure 2).

In the current study, having elaborated profile indicators which could form different types of latent profiles was essential under the assumption that profile indicators (observed data) represent a mixture of distributions of different level of problem processes. As mentioned earlier, previous researchers pointed out that successful problem solvers are characterized by applying explorations strategies, such as VOTAT and NOTAT (Lotz et al., 2017). Also, the time has been highlighted as a factor related to the success of CPS (Scherer et al., 2015). Therefore, based on the times recorded along with event types, the time students spent to familiarize themselves with the task was identified by subtracting time recorded with start event type from recorded time with the first event performed by students. Total action time was obtained by subtracting the time recorded with the first event from the last event performed by a student.

In order to extract exploration strategies, two adjacent experiments (i.e., rows) had to be compared. First, the number of NOTAT was counted if the same experiments were conducted in a sequence (i.e., clicking apply button with the same experiment setting). Second, VOTAT was operationalized as occurring for a pair of two experiments if two experiments differed in only one condition (e.g., either top, center, bottom). In contrast, if multiple input variables were manipulated at a time, this was distinguished as an action.

VOTAT was counted if the two experiments differed in only one condition when two adjacent experiments (i.e., rows) were compared. After extracting the VOTAT, this VOTAT strategy was further refined as effective VOTAT and redundant VOTAT. This was because students applied a repeated VOTAT strategy for input variables even though they already reached the optimal number of VOTAT (i.e., applying VOTAT for all input variables) and not all students showed applying the VOTAT strategy for three input variables. Therefore, instead of counting the total number of VOTAT or merely whether VOTAT is used or not, more elaborated VOTAT indicators (i.e., effective VOTAT, redundant VOTAT) were used.

In addition, it was noted that extreme outliers might bias the estimation of the final profile solution or lead to having profiles only with few extreme cases (Vermunt & Magidson, 2002). In order to avoid this issue, five students were dropped after they had been identified as outliers for latent profiles indicators using Mahalanobis distance (MD) with a 0.01 cutoff for the *p*-value (see Figure 3). Based on the samples' distance from the central mean, a high value of MD indicated that the data is placed far from most of the samples (Leys et al., 2018).

Estimator, Missing Data, and the Clustered Sample Structure

All analysis was conducted using M*plus* version 7.3 (Muthén & Muthén, 1998-2012) to answer the following research questions: the existence of latent profile (RQ1), which variables differentiate the latent profile membership (RQ2), and how the various profiles differ in terms of item performance on climate control, overall problem-solving performance (RQ3). The related sample code can be found in Appendix II. In all analyses, maximum likelihood estimation with robust standard errors was employed to handle possible bias that might be caused by the non-normality distribution of the sample data (M*plus* option ESTIMATOR = MLR; Berlin et al., 2014). Furthermore, missing data on covariates were handled with the full information maximum likelihood estimation (FIML) under the assumption that the missing data (3.9% of the data) occurred randomly (Enders, 2010).

The two-stage sampling of PISA 2012 had to be considered in this study. In the sampling procedure, students were randomly chosen within each of randomly selected schools (OECD, 2014b). This sampling design resulted in unequal probability sampling (Asparouhov, 2005). Hence, the final student weights were incorporated in all analyses (M*plus* option WEIGHT = W_FSTUWT), and standard errors and chi-square tests of model fit were corrected (M*plus* option TYPE = COMPLEX; Satorra & Bentler, 2010).

Latent Profile Analysis (LPA)

Under the assumption that subgroups of students might be identified with similar patterns of problem processes in a population, cross-sectional latent profile analysis was conducted based on six indicators of the problem-solving processes (see Figure 4). LPA represents a latent categorical variable modeling approach in which students can be classified into the most likely latent profiles on the basis of continuous indicators (Morin et al., 2011; Nylund et al., 2007; Vermunt & Magidson., 2002). The profiles students belong to are internally identical, but externally distinctive to other profiles (Berlin et al., 2014). The highlighted advantage of LPA over other methods, such as cluster analyses, is in terms of accuracy and flexibility. It is relatively accurate compared with class analysis as LPA provides statistical fit indices so that researchers can choose which model is most appropriate among competing models (Lanza et al., 2013). It is also a model-based technique, so latent profiles models can be extended by including covariates or distal outcomes in LPA models (Wang & Hanges, 2011).

To find the best fitting and meaningful solution, previous researchers have suggested using multiple criteria: not only relying on statistical fit indices but also content-based criteria, such as the qualitatively distinguished character of the profile with substantial profile size (Nylund et al., 2007; Spurk et al., 2020; Vermunt & Magidson, 2002). Following these guidelines, the LPA was conducted by specifying a series of exploratory models with a varying number of latent profiles, and compared comprehensively for deciding on profile enumeration using information criteria as relative model fit indices, classification quality information, likelihood-ratio tests, interpretability, and sample size. For the information criteria, the Log-Likelihood value (LL), Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC), the sample-sized adjust BIC (SABIC) were used. A model with the lowest value of information criteria is preferred as the best-fitting model (Marsh et al., 2009; Masyn, 2013). For the likelihood-ratio tests, Vuong–Lo–Mendell–Rubin likelihood ratio test (VLMR-LRT), Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) were used. These likelihood-ratio tests compare adjacent nesting models (i.e., n-1 versus n profile model). A significant *p*-value (p <.05) indicates that the n-profiles model is superior to the (n-1)-profiles model (Masyn, 2013; Nylund et al., 2007; Yungtai Lo et al., 2001). For the classification quality information, posterior classification probabilities and entropy were investigated. Posterior classification probabilities indicate the quantity of how entities were correctly classified into profiles. A mean value of 0.80 is commonly accepted as appropriate (Collins & Lanza, 2009). In addition, entropy did not serve as a selection criterion in the current study as previous studies demonstrated its poor selection on the number of profiles and recommended not to use it. (Morin et al., 2016; Tein et al., 2013).

Instead, entropy was used to see how well the profiles were classified. Higher entropy (close to 1) indicates a well-separated profile. Entropy with a higher value than 0.80 is often accepted as appropriate (Masyn, 2013). How well an additional profile provides substantial qualitative information was also considered. If not, a more parsimonious model was preferred (Berlin et al., 2014; Vermunt & Magidson, 2002). Lastly, profile size was considered. If an additional profile has a relatively small size in the profile, a strong argument was required to retain that additional profile unless it was not recommended due to the lower power (Masyn, 2013; Nylund et al., 2007).

Although an optimal solution is decided by the log-likelihood parameter at a maximum when its value is close to zero, there is a chance of obtaining a local maximum instead of a global maximum (Berlin et al., 2014). In order to avoid potential local solutions, the random starts and final stage optimizations were set as 800, 40 respectively (Morin et al., 2011). As a result, the output showed that the best loglikelihood value was replicated, indicating that the result was not from the local solution.

To circumvent convergence issues, the variances of indicators were constrained to be equal across all latent profiles, while their means were freely estimated (Morin et al., 2016).

Latent Profile Analysis with Regression and a Distal Outcome

To examine which student characteristics explain latent profile membership, predictors (i.e., gender, openness, perseverance, SES) were added to the extracted latent profile model (see Figure 4). Using a one-step approach, students' characteristics were treated as an indicator of the latent profiles. As a result, it returned estimates of the profile membership probability and the regression coefficients of the predictors together (Nylund-Gibson et al., 2019). That is a multinomial logistic regression with one profile as the reference group (Bulotsky-Shearer et al., 2012).

Students' problem-solving performance served as a distal outcome variable to estimate the possible differences between the latent profiles (see Figure 4). To attain students' overall problem-solving performance, the analyses were conducted using the five plausible values, and the parameter estimates were combined based on Rubin's rules (OECD, 2014b). Regarding the item performance on Climate Control, the manual BCH three-step approach was employed to compare differences across profiles in the item performance (coded as 0 = incorrect, 1 = correct) (Nylund-Gibson et al., 2019). In the BCH approach, a new data file was generated at the first stage using the M*plus* options AUXILIARY(CP025Q01) and SAVEDATA: SAVE = BCHWEIGHTS. Then this data file was used for estimating the model in which item performance was added to the latent profile model at the second stage (Nylund-Gibson et al., 2019).

Results

Descriptive Statistics and Correlations

Before extracting latent profiles, the present study examined the distribution and correlations of all used variables (i.e., indicators, demographical and motivational variables, students' problem-solving performance). Table 1 presents the descriptive statistics. These statistics suggested that a few variables in the sample deviated from a normal distribution (e.g., highest $skewness_{NOTAT}$= 2.28, $kurtosis_{NOTAT}$ = 6.51). Hence, applying MLR estimation was justified for handling the non-normality of continuous indicators (Berlin et al., 2014).

On average, Norwegian students spent 50 seconds before they initiated any action. Besides, they conducted a NOTAT strategy 12 times on average to observe how the system is changing itself without any interference. Given that the effective VOTAT was 2 on average, not all students applied VOTAT for all three variables. Moreover, their average of redundant VOTAT was 3. Hence, students applied VOTAT repeatedly three times on average, even after they already applied VOTAT for each input variable. Lastly, students spent about 60 seconds on the problem-solving task on average.

Correlations of all used variables are presented in Table 2. The highest correlation was found between effective VOTAT and redundant VOTAT (r = .57). In addition, a moderate size of correlation was found between redundant VOTAT and total action time (r = .56), effective VOTAT and total action time (r = .53), openness and perseverance (r =.51).

Latent Profile Analysis

Number of Profiles

The LPA was carried out based on the six variables of problem solving processes: familiar time, NOTAT, effective VOTAT, redundant VOTAT, action, and the total action time. A series of LPA analyses were conducted with increasing numbers of latent profiles and compared to competing models. LPAs were conducted with one to five profiles. Exploring more profile solutions was not possible given the minimum sample size of each profile type (i.e., fewer than 25 samples; Lubke & Neale, 2006). The decision of the most appropriate model was made based on comparisons of the model fit statistics and content decision criteria. As shown in Table 3, the four-profile solution was decided as the best fitting model as it showed substantial distinct characteristics for each profile and adequate profile size. While the five-profile showed the lowest information value and loglikelihood, it did not differ significantly from the model with four profiles. As a result, the four-profile solution was considered the most appropriate model. The VLMR and LMR likelihood-ratio tests supported this decision as they indicated that the four-profile LPA fitted the data better than the three-profile model (p = .027, p = .029 respectively). Furthermore, the four-profile LPA characterized an additional profile that was qualitatively different from the remaining three profiles. Additionally, the four-profile LPA had the second-lowest information criteria, and the smallest proportion of this solution was 19 % across the profiles. Lastly, the classification quality information was checked. Both entropy and mean posterior probabilities of the four-profile solution indicated a substantial precision of the latent profile assignment with values above the optimal size of .80 (see Table 3 and Table 4). Especially the range of average posterior probability was from .92 to 1, indicating high accuracy in class assignment. Overall, the current study identified four latent profiles of problem-solving processes based on six indicators with the Norwegian PISA 2012 log data.

Descriptions of Profiles

Figure 5 shows the four-profile plot with estimated means from the students' problem solving processes, reported as raw scores. Additionally, Table 5 provides the exact number for each profile with the estimated mean from six problem solving indicators. The identified four profiles were named after the distinctive characteristic of each profile: inactive, struggling, proficient, adaptive. That is, the inactive profile was characterized by relatively low levels in all indicators and rarely applied exploration strategies. Although students in struggling profile showed substantial explorations strategies compared to inactive profile, they ended up applying effective VOTAT strategies partially (i.e., effective VOTAT = 1.6). Note that the minimalistic approach for students to solve the climate control effectively was to execute three actions by applying the VOTAT strategy for each input variable (i.e., effective VOTAT = 3). While proficient profile and adaptive profile both showed to apply effective VOTAT fully, the proficient profile was more efficient in solving the assigned task than the adaptive profile. The detailed description of each profile will be explained in the following paragraph.

The Inactive profile comprised of 64 students (18 %) showed the lowest levels in all indicators. They spent the shortest time before conducting the first action ($M_{TIMEFAM}$ = 48.4s). Additionally, almost no student in this group applied VOTAT strategies (M_{EVOTAT} = 0, M_{RVOTAT} = 0) and they conducted the fewest NOTAT and Action (M_{NOTAT} = 5.6, M_{Action} = 1), resulting in the shortest action time ($M_{TIMEACT}$ = 17.8s).

The struggling profile comprised of 64 students (18 %) showed longest familiar time and highest executed action as much as those of adaptive profile ($M_{familartime}$ = 53.1s, M_{action} = 2.5). Although the struggling profile showed applying NOTAT as much as proficient profile($M_{notat(proficient)}$ = 11.2), this profile showed partially applying effective VOTAT (M_{EVOTAT} = 1.6) and showed relatively low Redundant VOTAT (M_{RVOTAT} = 1.4) compared to proficient and adaptive profile. This might result in the difference in total action time ($M_{action\ time}$ = 50.8s) which is shorter than that of the proficient profile.

The proficient profile comprised of 159 students (46 %) reported medium level in all indicators. This group had the largest proportion across all profiles and reported middle level of familiar time ($M_{familartime}$ = 49.0s). Although this group reached effective VOTAT fully (M_{EVOTAT} = 3), they executed adequate middle level of action, redundant VOTAT compared to other profiles, resulting in the medium level of action time (M_{NOTAT} = 11, M_{RVOTAT} = 3.4, $M_{ACT} = 1.7, M_{actiontime} = 60.8s$).

Although the adaptive profile comprised of 66 students (19 %) showed applying effective VOTAT as much as Proficient profile (M_{EVOTAT} = 3), they showed the most frequent NOTAT (M_{NOTAT} = 21.6), Redundant VOTAT (M_{RVOTAT} = 10.3), resulting in the longest total action time across the profiles ($M_{actiontime}$ = 108.1s).

Latent Profile Regression and Outcome Analysis

Latent Profile Regression

The distribution of students' covariates (i.e., gender, SES, openness, perseverance) across profiles was investigated (see Figure 6). Subsequently, students' covariates were added to the extracted four profile model and regressed on these profiles to see which covariates were related to profile membership.

Several significant covariates were found to differentiate the profile membership in the latent profile model (see Table 6). In terms of a demographic covariate, boys were more likely to be in the struggling profile than the inactive profile (OR = 2.78) and in the proficient profile rather than the inactive profile (OR = 2.01). Students with high SES were more likely to be in the adaptive profile than inactive profile (OR = 1.82). Furthermore, in terms of students' motivational characteristics related to problem solving, students with high openness were more likely to be in the adaptive profile than inactive profile (OR = 1.69). Interestingly, this study found that perseverance was not related to students' profile membership. Overall, students' demographic and motivational characteristics in this model explained 15.4 % of the variance in the profile membership.

Outcome Analysis

The extracted four profiles were validated with a comparison of two outcomes: item performance on climate control task and overall problem solving performance. With item performance on the climate control task, the potential association between profiles and item performance (coded as *0 = no credit*, *1 = full credit*) was investigated. Figure 7 provides the proportion of students' item performance across four profiles. The proportion of scoring correctly on the climate control task was highest in adaptive profile (75 %), then the proficient (71 %), struggling (45 %), and inactive profile (15 %). Interestingly, the proportion of scoring items correctly increased from 15 % to 45 % when there was a shift from inactive to struggling profile. With Pearson's chi-square test, a significant relationship between the profile membership and item performance was found with a moderate effect size, $\chi^2(3, N = 353) = 69.1$, $p < .01$, Cramer's $V = .44$).

Subsequently, this study investigated the item threshold differences between profiles against zero. Significant differences in the item threshold were found between all profiles except between the proficient and the adaptive profile. Specifically, significant item threshold differences were found between the inactive and struggling ($\Delta M = 1.55$, $SE = 0.49$, $p <. 01$, $d = 0.59$), as well as between the inactive and proficient ($\Delta M = 2.64$, $SE = 0.39$, $p <. 01$, $d = 1.03$), between inactive and adaptive ($\Delta M = 2.84$, $SE = 0.46$, $p <. 01$, $d = 0.70$), struggling and proficient ($\Delta M = 1.09$, $SE = 0.34$, $p <. 01$, $d = 0.48$), struggling and adaptive ($\Delta M = 1.29$, $SE = 0.45$, $p <. 01$, $d = 0.52$). The insignificant item threshold difference ($\Delta M = 0.20$, $SE = 0.39$, $p =. 61$) between proficient and adaptive profile was somewhat predictable as both proficient and adaptive profile showed to apply effective VOTAT fully (i.e., effective VOTAT = 3), which might lead to similar pattern of successful item performance.

Figure 8 provides the bar graph of overall problem solving performance by four profiles with error bars. With overall problem solving performance, the adaptive profile showed the highest average score (M = 572.4), then proficient (M = 545.1), struggling (M = 521.3), and inactive (M = 421.7). Subsequently, significant mean differences in overall problem solving were investigated across profiles. Specifically, significant mean differences were found between the inactive and struggling (ΔM = 99.7, SE = 18.5, p <. 01, d = 0.40), as well as between the inactive and proficient (ΔM = 131.8, SE = 13.5, p < .01, d = 0.64), lastly between struggling and adaptive (ΔM = 31.8, SE = 15.9, p < .01, d = 0.19). Despite the fact that there was no significant difference between struggling and proficient, the overall problem-solving performance in the proficient group was higher than that of the struggling group (ΔM = 23.7, SE = 15.9, p = .17). Likewise, the overall problem solving performance in the adaptive group was higher than that of the proficient group, but this was no significant difference. (ΔM = 27.4, SE = 15.9, p = .12). Profile membership explained about 24 % of the variance in students' problem-solving performance.

Overall, the findings indicated that Norwegian students could be divided into four distinct profiles (RQ1). Also, these four latent profiles were different in terms of gender, SES, and openness (RQ2). Lastly, problem solving performance was also related to profile membership to some extent, leading to profile differentiation (RQ3).

Discussion

The purpose of this study was to identify latent profiles of students' problem solving processes by jointly incorporating exploration strategies (NOTAT, effective VOTAT, redundant VOTAT, action) and time variables (i.e., familiar time, total action time) from the Climate Control task. Moreover, this study included students' demographic characteristics as well as their motivational characteristics to find out which covariates differentiated the profile membership. Lastly, the relationship between the profile membership and students' problem solving performance was investigated. This study extended the current literature by providing additional information regarding students' varying levels of problem solving processes beyond the results (i.e., problem solving performance) using the Norwegian log-file data.

The Profiles of the Problem Solving Process (RQ1)

Overall, the distinct four profiles of problem solving processes were identified through latent profile analysis. Specifically, students' different patterns of exploration strategies and total action time resulted in the profiles of inactive, struggling, proficient, adaptive. The extent of consistently applying the VOTAT strategy for input variables (i.e., effective VOTAT) was noticeably different across the four profiles. Based on these indicators, the proficient profile and adaptive profile were identified as the successful profile for acquiring the necessary information for controlling a complex system (e.g., the structure of a system, the relation between input and output variables). In contrast, struggling and inactive profile were identified as unsuccessful profile for capturing essential information about the complex system (Süß & Kretzschmar, 2018).

It was assumed that students in the inactive profile did not skip the task as the time taken before the first action (i.e., familiar time) was similar to that of the proficient profile. This group showed relatively low levels of interaction, resulting in the shortest total action time compared to all other profiles. These students' low interaction may be due to a lack of willingness to engage in problem solving rather than cognitive overload in the working memory capacity (Eichmann, Greiff, et al., 2020; Greiff et al., 2018; Teig et al., 2020). Indeed, Scherer and Gustafsson (2015) indicated that the willingness to engage in problem solving(i.e., openness, perseverance) plays a crucial role in performing and engaging student's problem solving. Interestingly, the openness and perseverance of inactive profile were lowest across profiles (see Figure 6).

Despite substantial efforts, students in the struggling profile failed to develop the schema related to the VOTAT exploration strategies. (Eichmann et al., 2020; Greiff et al., 2018; Teig et al., 2020). According to the cognitive load theory, random strategies can be attempted until the optimal solution is found, when the possible solution to an unfamiliar problem situation is not clear. This might increase the amount of information that needs to be processed in the working memory (Sweller, 1988; Sweller et al., 2011). It seems like the main strategy of the struggling profile was manipulating several input variables at a time; a strategy that was not relevant to solve the problem. Besides, the total interaction of this profile was still less than that of the proficient profile that was successful in applying effective VOTAT fully in a minimalistic way.

Students in the proficient profile applied effective VOTAT fully, which was required to gain the information to solve the problem in a minimalistic way. This profile exhibited a medium level of the total action time. It seems like this profile developed a well-structured schema about exploration strategy while they were solving the problem in an efficient way (Greiff et al., 2018; Teig et al., 2020). There was no difference between proficient and adaptive profile regarding the extent of applying the VOTAT strategy consistently for input variables (i.e., effective VOTAT = 3). Meanwhile, it seems that the adaptive profile managed to develop the schema of exploration strategy by actively interacting with the problem environment, even though they lacked knowledge about exploration strategy at first (Sweller, 1988). In addition, the adaptive profile showed a noticeably high number of total interactions resulting in the longest total action time. This might show their engagement with the problem solving environment and their excessive double-checking behavior (Eichmann, Greiff, et al., 2020).

The Association between Students' Covariates and Profile Membership (RQ2)

The latent profile regression provided several significant students' covariates that were related to the probability of students being in a particular profile compared to the referenced profile. The significant positive value indicated that the higher the score on the variable, the higher the probability of being a member of a particular profile compared to the reference profile (see Table 6).

In terms of gender, boys were more likely to be in the struggling profile than the inactive profile and the proficient profile more than the inactive profile with the lowest performance in problem solving. On average, across OECD countries, boys showed better performance in representing and formulating tasks and weaker performance in planning and executing tasks (OECD, 2013). Since Climate Control corresponded to representing and formulating tasks, this might explain why boys had a higher probability of being in the struggling and proficient profile compared to the inactive profile. These results were also consistent with the findings where boys were more likely to use optimal strategies more often than girls (Gnaldi et al., 2020; He et al., 2021; Wüstenberg et al., 2014). Specifically, Wittmann and Hattrup (2004) argued that boys may engage in more risky behavior when facing unfamiliar problems, thus taking advantage of finding more information and learning opportunities about the system and resulting in better performance. This finding was also supported by the meta-analysis result of boys showing more risk-taking behavior than girls in general (Cross et al., 2011).

Furthermore, students with high SES were more likely to be in the adaptive profile than inactive profile with the lowest performance in problem solving. This result was in line with PISA 2012 assessment where students with better socio economic status showed higher problem solving performance (OECD, 2013). Similarly, the education level of students' mothers significantly correlated with students' performance in the knowledge acquisition stage of problem solving (Csapó & Molnár, 2017). In the current study, the adaptive profile showed the highest SES while the inactive profile showed the lowest SES (see Figure 6). This indicated that although the strength of SES on problem solving performance in Norway was smaller compared to other countries, SES remains a strong predictor of performance in problem solving (OECD, 2013).

In terms of students' motivational characteristics related to problem solving, students with high openness were more likely to be in the adaptive profile than the inactive profile. Students' openness and perseverance to problem solving were investigated as motivational determinates of the learning process in PISA 2012: the willingness to engage in problem solving (OECD, 2013). In this context, the result from this study supported previous studies that highlighted the relevance of students' motivational process in problem solving (Meißner et al., 2016; Mustafić et al., 2019). Specifically, Mustafić et al. (2019) pointed out that students with positive learning motivational belief showed improved strategy over time during the assessment, indicating that one's perception of oneself is associated with a higher problem solving performance. One unanticipated finding was that perseverance was not differentiating any of the profile membership comparisons (see Table 6). One possible explanation for this finding is that the specific task 'Climate Control' may not require specific levels of perseverance as it only exposed students to a problem solving situation in a short term. Since there were not many prior studies regarding perseverance, this needs to be further investigated in future research.

The Association between Profile Membership and Problem Solving Performance (RQ3)

Students' different problem solving processes in each profile substantially differentiated their performance on knowledge acquisition and, to some degree, in overall problem solving performance. Especially, there was a clear difference in item performance regarding different problem solving processes: the proportion of scoring correctly on the climate control task was highest in adaptive profile (75 %), proficient (71 %), struggling (45 %), and inactive profile (15 %). Moreover, significant item threshold differences between profiles were found except between proficient and adaptive profile.

Several studies found a positive relationship between the amount of interaction and success in CPS (Dormann & Frese, 1994; Eichmann, Goldhammer, et al., 2020). Specifically, low achieving students showed too little interaction in the study of Naumann et al. (2014). Since prior knowledge was not available in this interactive task, the lowest item performance in inactive profile could be explained in terms of too little interaction or stopping their interaction too early with the problem. Interestingly, the proportion of scoring item correctly increased from 15 % to 45 % when there was a shift from inactive to struggling profile. Although struggling profile failed to consistently apply VOTAT for all input variables, they showed substantial interaction with the problem, which might lead to better performance on climate control compared to inactive profile.

There was no significant difference in item performance between proficient and adaptive profile. This could be explained by their consistent application of VOTAT behavior for each input variables (i.e., effective VOTAT=3), which led to getting all necessary information to solve the problem. Although redundant VOTAT behavior of adaptive profile showed significant positive relation to item performance (see Table 2), it seems that high frequency of redundant VOTAT didn’t differentiate item performance between adaptive and proficient profile. Therefore, the proficient profile could be interpreted as showing more efficient exploration with a medium level of total action time compared to that of the adaptive profile. This finding is in line with the results of prior studies (Eichmann, Greiff, et al., 2020; Naumann, 2015; Stadler et al., 2019).

Students' profile membership predicted an overall problem solving performance. The overall problem solving performance was highest in adaptive, then proficient, struggling, inactive profile. In addition, this current study found significant mean differences in the overall problem solving performance across profiles that range from a small to medium effect size, except between struggling and proficient, and proficient and adaptive.

Under the assumption that students showed a similar problem solving approach during CPS assessment, the lowest performance of inactive profile was not surprising. However, it was not clear why the inactive profile was not engaged in the problem solving as several explanations are possible. It might indicate low engagement with low-stake assessment such as PISA or effects of task position (Eichmann, Greiff, et al., 2020; Greiff et al., 2018) or these students might have difficulty understanding the task such as reading instructions or interpreting the graph (Eichmann, Greiff, et al., 2020). Therefore, this should be further investigated in future research through multi-modal data such as thinking aloud or eye-tracking devices while students solve the problem (Maddox et al., 2018). The significant mean difference between inactive and struggling profile also confirmed the results from previous studies, where perseverant non-targeted exploration group showed higher overall CPS performance than short sequences of non-targeted exploration group (Eichmann, Greiff, et al., 2020; Naumann et al., 2014). In addition, the significant mean difference between struggling and adaptive profile is also in the same line with the previous study (Greiff, Wüstenberg, et al., 2015), where students showing incomplete VOTAT application on a single task showed lower overall problem solving performance than students with applying VOTAT consistently for each input variables.

Both minimalistic explorations to solve problem and double-checking behavior were found to be significantly related to the CPS performance in prior studies. Specifically, students with double-checking behavior showed the highest CPS performance, and their performance was significantly higher than minimalistic explorers. It was argued that students showing a minimalistic approach might have a high probability of making mistakes, thus leading to give false responses than those who double checking (Eichmann, Greiff, et al., 2020; He et al., 2019). Similarly, the current study showed the overall performance of students who showed double-checking behavior (i.e., adaptive profile) was higher than that of students showing minimalistic exploration (i.e., proficient profile). However, this mean difference was not statistically significant. This insignificant difference in overall problem solving may be explained due to the composition of overall problem solving performance. That is, overall problem solving performance in PISA 2012 comprised of both interactive items (i.e., CPS items) and static items, and thus it may not be sensitive to the extracted profiles. Therefore, including only CPS items might be more accurate for investigating the relationship between extracted profile and their CPS performance in future research. The identical explanation could be used for insignificant overall problem solving performance between struggling and proficient.

Limitations and Future Research

There are some limitations of the present study that should be considered in future research: First, this study focused exclusively on students who interacted with a problem task. Therefore, about ten percent of the initial sample (i.e., 45 students) had to be excluded as they tried to answer the task question without any interaction with the problem. However, these students could make up a potential profile that is differed from the inactive profile showing low interactions with the problem task in the current study. Future studies should explore the mechanisms and possible reasons behind such non-interacting problem-solving behavior.

Second, theory-driven indicators describing the problem solving process were used in the current study. Specifically, the time variables (i.e., familiar time, total action time) used in this study were based on item level rather than action level (i.e., the time taken for a specific action). Given that differences in timing could indicate differences in the cognitive processes although the same strategy was applied (Ulitzsch et al., 2021; von Davier et al., 2017), action-level indicators (e.g., time taken before the first VOTAT) could draw a more fine-grained picture of the problem-solving process. But these indicators were not incorporated into the current study due to too many outliers and substantial homogeneity within the sample of Norwegian students. Although the theory-driven indicator approach identified varying levels of student's problem solving processes, exploring the extent to which data-driven indicators—for instance, identified via data-mining techniques—might also be useful to make visible additional aspects of the students' problem-solving processes that were not captured by the theory-driven indicators.

Third, the results were based on Norwegian students who worked on one specific problem-solving task (i.e., climate control) in the PISA 2012 assessment. Future studies need to cross-validate whether the existing profiles can be generalized across age groups and countries (Wu & Molnár, 2021), cultures (Eichmann, Goldhammer, et al., 2020), or problem solving tasks (Greiff, Fischer, et al., 2015). In addition, due to the cross-sectional design of the PISA 2012 data, the statement about the causal relation between students' background information and profile membership could not be made. Therefore, conducting a longitudinal study (e.g., latent class growth analysis, latent transition analysis) might provide insight into how students develop their problem solving approach after certain periods, whether there is a transition between profiles, and potential relation to the contextual variables such as school instruction regarding the problem solving strategy.

Conclusion

The current study identified four distinct profiles of problem solving processes based on indicators that jointly combined several exploration strategies and time variables. Specifically, students' exploration strategies were differentiated into efficient VOTAT, redundant VOTAT, manipulating multiple variables at a time; thus, more qualitatively different profiles compared to previous studies were identified. These profiles were validated through significant students' covariates of the profile membership and the relation to the problem solving performance. Providing information about the different profiles could support teachers to adapt their instruction to the specific student needs. For example, motivational support could be given to the inactive profile, while teaching about the VOTAT strategy might be required for the struggling profile. Both for proficient and adaptive profiles, teaching about inductive reasoning might be relevant as some students in those profiles failed to score correctly on the item although both profiles were successful to gain information to solve the problem (Molnár & Csapó, 2018). Further, it could be used to develop an automated teaching tool that provides instant feedback based on the profile membership and background information.

References

Albert, D., & Steinberg, L. (2011). Age Differences in Strategic Planning as Indexed by the Tower of London: Strategic Planning. *Child Development*, *82*(5), 1501–1517. https://doi.org/10.1111/j.1467-8624.2011.01613.x

Artelt, C., & Programme for International Student Assessment. (2003). *Learners for life: Student approaches to learning: results from PISA 2000*. OECD.

Asparouhov, T. (2005). Sampling Weights in Latent Variable Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *12*(3), 411–434. https://doi.org/10.1207/s15328007sem1203_4

Berlin, K. S., Williams, N. A., & Parra, G. R. (2014). An Introduction to Latent Variable Mixture Modeling (Part 1): Overview and Cross-Sectional Latent Class and Latent Profile Analyses. *Journal of Pediatric Psychology*, *39*(2), 174–187. https://doi.org/10.1093/jpepsy/jst084

Bulotsky-Shearer, R. J., Bell, E. R., & Domínguez, X. (2012). Latent profiles of problem behavior within learning, peer, and teacher contexts: Identifying subgroups of children at academic risk across the preschool year. *Journal of School Psychology*, *50*(6), 775–798. https://doi.org/10.1016/j.jsp.2012.08.001

Campion, W. M., & Rubin, D. (1989). *Multiple Imputation for Nonresponse in Surveys*. https://doi.org/10.2307/3172772

Chen, Z., & Klahr, D. (1999). All Other Things Being Equal: Acquisition and Transfer of the Control of Variables Strategy. *Child Development*, *70*(5), 1098–1120. https://doi.org/10.1111/1467-8624.00081

Collins, L. M., & Lanza, S. T. (2009). *Latent Class and Latent Transition Analysis: With Applications in the Social, Behavioral, and Health Sciences*. John Wiley & Sons.

Cross, C., Copping, L., & Campbell, A. (2011). Sex Differences in Impulsivity: A Meta-Analysis. *Psychological Bulletin*, *137*, 97–130. https://doi.org/10.1037/a0021591

Csapó, B., & Funke, J. (2017). *The development and assessment of problem solving in 21st-century schools* (pp. 19–32). https://doi.org/10.1787/9789264273955-3-en

Csapó, B., & Molnár, G. (2017). Potential for Assessing Dynamic Problem-Solving at the Beginning of Higher Education Studies. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.02022

Dormann, T., & Frese, M. (1994). Error training: Replication and the function of exploratory behavior. *International Journal of Human–Computer Interaction*, *6*(4), 365–372. https://doi.org/10.1080/10447319409526101

Dörner, D. (2013). PSI: A Computational Architecture of Cognition, Motivation, and Emotion. *Review of General Psychology*, *17*, 297–317. https://doi.org/10.1037/a0032947

Dubow, E., Boxer, P., & Huesmann, L. (2009). Long-term Effects of Parents' Education on Children's Educational and Occupational Success: Mediation by Family Interactions, Child Aggression, and Teenage Aspirations. *Merrill-Palmer Quarterly (Wayne State University. Press)*, *55*, 224–249. https://doi.org/10.1353/mpq.0.0030

Eichmann, B., Goldhammer, F., Greiff, S., Brandhuber, L., & Naumann, J. (2020). Using process data to explain group differences in complex problem solving. *Journal of Educational Psychology*. https://doi.org/10.1037/edu0000446

Eichmann, B., Goldhammer, F., Greiff, S., Pucite, L., & Naumann, J. (2019). The role of planning in complex problem solving. *Computers & Education*, *128*, 1–12. https://doi.org/10.1016/j.compedu.2018.08.004

Eichmann, B., Greiff, S., Naumann, J., Brandhuber, L., & Goldhammer, F. (2020). Exploring behavioural patterns during complex problem-solving. *Journal of Computer Assisted Learning*, *36*(6), 933–956. https://doi.org/10.1111/jcal.12451

Enders, C. K. (2010). *Applied Missing Data Analysis*. Guilford Press.

Fischer, A., Greiff, S., Wüstenberg, S., Fleischer, J., Buchwald, F., & Funke, J. (2015). Assessing analytic and interactive aspects of problem solving competency. *Learning and Individual Differences*, *39*, 172–179. https://doi.org/10.1016/j.lindif.2015.02.008

Frensch, P., & Funke, J. (1995). Definitions, traditions, and a general framework for understanding complex problem solving. In *In: In P. A. Frensch & J. Funke (Eds.), Complex problem solving: The European perspective (pp. 3-25). Hillsdale, NJ: Lawrence Erlbaum Associates, 1995* (pp. 3–25).

Funke, J. (2001). Dynamic systems as tools for analyzing human judgment. *Thinking and Reasoning*, *7*, 69–89. https://doi.org/10.1080/13546780042000046

Funke, J. (2010). Complex problem solving: A case for complex cognition? *Cogn Process*, 12.

Funke, J., & Frensch, P. A. (2007). Complex Problem Solving: The European Perspective—10 Years After. In D. H. Jonassen, *Learning to Solve Complex Scientific Problems* (1st ed., pp. 25–48). Routledge. https://doi.org/10.4324/9781315091938-2

Gnaldi, M., Bacci, S., Kunze, T., & Greiff, S. (2020). Students' Complex Problem Solving Profiles. *Psychometrika*, *85*(2), 469–501. https://doi.org/10.1007/s11336-020-09709-2

Goldhammer, F., Hahnel, C., & Kroehne, U. (2020). Analysing Log File Data from PIAAC. In D. B. Maehler & B. Rammstedt, *Large-Scale Cognitive Assessment: Analyzing PIAAC Data* (pp. 239–269). Springer International Publishing. https://doi.org/10.1007/978-3-030-47515-4_10

Goldhammer, F., Naumann, J., Rölke, H., Stelter, A., & Toth, K. (2017). *Relating Product Data to Process Data from Computer-Based Competency Assessment* (pp. 407–425). https://doi.org/10.1007/978-3-319-50030-0_24

Goldhammer, F., Naumann, J., Stelter, A., Tóth, K., Rölke, H., & Klieme, E. (2014). The time on task effect in reading and problem solving is moderated by task difficulty and skill: Insights from a computer-based large-scale assessment. *Journal of Educational Psychology*, *106*(3), 608. https://doi.org/10.1037/a0034716

Greiff, S., Fischer, A., Stadler, M., & Wüstenberg, S. (2015). Assessing complex problem-solving skills with multiple complex systems. *Thinking & Reasoning*, *21*(3), 356–382. https://doi.org/10.1080/13546783.2014.989263

Greiff, S., Molnár, G., Martin, R., Zimmermann, J., & Csapó, B. (2018). Students' exploration strategies in computer-simulated complex problem environments: A latent class approach. *Computers & Education*, *126*, 248–263. https://doi.org/10.1016/j.compedu.2018.07.013

Greiff, S., Niepel, C., Scherer, R., & Martin, R. (2016). Understanding students' performance in a computer-based assessment of complex problem solving: An analysis of behavioral data from computer-generated log files. *Computers in Human Behavior*, *61*, 36–46. https://doi.org/10.1016/j.chb.2016.02.095

Greiff, S., Wüstenberg, S., & Avvisati, F. (2015). Computer-generated log-file analyses as a window into students' minds? A showcase study based on the PISA 2012 assessment of problem solving. *Computers & Education*, *91*, 92–105. https://doi.org/10.1016/j.compedu.2015.10.018

Greiff, S., Wüstenberg, S., & Funke, J. (2012). Dynamic Problem Solving: A New Assessment Perspective. *Applied Psychological Measurement*, *36*(3), 189–213. https://doi.org/10.1177/0146621612439620

Greiff, S., Wüstenberg, S., Molnár, G., Fischer, A., Funke, J., & Csapó, B. (2013). Complex problem solving in educational contexts—Something beyond g: Concept, assessment, measurement invariance, and construct validity. *Journal of Educational Psychology*, *105*(2), 364. https://doi.org/10.1037/a0031856

Hautamäki, J., Arinen, P., Eronen, S., Hautamäki, A., Kupiainen, S., Lindblom, B., Niemivirta, M., Pakaslahti, L., Rantanen, P., & Scheinin, P. (2002). *Assessing learning-to-learn: A framework*.

He, Q., Borgonovi, F., & Paccagnella, M. (2021). Leveraging process data to assess adults' problem-solving skills: Using sequence mining to identify behavioral patterns across digital tasks. *Computers & Education*, *166*, 104170. https://doi.org/10.1016/j.compedu.2021.104170

He, Q., Liao, D., & Jiao, H. (2019). Clustering Behavioral Patterns Using Process Data in PIAAC Problem-Solving Items. In B. P. Veldkamp & C. Sluijter (Eds.), *Theoretical and Practical Advances in Computer-based Educational Measurement* (pp. 189–212). Springer International Publishing. https://doi.org/10.1007/978-3-030-18480-3_10

Kröner, S., Plass, J. L., & Leutner, D. (2005). Intelligence assessment with computer simulations. *Intelligence*, *33*(4), 347–368. https://doi.org/10.1016/j.intell.2005.03.002

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent Class Analysis With Distal Outcomes: A Flexible Model-Based Approach. *Structural Equation Modeling: A Multidisciplinary Journal*, *20*(1), 1–26. https://doi.org/10.1080/10705511.2013.742377

Leys, C., Klein, O., Dominicy, Y., & Ley, C. (2018). Detecting multivariate outliers: Use a robust variant of the Mahalanobis distance. *Journal of Experimental Social Psychology*, *74*, 150–156. https://doi.org/10.1016/j.jesp.2017.09.011

Lotz, C., Scherer, R., Greiff, S., & Sparfeldt, J. R. (2017). Intelligence in action – Effective strategic behaviors while solving complex problems. *Intelligence*, *64*, 98–112. https://doi.org/10.1016/j.intell.2017.08.002

Lubke, G., & Neale, M. (2006). Distinguishing Between Latent Classes and Continuous Factors: Resolution by Maximum Likelihood? *Multivariate Behavioral Research - MULTIVARIATE BEHAV RES*, *41*, 499–532. https://doi.org/10.1207/s15327906mbr4104_4

Maddox, B., Bayliss, A. P., Fleming, P., Engelhardt, P. E., Edwards, S. G., & Borgonovi, F. (2018). Observing response processes with eye tracking in international large-scale assessments: Evidence from the OECD PIAAC assessment. *European Journal of Psychology of Education*, *33*(3), 543–558. https://doi.org/10.1007/s10212-018-0380-2

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical Latent Profile Analysis of Academic Self-Concept Dimensions: Synergy of Person- and Variable-Centered Approaches to Theoretical Models of Self-Concept. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(2), 191–225. https://doi.org/10.1080/10705510902751010

Masyn, K. E. (2013). *Latent Class Analysis and Finite Mixture Modeling*. The Oxford Handbook of Quantitative Methods in Psychology: Vol. 2. https://doi.org/10.1093/oxfordhb/9780199934898.013.0025

Mayer, R. E. (1998). Cognitive, metacognitive, and motivational aspects of problem solving. *Instructional Science*, *26*(1–2), 49–63. Scopus. https://doi.org/10.1023/a:1003088013286

Mayer, R. E., & Wittrock, M. C. (2006). Problem solving. *Handbook of Educational Psychology*, 287–303. Scopus.

Meißner, A., Greiff, S., Frischkorn, G. T., & Steinmayr, R. (2016). Predicting Complex Problem Solving and school grades with working memory and ability self-concept. *Learning and Individual Differences*, *49*, 323–331. https://doi.org/10.1016/j.lindif.2016.04.006

Molnár, G., & Csapó, B. (2018). The Efficacy and Development of Students' Problem-Solving Strategies During Compulsory Schooling: Logfile Analyses. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00302

Molnár, G., Greiff, S., & Csapó, B. (2013). Inductive reasoning, domain specific and complex problem solving: Relations and development. *Thinking Skills and Creativity*, *9*, 35–45. https://doi.org/10.1016/j.tsc.2013.03.002

Morin, A. J. S., Meyer, J. P., Creusier, J., & Biétry, F. (2016). Multiple-Group Analysis of Similarity in Latent Profile Solutions. *Organizational Research Methods*, *19*(2), 231–254. https://doi.org/10.1177/1094428115621148

Morin, A. J. S., Morizot, J., Boudrias, J.-S., & Madore, I. (2011). A Multifoci Person-Centered Perspective on Workplace Affective Commitment: A Latent Profile/Factor Mixture Analysis. *Organizational Research Methods*, *14*(1), 58–90. https://doi.org/10.1177/1094428109356476

Mustafić, M., Yu, J., Stadler, M., Vainikainen, M.-P., Bornstein, M. H., Putnick, D. L., & Greiff, S. (2019). Complex problem solving: Profiles and developmental paths revealed via latent transition analysis. *Developmental Psychology*, *55*(10), 2090–2101. https://doi.org/10.1037/dev0000764

Muthén & Muthén. (1998). *Muthén, L.K. and Muthén, B.O. (1998-2015). Mplus User's Guide. Eighth Edition. Los Angeles, CA: Muthén & Muthén* (Seventh Edition).

Naumann, J. (2015). A model of online reading engagement: Linking engagement, navigation, and performance in digital reading. *Computers in Human Behavior*, *53*, 263–277. https://doi.org/10.1016/j.chb.2015.06.051

Naumann, J., & Goldhammer, F. (2017). Time-on-task effects in digital reading are non-linear and moderated by persons' skills and tasks' demands. *Learning and Individual Differences*, *53*, 1–16. https://doi.org/10.1016/j.lindif.2016.10.002

Naumann, J., Goldhammer, F., Rölke, H., & Stelter, A. (2014). Erfolgreiches Problemlösen in technologiebasierten Umgebungen: Wechselwirkungen zwischen Interaktionsschritten und Aufgabenanforderungen. *Zeitschrift für Pädagogische Psychologie*. https://econtent.hogrefe.com/doi/abs/10.1024/1010-0652/a000134

Novick, L. R., & Bassok, M. (2005). Problem Solving. In *The Cambridge handbook of thinking and reasoning* (pp. 321–349). Cambridge University Press.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Nylund-Gibson, K., Grimm, R. P., & Masyn, K. E. (2019). Prediction from Latent Classes: A Demonstration of Different Approaches to Include Distal Outcomes in Mixture Models. *Structural Equation Modeling: A Multidisciplinary Journal*, *26*(6), 967–985. https://doi.org/10.1080/10705511.2019.1590146

OECD. (2013). *PISA 2012 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy*. OECD. https://doi.org/10.1787/9789264190511-en

OECD. (2014a). *Creative problem solving: Students' skills in tackling real-life problems*. OECD.

OECD. (2014b). PISA 2012 Technical Report. In *OECD Publishing*. OECD Publishing.

OECD. (2014c). *PISA 2012 Results: Creative Problem Solving (Volume V): Students' Skills in Tackling Real-Life Problems*. OECD. https://doi.org/10.1787/9789264208070-en

OECD. (2017). *The Nature of Problem Solving: Using Research to Inspire 21st Century Learning* (B. Csapó & J. Funke, Eds.). OECD. https://doi.org/10.1787/9789264273955-en

R Team, R., Team, R. D. C., Team, R., Team, R., & Null, R. (2014). R: A language and environment for statistical computing. *Vienna, Austria: R Foundation for Statistical Computing*.

Rudolph, J., Niepel, C., Greiff, S., Goldhammer, F., & Kröner, S. (2017). Metacognitive confidence judgments and their link to complex problem solving. *Intelligence*, *63*, 1–8. https://doi.org/10.1016/j.intell.2017.04.005

Satorra, A., & Bentler, P. M. (2010). Ensuring Positiveness of the Scaled Difference Chi-square Test Statistic. *Psychometrika*, *75*(2), 243–248. https://doi.org/10.1007/s11336-009-9135-y

Scherer, R., Greiff, S., & Hautamäki, J. (2015). Exploring the Relation between Time on Task and Ability in Complex Problem Solving. *Intelligence*, *48*, 37–50. https://doi.org/10.1016/j.intell.2014.10.003

Scherer, R., & Gustafsson, J.-E. (2015). The relations among openness, perseverance, and performance in creative problem solving: A substantive-methodological approach. *Thinking Skills and Creativity*, *18*, 4–17. https://doi.org/10.1016/j.tsc.2015.04.004

Sewell, W. H., & Shah, V. P. (1968). Parents' education and children's educational aspirations and achievements. *American Sociological Review*, *33*(2), 191–209. https://doi.org/10.2307/2092387

Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. *Journal of Vocational Behavior*, *120*, 103445. https://doi.org/10.1016/j.jvb.2020.103445

Stadler, M., Fischer, F., & Greiff, S. (2019). Taking a Closer Look: An Exploratory Analysis of Successful and Unsuccessful Strategy Use in Complex Problems. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.00777

Süß, H.-M., & Kretzschmar, A. (2018). Impact of Cognitive Abilities and Prior Knowledge on Complex Problem Solving Performance – Empirical Results and a Plea for Ecologically Valid Microworlds. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00626

Sweller, J. (1988). Cognitive Load During Problem Solving: Effects on Learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive Load Theory*. Springer-Verlag. https://doi.org/10.1007/978-1-4419-8126-4

Teig, N., Scherer, R., & Kjærnsli, M. (2020). Identifying patterns of students' performance on simulated inquiry tasks using PISA 2015 log-file data. *Journal of Research in Science Teaching*, *57*(9), 1400–1429. https://doi.org/10.1002/tea.21657

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical Power to Detect the Correct Number of Classes in Latent Profile Analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, *20*(4), 640–657. https://doi.org/10.1080/10705511.2013.824781

Tóth, K., Rölke, H., Greiff, S., & Wüstenberg, S. (2014). *Discovering Students ' Complex Problem Solving Strategies in Educational Assessment*.

Tschirgi, J. E. (1980). Sensible Reasoning: A Hypothesis about Hypotheses. *Child Development*, *51*(1), 1–10. https://doi.org/10.2307/1129583

Ulitzsch, E., He, Q., Ulitzsch, V., Molter, H., Nichterlein, A., Niedermeier, R., & Pohl, S. (2021). Combining Clickstream Analyses and Graph-Modeled Data Clustering for Identifying Common Response Processes. *Psychometrika*. https://doi.org/10.1007/s11336-020-09743-0

Unterrainer, J. M., & Owen, A. M. (2006). Planning and problem solving: From neuropsychology to functional neuroimaging. *Journal of Physiology-Paris*, *99*(4), 308–317. https://doi.org/10.1016/j.jphysparis.2006.03.014

Vainikainen, M.-P., Wüstenberg, S., Kupiainen, S., Hotulainen, R., & Hautamäki, J. (2015). Development of learning to learn skills in primary school. *International Journal of Lifelong Education*, *34*. https://doi.org/10.1080/02601370.2015.1060025

Vermunt, J. K., & Magidson, J. (2002). Latent Class Cluster Analysis. In A. L. McCutcheon & J. A. Hagenaars (Eds.), *Applied Latent Class Analysis* (pp. 89–106). Cambridge University Press. https://doi.org/10.1017/CBO9780511499531.004

von Davier, A. A., Zhu, M., & Kyllonen, P. C. (2017). *Innovative Assessment of Collaboration*. Springer International Publishing. https://doi.org/10.1007/978-3-319-33261-1

Wang, M., & Hanges, P. J. (2011). Latent Class Procedures: Applications to Organizational Research. *Organizational Research Methods*, *14*(1), 24–31. https://doi.org/10.1177/1094428110383988

Wise, S. L., & Gao, L. (2017). A General Approach to Measuring Test-Taking Effort on Computer-Based Tests. *Applied Measurement in Education*, *30*(4), 343–354. https://doi.org/10.1080/08957347.2017.1353992

Wittmann, W. W., & Hattrup, K. (2004). The relationship between performance in dynamic systems and intelligence. *Systems Research and Behavioral Science*, *21*(4), 393–409. https://doi.org/10.1002/sres.653

Wu, H., & Molnár, G. (2021). Logfile analyses of successful and unsuccessful strategy use in complex problem-solving: A cross-national comparison study. *European Journal of Psychology of Education*. https://doi.org/10.1007/s10212-020-00516-y

Wüstenberg, S., Greiff, S., & Funke, J. (2012). Complex problem solving—More than reasoning? *Intelligence*, *40*(1), 1–14. https://doi.org/10.1016/j.intell.2011.11.003

Wüstenberg, S., Greiff, S., Molnár, G., & Funke, J. (2014). Cross-national gender differences in complex problem solving and their determinants. *Learning and Individual Differences*, *29*, 18–29. https://doi.org/10.1016/j.lindif.2013.10.006

Xu, H., Fang, G., Chen, Y., Liu, J., & Ying, Z. (2018). Latent Class Analysis of Recurrent Events in Problem-Solving Items. *Applied Psychological Measurement*, *42*, 014662161774832. https://doi.org/10.1177/0146621617748325

Yungtai Lo, Nancy R Mendell, & Donald B Rubin. (2001). Testing the Number of Components in a Normal Mixture. *Biometrika*, *88*(3), 767–778. https://doi.org/10.1093/biomet/88.3.767

Zoanetti, N. (2010). Interactive computer based assessment tasks: How problem-solving process data can inform instruction. *Australasian Journal of Educational Technology*, *26*(5), Article 5. https://doi.org/10.14742/ajet.1053

Table 1

Descriptive Statistics for the Profile Indicators, Covariates, and Outcome Variables

Indicators	Scale	*M*	*SD*	*Min*	*Max*	Skewness	Kurtosis
Problem Solving Processes							
FamiliarTime	In seconds	50.39	28.50	3.70	159.4	1.02	1.28
NOTAT	Frequency	12.04	18.32	0	124	2.28	6.51
EVOTAT	0-3	2.19	1.19	0	3	-1.03	-0.66
RVOTAT	Frequency	3.69	3.95	0	19	1.15	0.76
Act	Frequency	1.90	1.89	0	9	1.35	1.82
TotActTime	In seconds	59.79	41.33	0	233.4	1.00	1.75
Covariates							
GENDER	0-1	0.55	0.50	0	1	-0.20	-1.97
OPENPS	Continuous	0.32	1.18	-3.63	2.45	-0.01	0.44
PERSEV	Continuous	-0.17	0.99	-4.05	3.53	0.22	1.70
SES	Continuous	0.55	0.70	-2.37	2.40	-0.46	0.29
Problem Solving Performance							
CP025Q01	0-1	0.56	0.5	0	1	-0.24	-1.95
PVCPRO	Continuous	523.33	96.08	250.90	759.47	-0.17	-0.01

Note. Familiar time = time taken before first action (in seconds); NOTAT = The number of non-interfering observation strategy; EVOTAT = effective VOTAT, the number of required minimum VOTAT approach to gain information to solve the problem successfully, ranging from 0 to 3, VOTAT indicates changing one variable at a time; RVOTAT = the number of redundant VOTAT after VOTAT strategy is already applied for each input variable, ACT = the number of changing multiple inputs at a time; TotActTime =time taken until the last action of a student, Gender = students' gender coded as 0 (*female*) and 1 (*male*); OPENPS = the extent how willing students were to engage in problem situations; PERSEV= students' willingness to engage in problem solving when being confronted with difficult problems, SES = index of economic, cultural, social status; CP025Q01 = the item performance on climate control coded as 0 (incorrect) 1(correct); PVCPRO = the overall problem solving performance.

Table 2

Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11
Problem Solving Indicators											
FamiliarTime											
NOTAT	-.15**										
EVOTAT	.03**	.19**									
RVOTAT	.05**	.21**	.57**								
ACT	.01**	.27**	.16**	.11**							
TotActTime	0.07	.32**	.54**	.56**	.50**						
Covariates											
Gender	-.19**	.19**	.12**	.06**	.08**	-.01**					
OPENPS	.01**	.08**	.23*	.19*	.03**	.18*	.10**				
PERSEV	-.06**	.07**	.14**	.09**	.02**	.10**	.14**	.53**			
SES	.03**	.02**	.13**	.17**	.08**	.13**	.07**	.22**	.16**		
Problem Solving Performance											
CP025Q01	.03**	.02**	.45**	.38**	.04**	.24**	.05**	.14**	.16**	.17**	
PVCPRO	.08	.01	.48	.38	.12	.32	.05	.38	.30*	.28*	.51

Note. *$p < 0.05$, **$p < 0.01$; Familiar time = time taken before first action (in seconds); NOTAT = The number of non-interfering observation strategy; EVOTAT = effective VOTAT, the number of required minimum VOTAT approach to gain information to solve the problem successfully, ranging from 0 to 3, VOTAT indicates changing one variable at a time; RVOTAT = the number of repeated VOTAT after VOTAT is already applied for each input variable, ACT = the number of changing multiple inputs at a time; Action time =time taken until the last action of a student, Gender = students' gender coded as 0 (*female*) and 1 (*male*); OPENPS = the extent how willing students were to engage in problem situations; PERSEV= students' willingness to engage in problem solving when being confronted with difficult problems, SES = index of economic, cultural, social status; CP025Q01 = the item performance on climate control coded as 0 (incorrect) 1(correct); PVCPRO = the overall problem solving performance.

Table 3

Relative Model Fit for the Latent Profile Models with up to Five Profiles

#Profiles	LL	Npar	SCF	AIC	BIC	aBIC	Entropy	VLMR-LRT	LMR-LRT	Smallest group frequency
1	-7299.2	12	1.4535	14633.5	14668.9	14630.8	1.000			100%
2	-6977.1	19	1.3079	13992.3	14065.8	14005.5	0.999	$p < 0.001$	$p < 0.001$	26%
3	-6862.7	26	1.3088	13777.4	13878.0	13795.5	0.939	$p < 0.001$	$p < 0.001$	19%
4	**-6756.1**	**33**	**1.3369**	**13578.1**	**13705.7**	**13601.0**	**0.955**	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	**18%**
5	-6700.9	40	1.4056	13481.8	13636.5	13509.6	0.960	$p = 0.448$	$p = 0.454$	4%

Note. the most appropriate profile is presented with bold, LL= Loglikelihood, Npar = Number of parameters, SCF = Scaling correction factor, AIC= Akaike information criterion, BIC= Bayesian information criterion, aBIC= Adjusted Bayesian Information Criterion, VLMR-LRT = Vuong-Lo_mendell_Rubin Likelihood Ratio Test, LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio test.

Table 4

Average Latent Class Probabilities for the Four-Profile Model

Profile	*n*	1	2	3	4
1	64	**1**	0	0	0
2	64	0	**0.999**	0	0
3	159	0	0	**0.977**	0.023
4	66	0	-	0.084	**0.916**

Note. the probability that a student belongs to the assigned profile and to no to other profiles are called as posterior probabilities. The profile membership is determined by the posterior probabilities. The diagonal value in bold indicates the average class probability of most likely latent profile membership by profile(column) ranging from 0 to 1.

Table 5

Means of Six Problem Solving Indicators for the Four Identified Profiles (Standard Errors of the Means in Parentheses)

	Inactive (*n* = 64, 18 %)	Struggling (*n* = 64, 18 %)	Proficient (*n* = 159, 46 %)	Adaptive (*n* =66, 19 %)
Familiar Time	48.4 (3.96)	53.1 (2.95)	49.0 (2.39)	53.1 (3.86)
NOTAT	5.6 (1.09)	11.2 (2.42)	11.1 (1.47)	21.6 (3.75)
EVOTAT	0.0 (0)	1.6 (0.07)	3.0 (0)	3.0 (0)
RVOTAT	0.0 (0)	1.4 (0.21)	3.4 (0.25)	10.3 (0.48)
ACT	1.0 (0.16)	2.5 (0.22)	1.7 (0.16)	2.5 (0.37)
TotActTime	17.8 (2.71)	50.8 (4.15)	60.8 (2.20)	108.1 (7.35)

Note. Familiar time = time taken before first action (in seconds); NOTAT = The number of non-interfering observation strategy; EVOTAT = effective VOTAT, the number of required minimum VOTAT approach to gain information to solve the problem successfully, ranging from 0 to 3, VOTAT indicates changing one variable at a time; RVOTAT = the number of repeated VOTAT after VOTAT is already applied for each input variable, ACT = the number of changing multiple inputs at a time; TotActTime = time taken until the last action of a student

Table 6

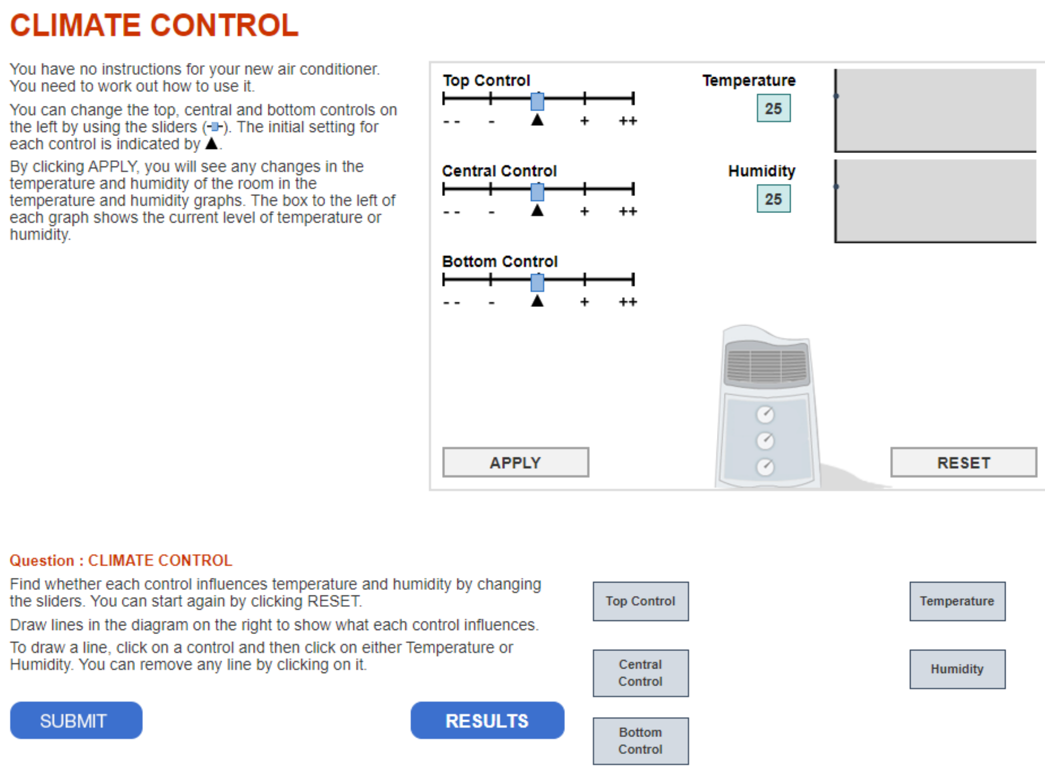
Logistic Regression Coefficients and Odds Ratios across Profiles

	Inactive ^{a} vs Struggling			Inactive ^{a} vs Proficient			Inactive ^{a} vs Adaptive		
Covariates	B(SE)	OR	95% CI	B(SE)	OR	95% CI	B(SE)	OR	95% CI
Gender	**1.02(0.41) ***	2.78	[1.42,5.47]	**0.70(0.31) ***	2.01	[1.20,3.35]	0.54(0.41)	1.72	[0.88,3.36]
OPENPS	0.39(0.26)	1.47	[0.96,2.25]	0.42(0.23)	1.53	[1.05,2.23]	**0.52(0.26) ***	1.69	[1.10,2.59]
PERSEV	-0.03(0.26)	0.97	[0.63,1.48]	-0.04(0.19)	0.96	[0.70,1.32]	0.01(0.34)	1.01	[0.58,1.76]
SES	0.15(0.30)	1.16	[0.71,1.89]	0.22(0.21)	1.24	[0.88,1.77]	**0.60(0.29) ***	1.82	[1.13,2.93]
	Struggling ^{a} vs Proficient			Struggling ^{a} vs Adaptive			Proficient ^{a} vs Adaptive		
Covariates	B(SE)	OR	95% CI	B(SE)	OR	95% CI	B(SE)	OR	95% CI
Gender	-0.33(0.34)	0.72	[0.41,1.26]	-0.49(0.41)	0.62	[0.32,1.20]	-0.16(0.32)	0.86	[0.51,1.46]
OPENPS	0.03(0.19)	1.03	[0.76,1.41]	0.14(0.23)	1.15	[0.78,1.68]	0.10(0.21)	1.11	[0.78,1.57]
PERSEV	0.00(0.21)	1.00	[0.71,1.41]	0.05(0.33)	1.04	[0.60,1.80]	0.05(0.33)	1.05	[0.61,1.80]
SES	0.07(0.26)	1.08	[0.70,1.65]	0.456(0.29)	1.58	[0.98,2.53]	0.38(0.27)	1.47	[0.95,2.27]

Note. *p <.05, ^{a} = Reference Profile, Gender = students' gender coded as 0 (*female*) and 1 (*male*); OPENPS = the extent how willing students were to engage in problem situations; PERSEV= students' willingness to engage in problem solving when being confronted with difficult problems, SES = index of economic, cultural, social status

Figure 1

Screenshot of Climate Control



Note. this item is available at https://www.oecd.org/pisa/test-2012/testquestions/question3/

Figure 2

An Example of Two Student Log Files

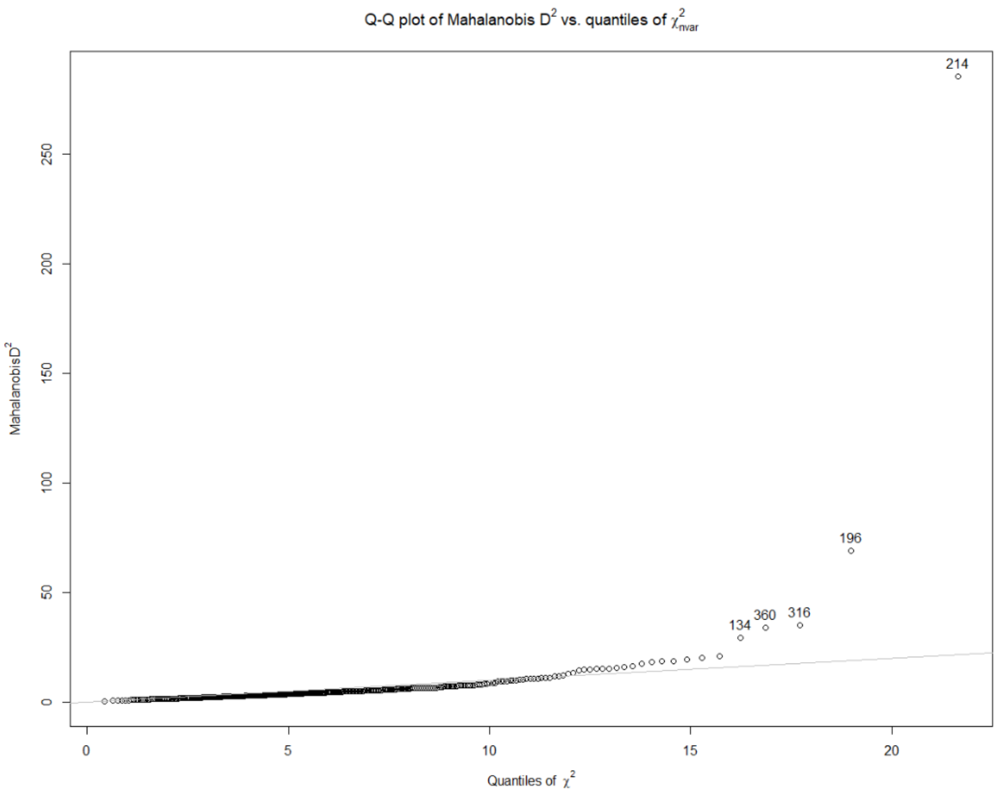
cnt	schoolid	StIDStd	event	time	event_number	event_type	top_setting	central_setting	bottom_setting	temp_value	humid_value	diag_state
<chr>	<chr>	<chr>	<chr>	<dbl>	<dbl>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>
NOR	0000036	00889	START_ITEM	1318.	1	NULL	NULL	NULL	NULL	NULL	NULL	NULL
NOR	0000036	00889	ACER_EVENT	1372.	2	apply	2	2	2	29	31	NULL
NOR	0000036	00889	ACER_EVENT	1378.	3	reset	0	0	0	25	25	NULL
NOR	0000036	00889	ACER_EVENT	1381	4	apply	0	0	2	25	29	NULL
NOR	0000036	00889	ACER_EVENT	1386.	5	Diagram	NULL	NULL	NULL	NULL	NULL	'000000
NOR	0000036	00889	ACER_EVENT	1388.	6	reset	0	0	0	25	25	NULL
NOR	0000036	00889	ACER_EVENT	1390.	7	apply	0	2	0	25	27	NULL
NOR	0000036	00889	ACER_EVENT	1394.	8	Diagram	NULL	NULL	NULL	NULL	NULL	'000001
NOR	0000036	00889	ACER_EVENT	1397.	9	Diagram	NULL	NULL	NULL	NULL	NULL	'000001
NOR	0000036	00889	ACER_EVENT	1398.	10	Diagram	NULL	NULL	NULL	NULL	NULL	'000101
NOR	0000036	00889	ACER_EVENT	1401.	11	reset	0	0	0	25	25	NULL
NOR	0000036	00889	ACER_EVENT	1405.	12	apply	2	0	0	29	25	NULL
NOR	0000036	00889	ACER_EVENT	1407.	13	Diagram	NULL	NULL	NULL	NULL	NULL	'000101
NOR	0000036	00889	ACER_EVENT	1408.	14	Diagram	NULL	NULL	NULL	NULL	NULL	'100101
NOR	0000036	00889	END_ITEM	1410.	15	NULL	NULL	NULL	NULL	NULL	NULL	NULL

cnt	schoolid	StIDStd	event	time	event_number	event_type	top_setting	central_setting	bottom_setting	temp_value	humid_value	diag_state
<chr>	<chr>	<chr>	<chr>	<dbl>	<dbl>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>
NOR	0000003	00065	START_ITEM	1082.	1	NULL	NULL	NULL	NULL	NULL	NULL	NULL
NOR	0000003	00065	ACER_EVENT	1088.	2	Diagram	NULL	NULL	NULL	NULL	NULL	'000000
NOR	0000003	00065	ACER_EVENT	1089	3	Diagram	NULL	NULL	NULL	NULL	NULL	'000000
NOR	0000003	00065	ACER_EVENT	1089.	4	Diagram	NULL	NULL	NULL	NULL	NULL	'100000
NOR	0000003	00065	ACER_EVENT	1090.	5	Diagram	NULL	NULL	NULL	NULL	NULL	'100000
NOR	0000003	00065	ACER_EVENT	1091.	6	Diagram	NULL	NULL	NULL	NULL	NULL	'100100
NOR	0000003	00065	ACER_EVENT	1092.	7	Diagram	NULL	NULL	NULL	NULL	NULL	'100100
NOR	0000003	00065	ACER_EVENT	1092.	8	Diagram	NULL	NULL	NULL	NULL	NULL	'100101
NOR	0000003	00065	ACER_EVENT	1094.	9	Diagram	NULL	NULL	NULL	NULL	NULL	'100101
NOR	0000003	00065	ACER_EVENT	1095.	10	Diagram	NULL	NULL	NULL	NULL	NULL	'100111
NOR	0000003	00065	END_ITEM	1106.	11	NULL	NULL	NULL	NULL	NULL	NULL	NULL

Note. In this example, the entire action each student executed is recorded as a log file. There are three types of events (start_item, acer_event, end_item). Both start_item and end_item is generated automatically by the system. In contrast, Acer_event represent the event performed by students. For CP025Q01 item, five event types are included in the log file: start_item, apply, reset, diagram, end_item. In apply events, the variables top_setting, central_setting, bottom_setting, temp_value and humid_value describe the state of the system after apply was clicked by students. When the reset is clicked, these variables return to their initial setting as 0. All students time are recorded in seconds from the beginning of the assessment (i.e., start_item). While the first student (i.e., StIDStd = 00889) actively interacted with problem, the second student (i.e., StIDStd = 00065) showed only drawing the line between input variables and output variables.

Figure 3

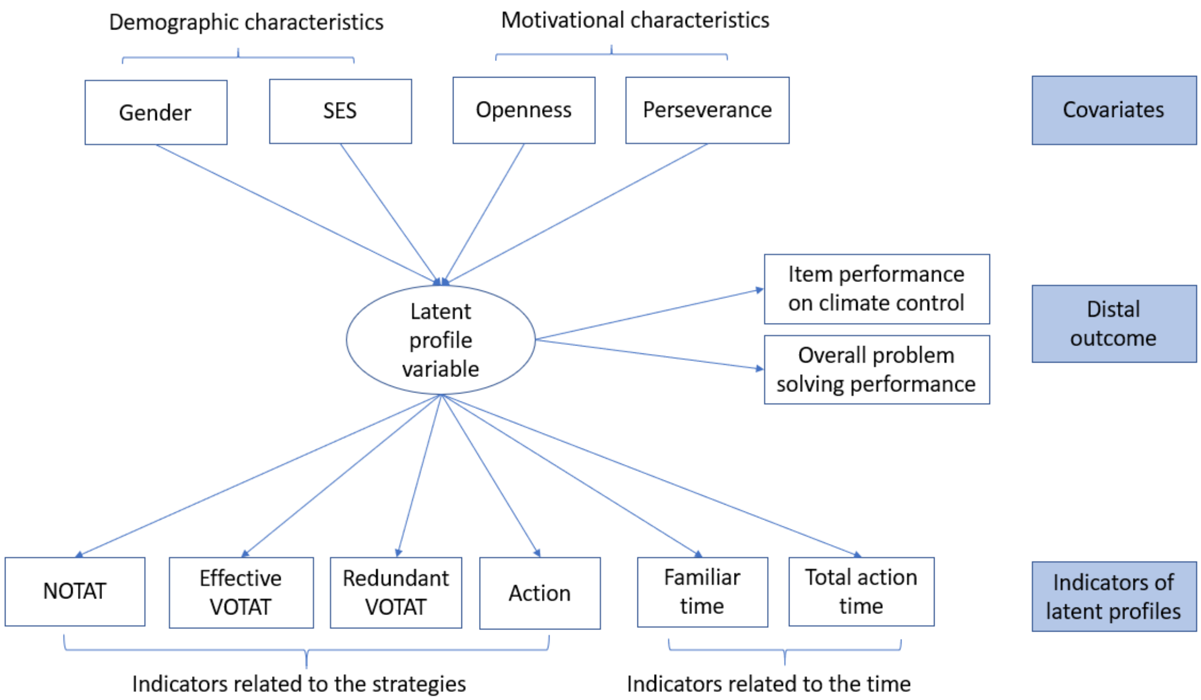
Five Identified Outliers using Multivariate Outlier Detection Approach (via MD)



Note. While most of samples follow in a line, five students were found as placed far away from the line (i.e., 134, 360, 316, 196, 214). Using cut-off score for a chi-square with 6 degrees of freedom (i.e., six latent profile indicators) those outliers were identified.

Figure 4

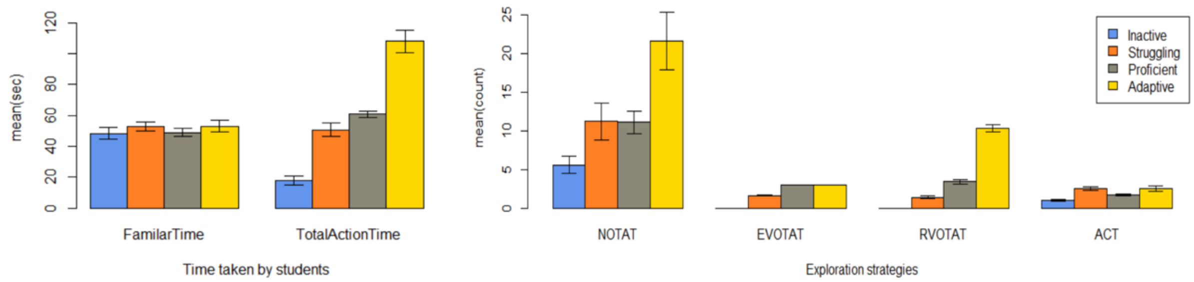
Full Model of Latent Profile Regression with Problem Solving Performance as the Distal Outcome



Note. Indicators related to the action and time are dependent.

Figure 5

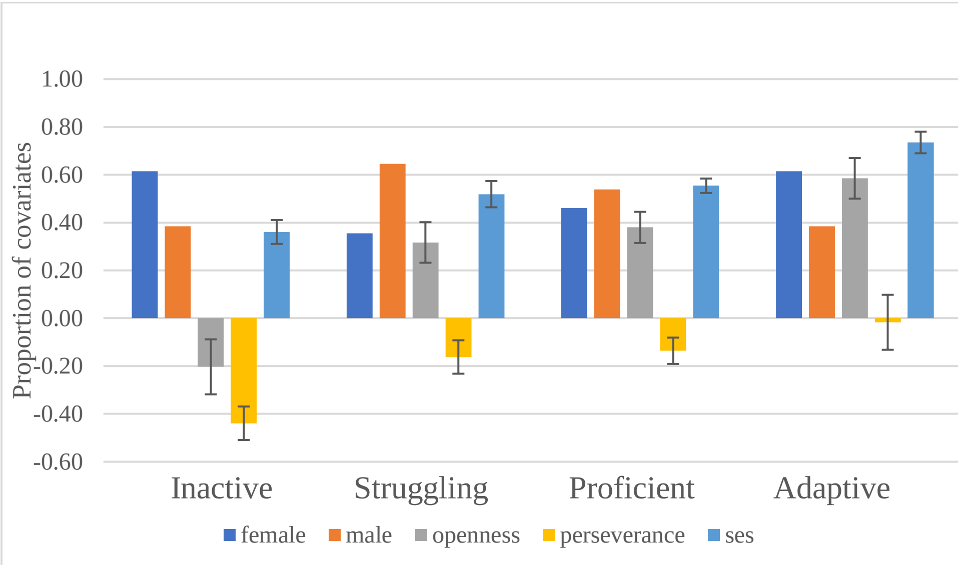
Profile Plot for Four-profile Model with Estimated Mean from Six Indicators



Note. Familiar time = time taken before first action (in seconds); NOTAT = The number of non-interfering observation strategy; EVOTAT = effective VOTAT, the number of required minimum VOTAT approach to gain information to solve the problem successfully, ranging from 0 to 3, VOTAT indicates changing one variable at a time; RVOTAT = the number of repeated VOTAT after VOTAT is already applied for each input variable, ACT = the number of changing multiple inputs at a time; TotActTime = time taken until the last action of a student; the error bars display standard errors.

Figure 6

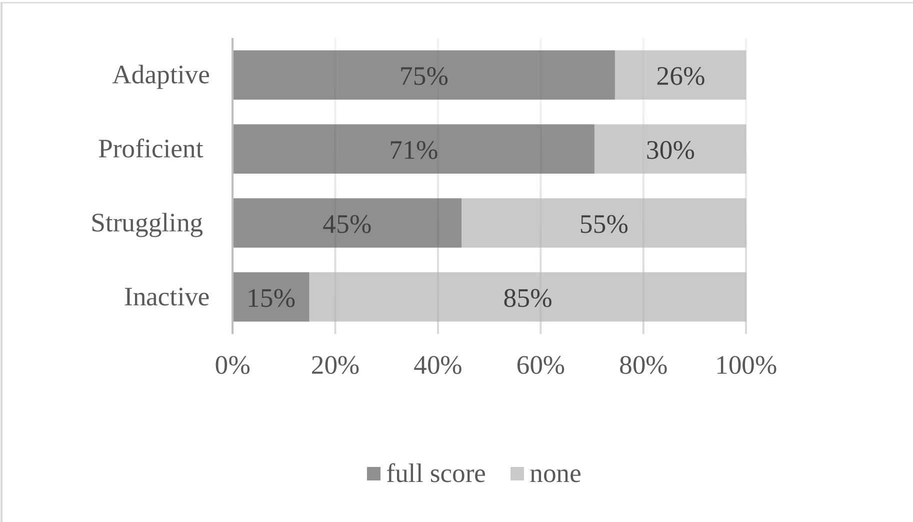
Distribution of Students' Covariates across the Four Profiles



Note. students' covariates: gender = students' gender coded as 0 (*female*) and 1 (*male*); OPENPS = the extent how willing students were to engage in problem situations; PERSEV= students' willingness to engage in problem solving when being confronted with difficult problems, SES = index of economic, cultural, social status; the error bars display standard errors

Figure 7

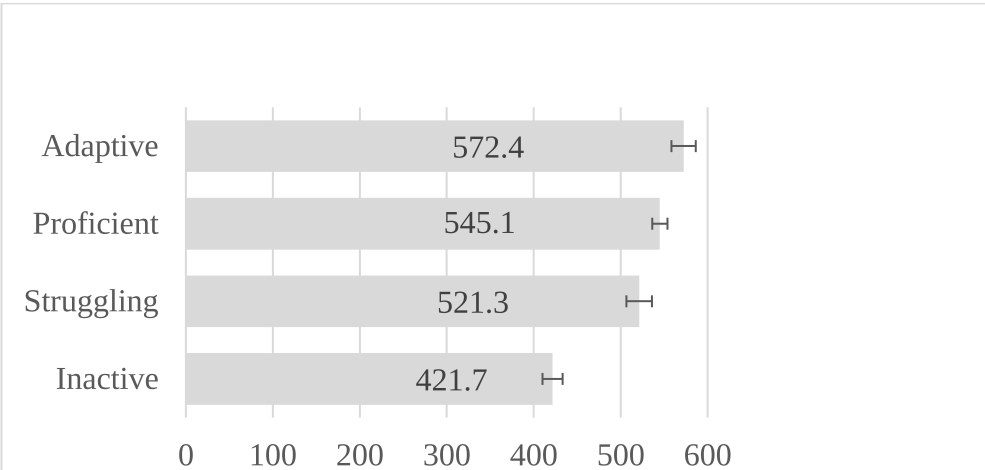
The Proportion of Students' Item Performance across Four Profiles



Note. significant item threshold difference found between profiles except between proficient and adaptive profile. the error bars display standard errors.

Figure 8

The Overall Problem Solving Performance by Four Profiles



Note. no significant difference found between struggling and proficient, proficient and adaptive profile. the error bars display standard errors.

Appendix I

GDPR Documentation

The current study was not subject to GDPR (General Data Protection Regulation) documentation as only pseudonymized data were used. Instead, I am forwarding the mock registration NSD (Norwegian Centre for Research Data) application form.

NOTIFICATION FORM (ENGLISH TRANSLATION) – NSD

- Personal data
- Types of data
- Project Information
- Responsibility
- Sample and Criteria
- Third Persons
- Documentation
- Other approvals
- Processing
- Information Security
- Duration of project
- Additional Information

Personal data

Which personal data will be processed?

Pseudonymized data

Personal data are any data about an identified or identifiable natural person (data subject). Pseudonymised data are also considered personal data. “Pseudonymisation” means processing collected data in way that the data can no longer be linked to individual persons, without the use of additional information. This usually involves removing identifiable information such as name, national ID number, contact details etc. from the collected data and giving each data subject a code/number. A scrambling key is the file/list of names and codes that makes it possible to identify individuals in the collected data. The scrambling key should be stored separately form the rest of the data. NB: processing pseudonymised data is still considered processing personal data, even if you do not have access to the scrambling key, and even if the scrambling key is being stored by an external party, such as SSB, the National registry etc.

Types of data

Name. First name and surname. N/A

National ID number or other personal identification number 11-digit personal identifier, D number, or other national identification number N/A

Date of birth. N/A

Address or telephone number N/A

Email address, IP address or other online identifier An email address is a unique address that is assigned to the user of an electronic mail service. An IP address is a unique address that is assigned to a device (e.g. a computer) in a computer network like the Internet. Dynamic IP addresses may also be considered personal data in certain cases. Cookies are an example of an online identifier. NB! If you are going use an online survey, and the service provider (data processor) will have access to email addresses or IP addresses, you must indicate this here.

N/A

Photographs or video recordings of persons Photographs and video recordings of faces are usually considered to be personal data. N/A

Audio recordings of persons. Audio recordings where personal data are recorded and/or where there exists a scrambling key that links the audio recordings to individual persons on the recordings. The voice of the person speaking may be considered personal data in combination with other background information. N/A

GPS data or other geolocation data, Data which indicate the geographical location of a person N/A

Demographic data that can identify a natural person E.g. a combination of information such as municipality of residence, workplace, position, age, gender etc. Age, Gender, ESCS

Genetic data, Personal data relating to the inherited or acquired genetic characteristics of a natural person, which give unique information about the physiology or health of that person. N/A

Biometric data, E.g. fingerprint, handprint, facial form, retina and iris scan, voice recognition, DNA. N/A

Other data that can identify a natural person, If you think that you will be processing personal data but cannot find a suitable alternative above, indicate this here. N/A

Will special categories of personal data or personal data relating to criminal convictions and offences be processed? N/A

Racial or ethnic origin, This includes belonging to an ethnic group, population, cultural sphere or society that has common characteristics. For example, information that a person is Sami is not considered to say anything about race but it says something about ethnicity. Norwegian

Political opinions, That a person is a member of a political party and/or what a person voted in an election, including political opinions and beliefs. However, this does not include information that a person is a conservative, radical or labour party supporter. N/A

Religious beliefs, That a person is a member of a religious organization/congregation. This does not include information that a person has a subscription to a religious newspaper. N/A

Philosophical beliefs, That a person is a member of a philosophical association, or that a person believes that knowledge is acquired through logical speculation and observation N/A

Trade Union Membership, That a person is a member of a trade union that organises employees within the same industry/subject area, e.g. LO, NTL, NAR etc. N/A

Health data, Personal data concerning a natural person's physical or mental health, including use of healthcare services. N/A

Sex life or sexual orientation, A person's sexual orientation (homosexual, lesbian, bisexual etc.) and/or sexual behaviour (e.g. that a personal has been unfaithful, indecent exposure, offensive gestures/language) N/A

Criminal convictions and offences, Personal data concerning convictions and offences, or related to security measures. N/A

Project Information

Title

Beyond the Result: Identifying Sutdnets' Problem Solving Processes on A Problem Solving Task

Project description

This study aims to identify students' problem solving processes based on more fine-grained indicators that jointly considered domain-general exploration strategies and time related to problem solving. For this purpose, this study will use the response processes from Norwegian

PISA 2012 CPS log files, especially focusing on a single CPS item 'Climate Control. The latent profile analysis will be conducted to identify subgroups of similar patterns of problem solving based on the combination of statistical criteria. Furthermore, to validate extracted profiles, whether these extracted profiles can be predicted by students' variables (i.e., gender, openness, perseverance, SES), and whether any relation exists between these profiles and problem solving performance will be investigated.

Subject area

Educational Science

Will the collected personal data be used for other purposes, in addition to the purpose of this project? Personal data should only be processed for specified, explicit and legitimate purposes. This means that each purpose for processing personal data must be identified and described clearly and accurately. In order for a purpose to be considered legitimate, it must also be in accordance with ethical and legal norms. N/A

Explain why it is necessary to process personal data, Explain why the personal data are adequate, relevant and limited to what is necessary for the purposes for which they are being processed. This includes limiting the amount of collected data to that which is necessary to realize the purposes of data collection. The purpose of using Pseudonymized data is to see whether students' demographic characterstic(i.e., gender) differnaite the profile membership.

External funding

- The Research Council of Norway (Norges forskningsråd - NFR)
- Public authorities E.g. research commissioned by a ministry
- Other E.g. funding from a pharmaceutical company or from private actors

Type of project

- Research Project and PhD thesis
- Student project, Master's thesis
- Student project, Bachelor's thesis
- Other student project

Responsibility for data processing

Data controller, The institution responsible for the processing of personal data. The data controller determines the purposes for which, and the manner in which, personal data are processed. UiO

Project leader (research assistant/ supervisor or research fellow/PhD candidate), The person responsible for the project.

Jayeong Song, Master Student, UiO, jayeongs@student.uv.uio.no

Ronny scherer, Supervisor, CEMO, UiO, ronny.scherer@cemo.uio.no

Will the responsibility for processing personal data be shared with other institutions (joint data controllers)? If two or more institutions together decide the purposes for which personal data are processed, they are joint data controllers. N/A

Joint data controllers Institution N/A

Institution not found in the list

Institution

Country

Postal address

Email address

Telephone number

Sample and criteria

Whose personal data will be processed? You must describe each group of people whose personal data you will be processing. Add and describe each sample individually. Pseudonymized data

Sample 1 Describe the sample Norwegian PISA 2012 log file and background information

Recruitment or selection of the sample, N/A

Describe how the sample will be recruited and how initial contact with the sample will be made. For example, whether you will make initial contact during field-work or via your own network, or whether a school, hospital or organization will contact its pupils, patients or members on your behalf. If the sample will not be recruited but will be selected from a registry or an administrative system etc., describe how the selection will be carried out and what the selection criteria will be.

Secondary analysis with pseudonymized data

Age this study will only use age for descriptive statstics of invstigating sample

Will you include adults (18 år +) who do not have the capacity to consent? N/A

i.e. the person has reduced capacity or lacks capacity to consent. For example, the person may have mental/cognitive impairment, significant physical/emotional ailments, or may be unconscious, conditions which make it difficult or impossible for the person to gain sufficient understanding in order to give valid consent. The central aspect is whether the person is capable of understanding the purpose of the processing/project in question, and of understanding potential positive and negative consequences (immediate and long-term).

Types of personal data - sample 1 N/A

Name N/A

National ID number or other personal identification number N/A

Date of birth Yes

Address or telephone number N/A

Email address, IP address or other online identifier N/A

Photographs or video recordings of persons N/A

Audio recordings of persons N/A

GPS data or other geolocation data N/A

Demographic data that can identify a natural person Gender

Genetic data N/A

Biometric data N/A

Other data that can identify a natural person N/A

Methods /data sources - sample 1

Select and/or describe the method(s) for collecting personal data and/or the source(s) of data

Personal interview N/A

Group interview Online survey Paper-based survey N/A

Participant observation Non-participant observation N/A

Field experiment / field intervention N/A

Web-based experiment N/A

Tests for pedagogical research / psychological tests N/A

Medical examination and/or physical tests N/A

Human biological material N/A

Social media – open forum N/A

Social media – closed forum N/A

Discussion board/forum for online newspapers/online debates N/A

Big data N/A

Medical records N/A

Biobank N/A

Data from another research project N/A

Other N/A

Statistics Norway - SSB N/A

Criminal records (Det sentrale straffe- og politiopplysningsregisteret, SSP) N/A

Medical Birth Registry of Norway (Medisinsk fødselsregister, MFR) N/A

Norwegian Registry of Pregnancy Termination (Register over svangerskapsavbrudd) N/A

Norwegian Cardiovascular Disease Registry (Hjerte- og karregisteret) N/A

Norwegian Cause of Death Registry (Dødsarsaksregisteret, DÅR) N/A

Norwegian Prescription Database - NorPD (Reseptregisteret) N/A

Norwegian Immunisation Registry (Nasjonalt vaksinasjonsregister, SYSVAK) N/A

Norwegian Surveillance System for Communicable Diseases (Meldesystem for smittsomme sykdommer, MSIS) N/A

Norwegian Surveillance System for use of antibiotics and healthcare related infections (Norsk overvåkingssystem for antibiotikabruk og helsetjenesteassosierte infeksjoner, NOIS) N/A

Norwegian Surveillance System for Antimicrobial Drug Resistance (Norsk overvåkingssystem for antibiotikaresistens hos mikrober, NORM) Norwegian Surveillance System for Virus Resistance (Norwegian Surveillance System for Virus Resistance, RAVN) N/A Norwegian Patient Registry (Norsk pasientregister, NPR) IPLOS-registeret Kommunalt pasient- og brukerregister (KPR) N/A Cancer registry of Norway (Kreftregisteret) N/A

Genetic Mass Survey of Newborns (Genetisk masseundersøkelse av nyfødte) N/A

Reseptformidleren N/A

Forsvarets helseregister N/A

Helsearkivregisteret N/A

Helseundersøkelsen i Nord Trøndelag (HUNT) N/A

Tromsø-undersøkelsen N/A

SAMINOR N/A

Den norske mor og barn undersøkelsen (MoBa) N/A

Nasjonalt register for langtids mekanisk ventilasjon N/A

Nasjonalt kvalitetsregister for barnekreft N/A

Norsk Kvalitetsregister Øre-Nese-Hals –Tonsilleregisteret N/A

Norsk vaskulittregister & biobank (NorVas) N/A

Norsk Parkinsonregister & biobank N/A

Norsk karkirurgisk register (NORKAR) N/A

Norsk hjertinfarkregister N/A

Gastronet N/A

Norsk register for analinkontinens N/A

Nasjonalt barnehofteregister N/A

Norsk kvalitetsregister for artrittsykdommer (NorArtritt) N/A

Norsk nakke- og ryggregister N/A

Nasjonalt korsbåndregister N/A

Nasjonalt register for leddproteser N/A

NorKog N/A

Norsk MS-register og biobank N/A

Nasjonalt register for KOLS N/A

Nasjonalt kvalitetsregister for lymfom og lymfoide leukemier N/A

Nasjonalt kvalitetsregister for lungekreft N/A

Nasjonalt kvalitetsregister for føflekkreft N/A

Nasjonalt kvalitetsregister for brystkreft N/A

Nasjonalt kvalitetsregister for prostatakreft N/A

Nasjonalt kvalitetsregister for tykk- og endetarmskreft N/A

Nasjonalt register for ablasjonsbehandling og elektrofysiologi i Norge (ABLA NOR) N/A

Norsk register for invasiv kardiologi (NORIC) N/A

Norsk hjertesviktregister N/A

Norsk pacemaker- og ICD- register N/A

Nasjonalt kvalitetsregister for gynekologisk kreft N/A

Norsk register for gastrokirurgi (NoRGast) N/A

Nasjonalt kvalitetsregister for behandling av spiseforstyrrelser (NorSpis) N/A

Information - sample 1

Will you inform the sample about processing their personal data? N/A

How? N/A

Written information (on paper or electronically)

Oral information,

See what you must give inform about and preferably use our template for the information letter.

Information should be given in writing or electronically. Only in special cases is it applicable to give oral information, if a participant asks for this. See what you must give information about.

Upload information letter N/A

Upload copy of oral information N/A

Explain why the sample will not be informed about the processing of their personal data.

+ Add sample Pseudonymized data

Third persons

Will you be processing personal data about third persons? This includes data about persons who are not included in the sample/are not participating in the project; information provided by a data subject that relates to another identified or identifiable natural person. Examples of this are when a data subject is asked about their mother's and father's education or country of origin, or when pupils are asked about their teacher's teaching methods. N/A

Describe the third persons N/A

Types of personal data about third persons N/A

Name N/A

National ID number or other personal identification number N/A

Date of birth N/A

Address or telephone number N/A

Email address, IP address or other online identifier N/A

Photographs or video recordings of persons N/A

Audio recordings of persons N/A

GPS data or other geolocation data N/A

Demographic data that can identify a natural person N/A

Genetic data N/A

Biometric data N/A

Other data that can identify a natural person N/A

Which sample will provide information about third persons? N/A

Sample 1

Sample 2 etc.

Will third persons consent to the processing of their personal data? N/A

Will third persons receive information about the processing of their personal data? N/A

Explain why third persons will not be informed. N/A

Documentation

Total number of data subjects in the project

(Data subjects: persons whose personal data you will be processing)

- 100-999 (353 students from Norwegian PISA 2012 log files, Pseudonymized data)

How can data subjects get access to their personal data or how they can have their personal data corrected or deleted? Pseudonymized data

Rights of data subjects (participants) include the right to access one's own personal data and to receive a copy of one's data if asked for. A data subject can request that their personal data are corrected if they feel that the information is wrong or lacking, and the data subject can withdraw consent and request that their personal data are deleted. Give a short description of the procedure for how a data subject can get access to their personal data, and how they can have their personal data corrected or deleted.

Other approvals

Will you obtain any of the following approvals or permits for the project? N/A

Indicate if you will obtain any of the following approvals or permits in order carry out the project. No need for any approval as this is secondary anaysis with Pseudonymized data

- Ethical approval from The Regional Committees for Medical and Health Research Ethics (REC)

- Confidentiality permit (exemption from the duty of confidentiality) from the Regional Committees for Medical and Health Research Ethics (REC), REC has the authority to grant a confidentiality permit for the processing of health data, both for health research and other research.
- Approval from own management for internal quality-assurance and evaluation of health services (intern kvalitetssikring) (The Health Personnel Act § 26)
- Confidentiality permit (exemption from the duty of confidentiality) from the Norwegian Directorate of Health, for quality-assurance and evaluation of health services (kvalitetssikring) (The Health Personnel Act § 29b)
- Biobank – approval for?
- Confidentiality permit (exemption from the duty of confidentiality) from Statistics Norway (SSB) Statistics Norway has the authority to grant a confidentiality permit for the data that they manage, e.g. data about population, education, employment and social security.
- Approval from The Norwegian Medicines Agency (Statens legemiddelverk, SLV) E.g. for a clinical drugs trial
- Confidentiality permit (exemption from the duty of confidentiality) from a department or directorate
- Other approval E.g. from a Data Protection Officer

Processing

Where will the personal data be processed? Pseudonymized data

“Processing” includes any collecting, registering, storing, collating, transferring etc. of data. You must indicate all processing of personal data that will take place in the project.

- Computer belonging to the institution responsible for the project, Computer owned/operated by the data controller. For example, processing data in a private or communal user area on the institution’s server. N/A
- Mobile device belonging to the data controller, Mobile device owned/operated by the data controller. A mobile device can be a laptop, camera, mobile phone etc. N/A
- Physically isolated computer belonging to the data controller, Not connected to other computers or to a network, neither internally nor externally. N/A
- External service or network, Such as providers of cloud storage, online surveys or data storage (such as TSD). Use of an external service or server requires that a data processor agreement is made between the data controller and the external party. N/A
- Private device, Data collection or storage on private devices such as your own computer or mobile phone etc. is not recommended and must be clarified with the institution responsible for the project. Data collection, storing or archiving on private devices such as your own computer, mobile phone, memory stick etc. is not recommended and must be clarified with the institution responsible for the project. N/A

Who will be processing/have access to the collected personal data?

- Project leader
- Student (student project)
- Internal co-workers

Employees of the data controller

  - External co-workers/collaborators inside the EU/EEA, Employees of other institutions that have formalised cooperation with the data controller, or employees of other institutions that are joint data controllers. N/A

- Data processor, An external person or entity that processes personal data on behalf of the data controller, such as an online survey provider, cloud storage provider, translator or transcriber. There must be a data processor agreement or other legal agreement between the data controller and the external party. N/A
- Others with access to the personal data, N/A

Which others will have access to the collected personal data? N/A

Will the collected personal data be made available to a third party or international organisation outside the EEA? This includes when personal data are sent to and stored in a country outside the EEA, or when persons outside this area are given access to personal data stored within the EEA. This means that you cannot use a service provider or outsourced supplier outside the EEA, unless there is a valid basis for the transfer of personal data. N/A

Give the name of the institution/organisation N/A

Give the country of the institution/organisation N/A

On what basis will the collected personal data be transferred? Personal data can be transferred on the basis of an adequate level of protection (art. 45) or on the basis of appropriate safeguards (art. 46). Personal data can also be transferred on the basis of the exception for special situations, but only if the transfer is not repeated, concerns only a limited number of data subjects, is necessary for the purposes of compelling legitimate interests pursued by the data controller (which are not overridden by the interests or rights and freedoms of the data subject), and if the data controller has assessed all the circumstances surrounding the data transfer and has provided suitable safeguards with regard to the protection of personal data (art. 49). N/A

Information Security

Will directly identifiable personal data be stored separately from the rest of the collected data (in a scrambling key)? It is common practice to remove directly identifiable data (name, national ID number, contact details etc.) from the collected data and give each data subject a code/number. A scrambling key is the file/list of names and codes that makes it possible to directly identify data subjects in the collected data. It should be stored separately from the rest of the collected data. In practice, this means that the scrambling key cannot be stored in the same network as the rest of the data, unless the scrambling key is encrypted. Pseudonymized data

Explain why directly identifiable personal data will be stored together with the rest of the collected data. For reasons of information security we recommend the use of a scrambling key in most projects, especially in projects where special categories of personal data (previously "sensitive" personal data) or personal data relating to criminal convictions and offences will be processed. N/A

Which technical and practical measures will be used to secure the personal data? Pseudonymized data

- Personal data will be anonymized as soon as no longer needed

Anonymisation involves processing the data in such a way that no individual persons can be identified in the data that you're left with, i.e. the data can no longer be linked to individual persons in any way. Anonymisation usually involves: *deleting directly identifiable personal data (including scrambling key/list of names) *deleting or rewriting indirectly identifiable personal data (e.g. deleting or categorizing variables such as age, place of residence, school etc.) *deleting or editing audio recordings, photographs and video recordings

- Personal data will be transferred in encrypted form, Encryption is a mathematical method for ensuring confidentiality in that information cannot be read by unauthorized persons.

For example, using an encrypted VPN tunnel or equivalent measure for external login to work-place network. N/A

- Personal data will be stored in encrypted form, Encryption is a mathematical method for ensuring confidentiality in that information cannot be read by unauthorized persons. For example, the encryption of a hard drive to ensure the confidentiality of data when the computer is turned off. N/A
- Record of changes, Changes in the collected data are recorded/documented with the time of the change and information about the person who made that change. N/A
- Multi-factor authentication, A method of access control where a user is granted access after presenting two or more separate pieces of evidence to prove their identity (e.g. password + code sent by text message) N/A
- Restricted access, Blocking or restricting access to the collected data for unauthorized persons N/A
- Access log, An access log shows who has accessed the collected data and when Other security measures, For example, locking away documents, automatic screen lock after a short time for mobile devices, partitioning of hard drive, checksum/integrity check etc. N/A
- Indicate which measures N/A

Duration of project

Project period 20/08/01~21/05/14

Will personal data be stored beyond the end of project period? Personal data should not be further processed a way that is inconsistent with the initial purpose(s) for which the data were collected. Anonymous/anonymised data may be stored indefinitely, so long as nothing else has been agreed to by the data subjects.

- No, all collected data will be deleted
- No, the collected data will be stored in anonymous form

Stored in a form where the data can no longer be linked to individual persons in any way

- Yes, collected personal data will be stored until
- Yes, collected personal data will be stored indefinitely.

For what purpose(s) will the collected personal data be stored? N/A

- Research
- Other

Where will the collected personal data be stored? N/A

- At the institution responsible for the project (data controller)
- Other

Additional information

Will the data subjects be identifiable (directly or indirectly) in the thesis/publications for the project? If personal data are to be published, there should be a scientific purpose for this. Data is usually published in anonymous form. N/A

Explain why Pseudonymized data

Additional information, Here you can provide information that may have significance for our assessment of the project, including more detailed information about points covered in the form and information that is not covered by points in the form. N/A

Other attachements, e.g. interview guide, questionnaire, information letter and consent form etc.

N/A

Appendix II

Data Management and Analysis Code

The following syntax code is presented for reproducibility of the findings. To clean and prepare the log file, R version 4.0.1 was employed (R Team et al., 2014) while all data anayasis were conducted using M*plus* version 7.3 (Muthén & Muthén, 1998-2012)

Data Management Code in R

```
################################################################################
##Master Sample R Code
##Writer: Jayeong Song
##Written date: 15 March 2021
##Purpose: After importing 4 datasets, i extracted specific indicators on the basis of log file
using loop function, and merge with students' covariates, item performance, overall performance.
################################################################################

#outline
#1.Preparations for R
##1.1 load packages
##1.2 import norwegian dataset

#2.Data wrangling
###2.1 clean the missing IDs
###2.2 extract VOTAT data
###2.3 exclude students who have only 1 action based on the frequency of action
###2.4 VOTAT evaluation
###2.5 Derived variable
#####2.5.1 total number of VOTAT
#####2.5.2 effective VOTAT(EVOTAT)
#####2.5.3 total action time (TotActTime)
#####2.5.4 Familiar time
#####2.5.5 NOTAT

#3.Merging Dataset
###3.1 indicators (RQ1) : not nested, auditing, missing values, outlier check
#####3.1.1 not nested
#####3.1.2 auditing (negative value for time)
#####3.1.3 outlier check using Mahalanobis distance
```

```
#3.2 predictors (RQ2) : gender,SES,openness,perseverance
#3.3 problem solving performance (RQ3)
###3.1 item performance (CP025Q01)
###3.2 overall problem solving performance

#4.Mplus Automation

###########################################################################
###############1.Preparations for R
###########################################################################

##1.1 load packages
library("haven")   # import foreign statistical formats into R (e.g., SPSS)
library("dplyr")   # manipulate, clean and summarize unstructured data
library("tidyverse") #tidy data
library("corrplot") # correlation analysis
library("ggplot2") # graph
library("psych") # outlier detection
library("MplusAutomation") #Mplus automation package

##1.2 import dataset
setwd("G:/My Drive/thesis/200725 data") # set working directory
getwd() # get working directory

pisa_cp025q01 <- read_sav("G:/My Drive/thesis/200725 data/PISA
data/CBA_cp025q01_logs12_SPSS.sav") #indicators
INT_STU12_DEC03 <- read_sav("G:/My Drive/thesis/200725 data/PISA
data/INT_STU12_DEC03.sav") #predictors
CBA_COG12_S_MAR31 <- read_sav("G:/My Drive/thesis/200725 data/PISA
data/CBA_COG12_S_MAR31.sav") #item performance
CBA_STU12_MAR31 <- read_sav("G:/My Drive/thesis/200725 data/PISA
data/CBA_STU12_MAR31.sav") #plausible values

names(pisa_cp025q01) ;summary(pisa_cp025q01) ;dim(pisa_cp025q01) ;unique(pisa_cp025q01
$cnt) #get to know the data # 44 countries participated.

#extract only Norwegian data and arrange the data based on the ID
norway <- pisa_cp025q01 %>% filter(cnt == "NOR") #only extract Norwegian
norway <- norway %>% arrange(StIDStd) #arrange by ID 1,2,3,4
head(norway) ;tail(norway) ;dim(norway) ;summary(norway) #get to know norway


###########################################################################
###############2.Data wrangling
###########################################################################
###2.1 clean the missing IDs
```

```
unique(norway$StIDStd) # how many unique students participated in this CBA # 405+5(""
students)=410 students
View(filter(norway, StIDStd== "")) # 5 students who doesn't have information on student ID
norway <- filter(norway, StIDStd!= "") #excepting "" students
unique(norway$StIDStd) # 405 students after excluding "" students(n=5)
norway[norway$StIDStd == "00065",] # the action of 1 student


###2.2 extract VOTAT data
#extract data without end(event)
votat405 <- norway %>% filter(event == "START_ITEM" | event =="ACER_EVENT")
#except end
#extract data without diagram(event_type)
votat405 <- votat405 %>% filter(event_type == "apply" | event_type =="reset"| event_type
=="NULL") #except diagram
#assigning 0 to the Null at start setting
votat405$top_setting <- ifelse(votat405$top_setting == 'NULL', 0, votat405$top_setting)
votat405$central_setting <- ifelse(votat405$central_setting == 'NULL', 0,
votat405$central_setting)
votat405$bottom_setting <- ifelse(votat405$bottom_setting == 'NULL', 0,
votat405$bottom_setting)


###2.3 exclude students who have only 1 action based on the frequency of action
#create the final data frame to save all the information
final <- table(votat405$StIDStd) # the frequency of action
final <- data.frame(final) #make as data.frame
names(final) <- c("ID", "tot.act") #name the column
#exclude from final
final[final$tot.act ==1,] #students who have only 1 action=row
nrow(final[final$tot.act ==1,]) # 45 students who have only 1 action=row
final <- final %>% filter(tot.act != 1)  # exclude students with 1 action
nrow(count(unique(final))) #405-45 = 360 students
#exclude from votat data
unique(votat405$StIDStd) #still 405 studnets in norwegian votat data
# student number who has only 1 row (e.g., 00065, 00075, 00116, 00522 actual student id)
one <- c("00065", "00075", "00116", "00522", "00595", "00599", "00674", "00853", "00920",
"01051", "01084", "01092", "01355", "01439", "01440", "01670", "01692", "01701", "01718",
"01806", "01859", "01946", "02090", "02115", "02208", "02211", "02236", "02239", "02539",
"02693", "02911", "02920", "02924", "03014", "03053", "03101", "03318", "03408", "03629",
"03729", "03779", "03893", "03954", "04277", "04649")
votat360 <- votat405[!votat405$StIDStd %in% one,] #data with students available(especially
that has more than 1 row)
#save(votat360, file ="votat360.rda") #save as rda
```

```
###2.4 VOTAT evaluation
#preparation for VOTAT evaluation (e.g., making ID as list)
ID <- unique(votat360$StIDStd) ; length(ID) #360
stu_seq <- list() # making as list, using indexing
stu_seq[[1]] <- votat360[votat360$StIDStd==ID[1],] #example of student "1"
#View(stu_seq[[1]])#example of student 1
#numbering
final <- table(votat360$StIDStd)# n= how many rows each student has
final <- data.frame(final)
names(final) <- c("ID", "total_act") #name change
#saving the result after the iteration
data <- list() #creating the list
#VOTAT evaluation for 360 students
for(j in 1:360) {
  stu_seq[[j]] <- votat360[votat360$StIDStd==ID[j],]
  data[[j]] <- data.frame(matrix(nrow= final[j,2]-1, ncol=5))
  names(data[[j]]) = c("flagt", "flagc", "flagb", "votat", "time")
  for(i in 1:final[j,2]-1){
    data[[j]]$flagt[i]<- ifelse(stu_seq[[j]]$top_setting[i] != stu_seq[[j]]$top_setting[i+1],1,0)
    data[[j]]$flagc[i] <- ifelse(stu_seq[[j]]$central_setting[i] !=
stu_seq[[j]]$central_setting[i+1],1,0)
    data[[j]]$flagb[i] <- ifelse(stu_seq[[j]]$bottom_setting[i] !=
stu_seq[[j]]$bottom_setting[i+1],1,0)
    data[[j]]$votat[i] <- ifelse(data[[j]]$flagt[i]+data[[j]]$flagc[i]+data[[j]]$flagb[i] == 1, 1, 0)
  }
  data[[j]]$time <- stu_seq[[j]]$time[-1]-stu_seq[[j]]$time[1]
}
#data[[1]] #example of one student with VOTAT evaluation


###2.5 Derived variable
#####2.5.1 total number of VOTAT
tot_votat <- rep(0,360) #create the vector
for (j in 1:360) {
  tot_votat[j] <- sum(data[[j]]$votat)
} #count the total number of votat
final$tot_votat <- tot_votat #add the data to the final dataset
names(final) #total_act; total number of action(e.g., reset,apply), #tot_votat; total number of
VOTAT

#####2.5.2 effective VOTAT(EVOTAT)
#initial setup
a <- 0; b <- 0; c <- 0
#create new column(i.e., a,b,c) to the 'data' for 360 students
for(j in 1:360){
  data[[j]]$a <- rep(0, dim(data[[j]])[1])
```

```
  data[[j]]$b <- rep(0, dim(data[[j]])[1])
  data[[j]]$c <- rep(0, dim(data[[j]])[1])
}
#evaluating whether students applied VOTAT for each input variable
for(j in 1:360){for(i in 1:nrow(data[[j]])){
  if(i > 1){
    data[[j]]$a[i] <- data[[j]]$a[i-1]
    data[[j]]$b[i] <- data[[j]]$b[i-1]
    data[[j]]$c[i] <- data[[j]]$c[i-1]
  }
  if(data[[j]]$votat[i] ==1){
    if(data[[j]]$flagt[i]==1){data[[j]]$a[i] <- 1}
    if(data[[j]]$flagc[i]==1){data[[j]]$b[i] <- 1}
    if(data[[j]]$flagb[i]==1){data[[j]]$c[i] <- 1}
  }
}}
#add Rvotat column to the 'data'
for(j in 1:360){data[[j]]$Rvotat <- data[[j]]$a*data[[j]]$b*data[[j]]$c} #find out students who
used 3 VOTAT for each input variable
for(j in 1:360){data[[j]]$Cvotat <- data[[j]]$a+data[[j]]$b+data[[j]]$c} #effective VOTAT
#counting effective VOTAT without redundnat VOTAT
cat_votat <- rep(0,360) #create the vector
for(j in 1:360){
  cat_votat[j] <- max(data[[j]]$Cvotat)
} #counting the max of effective VOTAT
table(cat_votat)# never applied VOTAT(N=65), applied VOTAT for one input(N=31), appplied
VOTAT for two inputs(N=32), applied VOTAT for three input variables(N=232)
final$cat_votat <- cat_votat #add to the final dataset

#####2.5.3 total action time (TotActTime)
#total action time (not overlapped with familiar time)
stu_seq[[6]]$time[final$total_act[[6]]]-stu_seq[[6]]$time[[2]] #100.6
stu_seq[[6]]$time[final$total_act[[6]]] #401.8
stu_seq[[6]]$time[[2]] #301.2
#stu_seq[[6]]$time[final$total_act[[6]]]-stu_seq[[6]]$time[[2]] #code for same result 100.6
#data[[6]]$time[[9]]-data[[6]]$time[[1]] #code for same result 100.6
time_action <- rep(0,360) #create the vector
for (j in 1:360) {
  time_action[j] <- data[[j]]$time[[final[j,2]-1]]-data[[j]]$time[[1]]
} #calculating the total action time for 360 students
final$time_action <- time_action #add to final dataset

#####2.5.4 Familiar time
time_familiar <- rep(0,360) #create the vector
for (j in 1:360) {
  time_familiar[j] <- stu_seq[[j]]$time[2]-stu_seq[[j]]$time[1]
```

```
} #getting familar time for 360 students
final$time_familiar <- time_familiar #add to the final dataset
#####2.5.5 NOTAT
notat_data <- list() #create the list
#NOTAT evaluation for 360 students
for(j in 1:360) {
  stu_seq[[j]] <- votat360[votat360$StIDStd==ID[j],]
  notat_data[[j]] <- data.frame(matrix(nrow= final[j,2]-1, ncol=4))
  names(notat_data[[j]]) = c("flagt", "flagc", "flagb", "notat")
  for(i in 1:final[j,2]-1){
    notat_data[[j]]$flagt[i]<- ifelse(stu_seq[[j]]$top_setting[i] ==
stu_seq[[j]]$top_setting[i+1],1,0)
    notat_data[[j]]$flagc[i] <- ifelse(stu_seq[[j]]$central_setting[i] ==
stu_seq[[j]]$central_setting[i+1],1,0)
    notat_data[[j]]$flagb[i] <- ifelse(stu_seq[[j]]$bottom_setting[i] ==
stu_seq[[j]]$bottom_setting[i+1],1,0)
    notat_data[[j]]$notat[i] <-
ifelse(notat_data[[j]]$flagt[i]+notat_data[[j]]$flagc[i]+notat_data[[j]]$flagb[i] == 3, 1, 0)
  }
}
final$tot_notat <-0 #assign 0
for(i in 1:360){final$tot_notat[i] <- sum(notat_data[[i]]$notat)} #getting NOTAT for 360
students
table(final$tot_notat) #distribution check


###########################################################################
###############3.Merging Dataset
###########################################################################
###3.1 indicators (RQ1) : not nested, auditing, missing values, outlier check
#####3.1.1 not nested indicators
final$total_act <- final$total_act-1 # due to start setting(initial row)
final$tot_votat <- final$tot_votat-final$cat_votat #substracting effective votat from total number
of votat
final$total_act <- final$total_act-(final$tot_notat+final$tot_votat+final$cat_votat) #the result
equals to the action(e.g., manipulating variables at a same time)

#####3.1.2 auditing (negative value for time)
which(final$time_action < 0) #135,230 were identified
which(final$time_familiar < 0) #none
#data[[135]] ; View(stu_seq[[135]]) #unknown error(e.g., two start time) #stIDStd=01690
#data[[230]] ; View(stu_seq[[230]]) #unknow error(e.g., two start time) #stIDStd=03183
two <- c("00065", "00075", "00116", "00522", "00595", "00599", "00674", "00853", "00920",
"01051", "01084", "01092", "01355", "01439", "01440", "01670", "01690", "01692", "01701",
"01718", "01806", "01859", "01946", "02090", "02115", "02208", "02211", "02236", "02239",
```

```
"02539", "02693", "02911", "02920", "02924", "03014", "03053", "03101", "03183", "03318",
"03408", "03629", "03729", "03779", "03893", "03954", "04277", "04649")
final <- final[!final$ID %in% two,] #358 students

#####3.1.3 multivariate outliers check using Mahalanobis distance
outlier(final[,c(2:7)]) #to identify and deal with multivariate outliers is to use Mahalanobis
Distance (MD). MD calculates the distance of each case from the central mean. Larger values
indicate that a case is farther from where most of the points cluster. the outlier function in the
psych package can calculates and plots MDs
#five students were identified as outliers. In contrast, most of the students appear to follow in
line.
#formal test of outliers by using a cut-off score for MD.
data_outlier <- final[,c(2:7)] # 6 indicators
md <- mahalanobis(data_outlier, center = colMeans(data_outlier), cov = cov(data_outlier))
# recalculate the MDs using the mahalanobis function and identify those that fall above the cut-
off score for a chi-square with k degrees of freedom(6 for 6 variables)
alpha <- .001
cutoff <- (qchisq(p = 1 - alpha, df = ncol(data_outlier))) #degree of freedm(the number of
indicators)
names_outliers_MH <- which(md > cutoff) #using cut-off, five outliers were identified.
final[,c(2:7)][names_outliers_MH, ] # original value of identified five outliers
(01680,02588,02936,04239,04675)
#data set (n=353)
three <- c("00065", "00075", "00116", "00522", "00595", "00599", "00674", "00853", "00920",
"01051", "01084", "01092", "01355", "01439", "01440", "01670", "01680","01690", "01692",
"01701", "01718", "01806", "01859", "01946", "02090", "02115", "02208", "02211", "02236",
"02239", "02539", "02588","02693", "02911", "02920", "02924", "02936", "03014", "03053",
"03101", "03183", "03318", "03408", "03629", "03729", "03779", "03893", "03954",
"04239","04277", "04649","04675")
final <- final[!final$ID %in% three,] #exclude five outliers, the remaining sample N=353
final <-
final[,c("ID","time_familiar","tot_notat","cat_votat","tot_votat","total_act","time_action")]#
reorder


#3.2 predictors (RQ2) : gender,SES,openness,perseverance
#extract Norwegian sample and 353 students
norway_stu <- INT_STU12_DEC03 %>% filter(CNT == "NOR") #extract norway
norway_stu <- norway_stu %>% arrange(StIDStd) #arrange
norway_stu <- norway_stu[norway_stu$StIDStd %in% final$ID,] #353 students
#only select necessary variables
predictors <- norway_stu %>%
select(c("StIDStd","SCHOOLID","ST04Q01","OPENPS","PERSEV","ESCS","W_FSTUWT"))
#"StIDStd"=ID; SCHOOLID = school id; "ST04Q01"=gender, 1=female, 2=male;OPENPS =
openness; PERSEV = perseverance, ESCS = index of economic, social and cultural status;
W_FSTUWT : finalweight
```

```
#checking the missing dta
summary(predictors) #the number of missing data in openness = 125; perseverance =125;
#ESCS = 12
#assining "-999" to missing data
predictors$OPENPS <- ifelse(is.na(predictors$OPENPS), -999, predictors$OPENPS)
predictors$PERSEV <- ifelse(is.na(predictors$PERSEV), -999, predictors$PERSEV)
predictors$ESCS <- ifelse(is.na(predictors$ESCS), -999, predictors$ESCS)
names(predictors)[1]<-"ID" #rename
mdata <- merge(final, predictors, by="ID") #merging two dataset(final, predictors)
names(mdata) <-
c("ID","time_familiar","tot_notat","cat_votat","tot_votat","total_act","time_action","SCHOOLI
D","GENDER","OPENPS","PERSEV","ESCS","W_FSTUWT") #rename
mdata <-
mdata[,c("ID","SCHOOLID","time_familiar","tot_notat","cat_votat","tot_votat","total_act","tim
e_action","GENDER","OPENPS","PERSEV","ESCS","W_FSTUWT")] #reorder


#3.3 problem solving performance (RQ3)
###3.1 item performance (CP025Q01)
#extract Norwegian data & 353 students
norway_cogs <- CBA_COG12_S_MAR31 %>% filter(CNT == "NOR") #Norwegian
norway_cogs <- norway_cogs %>% arrange(StIDStd) #arrange
norway_cogs <- norway_cogs[norway_cogs$StIDStd %in% final$ID,] ; dim(norway_cogs) #353
Norwegian students
#only select necessary variables
itemscore <- norway_cogs %>% select(c("CP025Q01")) # knowlege acqustion stage of climate
control
itemscore$CP025Q01 <- as.numeric(unclass(itemscore$CP025Q01)) ; str(itemscore) #unclass
###3.2 overall problem solving performance
#extract Norwegian data & 353 students
norway_cog <- CBA_STU12_MAR31 %>% filter(CNT == "NOR") #Norwegian
norway_cog <- norway_cog %>% arrange(StIDStd) #arrange
norway_cog <- norway_cog[norway_cog$StIDStd %in% final$ID,] #353 students
overallscore <- norway_cog %>%
select(c("PV1CPRO","PV2CPRO","PV3CPRO","PV4CPRO","PV5CPRO")) #five plausible
scores of overall problem solving performance
outcomes <- cbind(itemscore, overallscore) #merge itemscore and overallscore
#unclass
outcomes$PV1CPRO <- unclass(outcomes$PV1CPRO)
outcomes$PV2CPRO <- unclass(outcomes$PV2CPRO)
outcomes$PV3CPRO <- unclass(outcomes$PV3CPRO)
outcomes$PV4CPRO <- unclass(outcomes$PV4CPRO)
outcomes$PV5CPRO <- unclass(outcomes$PV5CPRO)
#merge
mdata <- cbind(mdata, outcomes)
#before fitting into Mplus, unclass all variables
```

```
mdata$ID <- as.numeric(as.character(mdata$ID))
mdata$SCHOOLID <- as.numeric(mdata$SCHOOLID)
mdata$GENDER <- unclass(mdata$GENDER)
mdata$W_FSTUWT <- unclass(mdata$W_FSTUWT)
#recoding for gender, item performance
mdata$CP025Q01 <- ifelse(mdata$CP025Q01 == 2, 1 , 0) # as binary score
mdata$GENDER <- ifelse(mdata$GENDER == 1, 0 , 1) #female =0, male=1
length((which(mdata$GENDER=="0"))) #159 =female
length((which(mdata$GENDER=="1"))) #194 male

#saveRDS(mdata, file = "final210315.rds") #save as RDS


###############################################################################
###############4.Mplus Automation
###############################################################################
setwd("C:/Users/user/Desktop/210315 RESULT/RQ1") #set working directory
prepareMplusData(mdata, "NewData.dat",
keepCols=c("ID","SCHOOLID","time_familiar","tot_notat","cat_votat","tot_votat","total_act","time_action","GENDER","OPENPS","PERSEV","ESCS","W_FSTUWT","CP025Q01","PV1CPRO","PV2CPRO","PV3CPRO","PV4CPRO","PV5CPRO")) #remove colunm names for Mplus
runModels("C:/Users/user/Desktop/210315 RESULT/RQ1",
        recursive=TRUE, replaceOutfile="modifiedDate") #run models in the folder and create OUT files
```

Analysis Code in Mplus

TITLE: LPA of problem solving profiles without covariates (RQ1)

```
  DATA:
        FILE IS NewData.dat;
              FORMAT IS FREE;

  VARIABLE:

              NAMES ARE
        ID
        SCHOOLID
          time_familiar
          tot_notat
          cat_votat
          tot_votat
          total_act
          time_action
          GENDER
```

```
    OPENPS
    PERSEV
    ESCS
    W_FSTUWT
    CP025Q01
    PV1CPRO
    PV2CPRO
    PV3CPRO
    PV4CPRO
    PV5CPRO;


        MISSING ARE ALL(-999);

        IDVARIABLE = ID;
        ! student ID to appear in the output files

        WEIGHT = W_FSTUWT;
         ! students' final weights

   CLUSTER = SCHOOLID;

        USEVARIABLES ARE
    time_familiar
    tot_notat
    cat_votat
    tot_votat
    total_act
    time_action;

        CLASSES = c(4);
        ! specify the number of profiles

ANALYSIS:

        TYPE = MIXTURE COMPLEX;
        ESTIMATOR = MLR;
        STARTS = 800 40;
        STITERATIONS = 40;
        LRTBOOTSTRAP = 100;
        LRTSTARTS = 10 5 80 20;
        ! source: Morin et al, (2011) OrgResMeth

   PROCESSORS = 4;

MODEL:
```

```
        %OVERALL%
%c#1%
        [time_familiar
tot_notat
  cat_votat
  tot_votat
  total_act
  time_action];
        ! request means and estimate profiles based on them

time_familiar-time_action(v1-v6);
! name variances to constrain them to be equal across
! profiles

%c#2%
        [time_familiar
tot_notat
  cat_votat
  tot_votat
  total_act
  time_action];

time_familiar-time_action(v1-v6);
! name variances to constrain them to be equal across
! profiles

%c#3%
        [time_familiar
tot_notat
  cat_votat
  tot_votat
  total_act
  time_action];

time_familiar-time_action(v1-v6);
! name variances to constrain them to be equal across
! profiles

%c#4%
        [time_familiar
tot_notat
  cat_votat
  tot_votat
  total_act
  time_action];
```

```
        time_familiar-time_action(v1-v6);
        ! name variances to constrain them to be equal across
        ! profiles


  OUTPUT:
              SAMP;
              STAND;

              ! technical outputs
              TECH1;
              TECH7;
              TECH11;
              TECH14;

              ! confidence intervals
              CINTERVAL;

              PLOT:
                    TYPE = PLOT3;
                    SERIES =    time_familiar(1) tot_notat(2) cat_votat(3)
                                      tot_votat(4)
                                      total_act(5)
                                      time_action(6); ! or use an asteriks

  SAVEDATA:
              FILE IS lpa4.dat;
              SAVE = CPROBABILITIES; ! save class probabilities
              FORMAT IS FREE; ! or use F6,0
```

TITLE: LPA of problem solving user profiles with covariates (RQ2)

```
  DATA:
        FILE IS NewData.dat;
              FORMAT IS FREE;

  VARIABLE:

              NAMES ARE
        ID
        SCHOOLID
          time_familiar
          tot_notat
          cat_votat
          tot_votat
```

```
    total_act
    time_action
    GENDER
    OPENPS
    PERSEV
    ESCS
    W_FSTUWT
    CP025Q01
    PV1CPRO
    PV2CPRO
    PV3CPRO
    PV4CPRO
    PV5CPRO;

        MISSING ARE ALL(-999);

        IDVARIABLE = ID;
        ! student ID to appear in the output files

        WEIGHT = W_FSTUWT;
   ! students' final weights

   CLUSTER = SCHOOLID;
   ! School ID

        USEVARIABLES ARE
   time_familiar
   tot_notat
   cat_votat
   tot_votat
   total_act
   time_action
    GENDER
    OPENPS
    PERSEV
    ESCS;

        CLASSES = c(4);
        ! specify the number of profiles

ANALYSIS:

        TYPE = MIXTURE COMPLEX;
        ESTIMATOR = MLR;
        STARTS = 800 40;
        STITERATIONS = 40;
```

```
            LRTBOOTSTRAP = 100;
            LRTSTARTS = 10 5 80 20;
        INTEGRATION = MONTECARLO;
        ALGORITHM=INTEGRATION;
            ! source: Morin et al, (2011) OrgResMeth

        PROCESSORS = 4;

    MODEL:
    %OVERALL%
        c#1-c#3 ON  GENDER
          OPENPS
          PERSEV
          ESCS;

         GENDER OPENPS PERSEV ESCS;
        ! multinominal logistic regression
        ! use one class as the reference

        %c#1%
            [time_familiar*53.100
         tot_notat*11.193
          cat_votat*1.551
          tot_votat*1.380
          total_act*2.531
          time_action*50.803];
            ! request means and estimate profiles based on them

         time_familiar-time_action(v1-v6);
         ! name variances to constrain them to be equal across
         ! profiles

         %c#2%
            [time_familiar*49.033
         tot_notat*11.116
          cat_votat*3.000
          tot_votat*3.441
          total_act*1.746
          time_action*60.849];

         time_familiar-time_action(v1-v6);
         ! name variances to constrain them to be equal across
         ! profiles

        %c#4%
            [time_familiar*48.390
```

```
        tot_notat*5.624
          cat_votat*0.000
          tot_votat*0.000
          total_act*1.025
          time_action*17.777];

        time_familiar-time_action(v1-v6);
        ! name variances to constrain them to be equal across
        ! profiles

       %c#3%
              [time_familiar*53.130
        tot_notat*21.601
          cat_votat*3.000
          tot_votat*10.319
          total_act*2.517
          time_action*108.136];

        time_familiar-time_action(v1-v6);
        ! name variances to constrain them to be equal across
        ! profiles

OUTPUT:
        SAMP;
        STAND;

        ! technical outputs
        TECH1;
        TECH7;
        TECH11;
        TECH14;

        ! confidence intervals
        CINTERVAL;

        PLOT:
              TYPE = PLOT3;
              SERIES =     time_familiar(1) tot_notat(2) cat_votat(3)
                                 tot_votat(4)
                                 total_act(5)
                                 time_action(6); ! or use an asteriks

SAVEDATA:
        FILE IS lpa4covinact.dat;
        SAVE = CPROBABILITIES; ! save class probabilities
        FORMAT IS FREE; ! or use F6,0
```

TITLE: LPA of problem solving profiles with covariates and distal outcome (RQ3)

```
DATA:
    FILE IS PISA2012-NOR-PVlist.dat;
    TYPE = IMPUTATION;
        FORMAT IS FREE;

VARIABLE:

        NAMES ARE
    ID
    SCHOOLID
     time_familiar
     tot_notat
     cat_votat
     tot_votat
     total_act
     time_action
     GENDER
     OPENPS
     PERSEV
     ESCS
     W_FSTUWT
     CP025Q01
     PVCPRO;

        MISSING ARE ALL(-999);

        IDVARIABLE = ID;
        ! student ID to appear in the output files

        WEIGHT = W_FSTUWT;
    ! students' final weights

    CLUSTER = SCHOOLID;
    ! School ID

        USEVARIABLES ARE
     time_familiar
     tot_notat
     cat_votat
     tot_votat
     total_act
     time_action
```

```
      PVCPRO;

           CLASSES = c(4);
           ! specify the number of profiles

  ANALYSIS:

           TYPE = MIXTURE COMPLEX;
           ESTIMATOR = MLR;
           STARTS = 800 40;
           STITERATIONS = 40;
           LRTBOOTSTRAP = 100;
           LRTSTARTS = 10 5 80 20;
     INTEGRATION = MONTECARLO;
     ALGORITHM=INTEGRATION;
           ! source: Morin et al, (2011) OrgResMeth

     PROCESSORS = 4;

  MODEL:
  %OVERALL%
[PVCPRO]

     %c#1%
           [time_familiar
     tot_notat
      cat_votat
      tot_votat
      total_act
      time_action];
           ! request means and estimate profiles based on them

     time_familiar-time_action(v1-v6);
     ! name variances to constrain them to be equal across
     ! profiles

      [PVCPRO](p1);
    ! mean of the distal outcome in c#1

     %c#2%
           [time_familiar
     tot_notat
      cat_votat
      tot_votat
      total_act
      time_action];
```

```
  time_familiar-time_action(v1-v6);
  ! name variances to constrain them to be equal across
  ! profiles

    [PVCPRO](p2);
! mean of the distal outcome in c#2

  %c#3%
            [time_familiar
  tot_notat
    cat_votat
    tot_votat
    total_act
    time_action];

  time_familiar-time_action(v1-v6);
  ! name variances to constrain them to be equal across
  ! profiles

    [PVCPRO](p3);
! mean of the distal outcome in c#3

  %c#4%
            [time_familiar
  tot_notat
    cat_votat
    tot_votat
    total_act
    time_action];

  time_familiar-time_action(v1-v6);
  ! name variances to constrain them to be equal across
  ! profiles

    [PVCPRO](p4);
! mean of the distal outcome in c#4

MODEL CONSTRAINT:

NEW(o12 o13 o14 o23 o24 o34 );

o12=p1-p2;
o13=p1-p3;
o14=p1-p4;
o23=p2-p3;
```

```
     o24=p2-p4;
     o34=p3-p4;




  OUTPUT:
             SAMP;
             STAND;

             ! technical outputs
             TECH1;
             TECH7;
             TECH11;
             TECH14;

             ! confidence intervals
             CINTERVAL;

             PLOT:
                    TYPE = PLOT3;
                    SERIES =     time_familiar(1) tot_notat(2) cat_votat(3)
                                        tot_votat(4)
                                        total_act(5)
                                        time_action(6); ! or use an asteriks

  SAVEDATA:
             FILE IS lpa4distaloutcome.dat;
             SAVE = CPROBABILITIES; ! save class probabilities
             FORMAT IS FREE; ! or use F6,0
```

TITLE: manual BCH first stage (to save bchweights)

```
   DATA:
      FILE IS NewData.dat;
             FORMAT IS FREE;

  VARIABLE:

             NAMES ARE
      ID
      SCHOOLID
       time_familiar
       tot_notat
       cat_votat
       tot_votat
```

```
    total_act
    time_action
    GENDER
    OPENPS
    PERSEV
    ESCS
    W_FSTUWT
    CP025Q01
    PV1CPRO
    PV2CPRO
    PV3CPRO
    PV4CPRO
    PV5CPRO;

        AUXILIARY = CP025Q01;

        MISSING ARE ALL(-999);

        IDVARIABLE = ID;
        ! student ID to appear in the output files

        WEIGHT = W_FSTUWT;
         ! students' final weights

   CLUSTER = SCHOOLID;

        USEVARIABLES ARE
    time_familiar
    tot_notat
    cat_votat
    tot_votat
    total_act
    time_action;

        CLASSES = c(4);
        ! specify the number of profiles

 ANALYSIS:

        TYPE = MIXTURE COMPLEX;
        ESTIMATOR = MLR;
        STARTS = 800 40;
        STITERATIONS = 40;
        LRTBOOTSTRAP = 100;
        LRTSTARTS = 10 5 80 20;
        ! source: Morin et al, (2011) OrgResMeth
```

```
    PROCESSORS = 4;
MODEL:
        %OVERALL%
    %c#1%
        [time_familiar
    tot_notat
     cat_votat
     tot_votat
     total_act
     time_action];
        ! request means and estimate profiles based on them

    time_familiar-time_action(v1-v6);
    ! name variances to constrain them to be equal across
    ! profiles

    %c#2%
        [time_familiar
    tot_notat
     cat_votat
     tot_votat
     total_act
     time_action];

    time_familiar-time_action(v1-v6);
    ! name variances to constrain them to be equal across
    ! profiles

    %c#3%
        [time_familiar
    tot_notat
     cat_votat
     tot_votat
     total_act
     time_action];

    time_familiar-time_action(v1-v6);
    ! name variances to constrain them to be equal across
    ! profiles

    %c#4%
        [time_familiar
    tot_notat
```

```
    cat_votat
    tot_votat
    total_act
    time_action];

  time_familiar-time_action(v1-v6);
  ! name variances to constrain them to be equal across
  ! profiles




OUTPUT:
        SAMP;
        STAND;

        ! technical outputs
        TECH1;
        TECH7;
        TECH11;
        TECH14;

        ! confidence intervals
        CINTERVAL;

        PLOT:
            TYPE = PLOT3;
            SERIES =    time_familiar(1) tot_notat(2) cat_votat(3)
                            tot_votat(4)
                            total_act(5)
                            time_action(6); ! or use an asteriks

SAVEDATA:
        FILE IS step1bch.dat;
        SAVE = bchweights; ! save class probabilities
        FORMAT IS FREE; ! or use F6,0
```

TITLE: manual BCH second stage with categorial distal outcome

```
DATA:
  FILE IS step1bch.dat;
        FORMAT IS FREE;

VARIABLE:

        NAMES ARE
```

```
FAMTIME
NOTAT
CATVOTAT
VOTAT
ACTION
ACTTIME
CP025Q01
BCHW1
BCHW2
BCHW3
BCHW4
CPROB1
CPROB2
CPROB3
CPROB4
C
W_FSTUWT
ID
SCHOOLID;

        MISSING ARE ALL(-999);

        IDVARIABLE = ID;
        ! student ID to appear in the output files

        WEIGHT = W_FSTUWT;
! students' final weights

CLUSTER = SCHOOLID;
! School ID

        USEVARIABLES ARE
BCHW1
BCHW2
BCHW3
BCHW4
CP025Q01;

training = BCHW1-BCHW4(bch);
CATEGORICAL = CP025Q01;

        CLASSES = c(4);
        ! specify the number of profiles

  ANALYSIS:
        TYPE = MIXTURE COMPLEX;
```

```
            ESTIMATOR = MLR;
            STARTS = 800 40;
            STITERATIONS = 40;
            LRTBOOTSTRAP = 100;
            LRTSTARTS = 10 5 80 20;
            ! source: Morin et al, (2011) OrgResMeth
        PROCESSORS = 4;


    MODEL:

    %OVERALL%


        %c#1%
        !estimate and name all item thresholds
        [CP025Q01$1](a1);

        %c#2%
        [CP025Q01$1](b1);


        %c#3%
        [CP025Q01$1](c1);

        %c#4%
        [CP025Q01$1](d1);


    MODEL TEST:

    ! Test the item threshold differences against zero
        0 = a1-b1;
        0 = a1-c1;
        0 = a1-d1;
        0 = b1-c1;
        0 = b1-d1;
        0 = c1-d1;

    MODEL CONSTRAINT:

    ! Define new parameters as the differences between the item thresholds
    New(a1b1 a1c1 a1d1 b1c1 b1d1 c1d1);

    a1b1 = a1-b1;
    a1c1 = a1-c1;
```

```
a1d1 = a1-d1;

b1c1 = b1-c1;
b1d1 = b1-d1;
c1d1 = c1-d1;



OUTPUT:
        SAMP;
        STAND;

        ! technical outputs
        TECH1;
        TECH7;
        TECH11;
        TECH14;

        ! confidence intervals
        CINTERVAL;


SAVEDATA:
        FILE IS lpa4bch.dat;
        SAVE = CPROBABILITIES; ! save class probabilities
        FORMAT IS FREE; ! or use F6,0
```