

# 區分問題解決專家和新手的任務和非任務 特定因素：比較 PISA 2012 前十名東西方 經濟體學生之表現

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## 摘 要

### 研究目的

本研究旨在利用電腦生成的 log 文檔探索「交通」這道題解難過程中的任務特定指標變量，然後加上整理自「學生能力國際評估計劃（PISA）2012」問卷資料的非任務特定變量，檢視區分高表現問題解決專家和低表現問題解決新手有哪些相對重要的因素。

### 研究設計／方法／取徑

本研究在 PISA 2012 電子問題解決測試排名前十名的高表現經濟體的 15 歲學生中，選取參與回答「交通」這一道題的高表現問題解決專家和低表現問題解決新手，人數合共 2,651 名。接著將學生分為東方高表現經濟體組和西方高表現經濟體組，分別以教育數據探勘工具「分類與回歸樹」作為主要的分析技術，找出區分高表現問題解決專家和低表現問題解決新手的因素，並將影響東方高表現經濟體和西方高表現經濟體學生表現的因素進行比較。

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## 研究發現或結論

影響東方高表現經濟體和西方高表現經濟體學生表現的因素有同有異。在東方經濟體中，探索出的影響因素按重要性排序依次為：找到任務的最佳解決路徑，數學自我效能感，和在學校中完成純數學任務的體驗。在西方經濟體中，結果依次為：數學自我效能感，找到任務的最佳解決路徑，熟悉數學概念，和數學中的敬業態度。

## 研究原創性／價值性

根據研究結果，有助教育工作者在各自的環境中設計基於問題的學習方案。此外，本研究的分析方法，亦能夠為未來的電子問題解決研究提供新的思路。

**關鍵詞：**問題解決、教育數據探勘、log 文檔、分類與回歸樹、PISA

# **TASK- AND NON-TASK-SPECIFIC FACTORS CLASSIFYING PROBLEM-SOLVING EXPERTS AND NOVICES: COMPARING STUDENTS OF THE TOP TEN HIGH-PERFORMING EASTERN AND WESTERN ECONOMIES IN PISA 2012**

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## **ABSTRACT**

### **Purpose**

The purpose of this study is to make use of the computer-generated log files to derive task-specific indicator variables of problem-solving processes of an exemplary problem task (TRAFFIC) to examine factors of relative importance and thereby classify and differentiate high-performing problem-solving experts from low-performing problem-solving novices. Added to the task-specific indicators are non-task-specific variables collated from questionnaires administered in the Programme for International Student Assessment (PISA) 2012 study.

### **Design/methodology/approach**

The participants are 2,651 fifteen-year-old high-performing problem-solving experts and low-performing problem-solving novices who have responded to the TRAFFIC problem task coming from the top ten high-performing economies in the PISA 2012 digital problem-solving study. The educational data mining tool Classification and Regression Tree (CART) is the main analytic technique used. Factors found for the students of the top ten high-performing Eastern economies are compared with those of high-performing Western economies.

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## **Findings**

The factors affecting student performance in Eastern and Western high-performing economies share commonalities and differences. In the Eastern economies, the factors identified in descending order of relative importance are: Discovery of the optimal solution path of the problem task, mathematics self-efficacy, and experience with pure mathematics tasks at school. In the Western economies, the factors identified in descending order of relative importance are: Mathematics self- efficacy, discovery of the optimal solution path of the problem task, familiarity with mathematical concepts, and mathematics work ethics.

## **Originality/value**

Based on the findings, educational practitioners may be informed how to design problem-based learning (PBL) in their respective economies. Furthermore, it is hoped that the methodologies developed are useful in furnishing new ideas to the future studies of digital problem solving.

*Keywords:* *problem solving, educational data mining, log file, classification and regression tree (CART), PISA*

## Purpose of Study

Problem-solving is one of the core skills of the 21st century, having gained attention from educational researchers seeking to examine its effective processes and behavioral indicators (Scherer & Gustafsson, 2015; Trilling & Fadel, 2009). According to a survey conducted in the United States, problem-solving was one of the top five most important skills in the workplace for new entrants (Casner-Lotto & Barrington, 2006). 70% of employers reported that high school graduates were deficient in problem-solving competence. Admittedly, this is not an isolated case in one country; rather, problem-solving deficiency is emerging as a global issue worthy of educational researchers' attention.

According to the results of past PISA studies with assessment domains on problem-solving (i.e., PISA 2003 and PISA 2012), many students' problem-solving competence could not be classified above the baseline level (Organization for Economic Cooperation and Development [OECD], 2004, 2014a). The PISA 2003 study indicated four progressive levels of problem-solving competence: *Below level 1, followed by levels 1-3*. On average, roughly 50% of 15-year-old students in 30 participating economies were assessed with problem-solving proficiency *below level 1* (OECD, 2004). A decade later, PISA 2012 evaluated students' problem-solving competence around the world a second time indicating seven progressive levels of problem-solving competence: *Below level 1, followed by levels 1-6*. On average, 20% of the students in 34 participating economies were found proficient below the baseline level (i.e., *level 2*) (OECD, 2014a). These low-performing problem-solving novices can hardly solve a generally unfamiliar or complex problem. These surmised *problem-solving novices* are the target students examined in this study.

On the contrary, some students were proficient in solving complex and unfamiliar problems. 18% of students in 2003 were at the highest level (*level 3*) (OECD, 2004). They tended to consider and manage various conditions, approach problems systematically, and construct their own representations to solve problems and verify solutions. In 2012, 11% of all students were above *level 4* (OECD, 2014a). These students can think ahead to find an optimal strategy that addresses all the given constraints. They are regarded as *problem-solving experts* to be examined in this study.

What makes these students vary significantly in problem-solving performance in PISA 2012? What factors are significant and aid in accurately classifying *problem-solving experts* versus *problem-solving novices*? Can educators use these identified factors to help students develop problem-solving competence?

The PISA study is an international large-scale sampled survey that aims to provide valuable information for educational practitioners to improve education by learning from high-performing economies. The PISA 2012 Digital Problem-solving Study (i.e., PISA 2012 DPS), an optional component of the PISA 2012 Study, assessed 15-year-old students' problem-solving competence by examining computer use at a developmental stage before entering the workplace or higher level of academic study (OECD, 2013). This international study is thus ideal for examining students' problem-solving characteristics and dispositions on a global scale. The problem-solving database released in 2013 comprises computer-generated log files of four released problem tasks (out of a total of 16 problem tasks, also called PISA 2012 DPS test units), which provide comprehensive information documenting the behavioral actions of each examinee. Although PISA 2015 released data last year, collaborative problem-solving data has not yet been released. Therefore, for the present, no log files of the PISA 2015 problems are available for public analysis. Hence, the present study focuses on the data of PISA 2012 log files of problem tasks released for public scrutiny. Due to the limitations of methodology and tools to analyze the substantial and disorderly log file data, educational researchers, since its public release in 2013, seldom examined these log files in-depth in their research of student problem-solving processes and behaviors (Greiff, Wüstenberg, & Avvisati, 2015).

As a pioneering trial study, this analysis will deploy Educational Data Mining (EDM) to analyze the computer-generated log file data collected in PISA 2012. According to Baker (2010), EDM is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings in which they learn. Admittedly, the educational settings in which student learning occurs are highly influenced by national culture and economy. Many researchers contend that differences between

Eastern and Western cultures have a bearing on educational environments, resulting in the differing learning styles and problem-solving approaches of students (see Biggs, 1994; Cai, 1995; Chang et al., 2011; Hess & Azuma, 1991). Particularly, Ho (1991) has explained the cognitive socialization processes of *Confucian Heritage Culture* commonly found in Eastern countries or economies, e.g., Mainland China, Taiwan, Hong Kong, Macao, Japan, Singapore, and Korea. Differences do exist between schools of Eastern and Western cultures regarding what factors are essential for effective schooling (Biggs, 1994). It is the intention of this study to uncover some of these differences between students of the top ten high-performing Eastern and Western economies when they engage in the problem-solving processes of some exemplary problem tasks as demonstrated in PISA 2012 DPS.

Under this backdrop, the purpose of the present study is to explore task-specific indicators generated from the log files of one released problem task (i.e., TRAFFIC), and use these indicators alongside an array of explanatory variables (the non-task-specific indicators) drawn from the PISA 2012 student, parent and school questionnaires to discern, in descending order of relative importance, what factors are able to classify whether a student is a *high-performing problem-solving expert* or a *low-performing problem-solving novice*, respectively, in the top ten PISA 2012 high-performing Eastern and Western economies.

## **Analysis of the Big Log-File Data in PISA 2012 DPS**

### **Factors Affecting Problem-Solving Performance**

In response to the need for cross-country comparison of student performance, the OECD launched PISA. The assessment takes place every three years, assessing 15-year-old students' domain-specific knowledge, skills, and attitudes which are essential for life-long learning. PISA 2012 covered the domains of reading, mathematics, science, and problem-solving. Altogether, 44 economies participated in PISA 2012 DPS, an optional component of PISA 2012 with 65 participating economies. Problem-solving competence is defined by OECD (2013) as follows:

Problem-solving competency is 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 in order to achieve one's potential as a constructive and reflective citizen (p. 122).

To answer the research question of this study, a *conceptual model of task-specific and non-task-specific factors affecting problem-solving performance* is delineated (see Figure 1). This model is adapted from the research frameworks of OECD's assessment of global competence (OECD, 2016) and the PISA 2012 Study (OECD, 2013). As seen in Figure 1, there are *student-level* personal factors pertaining to their *knowledge, skills, attitudes and beliefs*, as well as *system-level* environmental factors (e.g., *society, family, school, and classroom*) that have a bearing on student problem-solving competence. This problem-solving competence, when deployed in the contexts of specific problem-solving tasks, such as one of the four exemplary PISA 2012 DPS released test units (i.e., TRAFFIC examined in this study), affects the problem-solving processes resulting in the differing levels of problem-solving performance (i.e., *high-performing problem-solving experts versus low-performing problem-solving novices*).

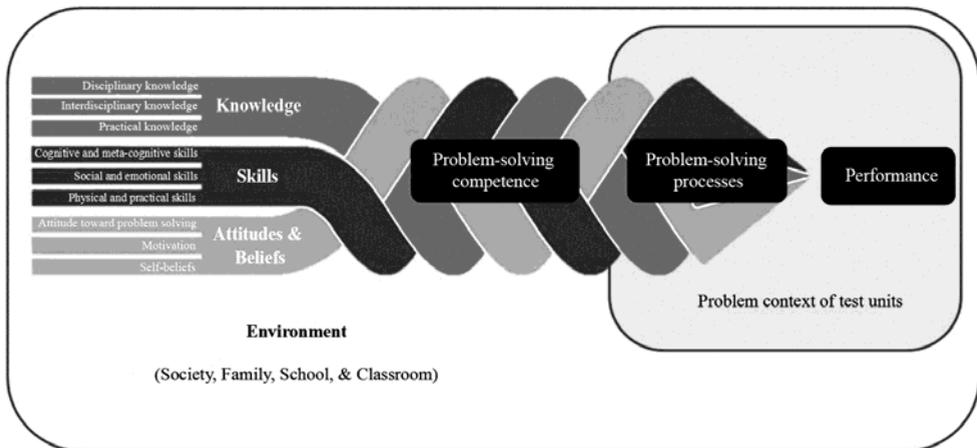


Figure 1. Conceptual model of task-specific and non-task-specific factors affecting problem-solving performance (Adapted from: OECD, 2013, p. 185; OECD, 2016, p. 2)

Past research shows that *environment, knowledge, skills, attitudes and beliefs* do have a bearing on the formation and development of students' problem-solving competence. For instance, in the schooling environment, external influences such as access to tools or teacher classroom management style influence students' problem-solving competence (OECD, 2013, 2014a). Additionally, Peter, Judith, and Robyn (2009) found that there are many important environmental factors that can help students solve unfamiliar problems, e.g., classroom resources, organization and climate, interpersonal interactions and relationships, social and cultural contexts, family expectations, and school organization.

Knowledge and problem-solving skills, such as the use of metacognitive strategies, are influential factors differentiating between problem-solving experts and novices (Brand-Gruwel, Wopereis, & Vermetten, 2005; Elio & Scharf, 1990; Mayer, 1998; Smith & Good, 1984). Additionally, Brand-Gruwel et al. (2005) found that problem-solving experts read tasks and activate their relevant prior knowledge more often than novices. In Smith and Good's (1984) study, 32 problem-solving strategies used by successful problem solvers are identified. These strategies must be fostered in problem-solving novices. It is noteworthy that Goos and Galbraith (1996) remarked that the use of metacognitive strategies is highly correlated with student mathematical problem-solving performance.

Former research conducted in the past few decades reveals that students' attitudes and beliefs influence their problem-solving competence as well. Put simply, belief is the state of mind in which a person thinks something is true or not true. According to Mayer (1998), a student's feelings and beliefs about his/her interest and ability to solve the problems assigned to them (e.g., interest, self-efficacy, and attributions) have significant influence on his/her problem-solving performance. Additionally, Peter et al. (2009) emphasized that students' motivation and expectations of their futures can influence their problem-solving competence. Besides these psychological dispositions, attitudes can also correlate and predict student performance in problem-solving (Nicolaidou & Philippou, 2003). Aiken (1980) has long conceptualized attitude as a "learned predisposition to respond positively or negatively to certain objects, situations, concepts, or persons" (p. 2), and

Neale (1969) has defined attitude towards mathematics as an aggregated measure of “a liking or disliking of mathematics, a tendency to engage in or avoid mathematical activities, a belief that one is good or bad at mathematics, and a belief that mathematics is useful or useless” (p. 632). Recently, Scherer and Gustafsson (2015) pointed out that student openness and perseverance in problem-solving are promising indicators of student willingness to engage in problem-solving.

The overall PISA 2012 assessment framework, on which the PISA 2012 DPS is based, examines hundreds of variables potentially affecting student performance in digital problem-solving. These variables are conceptualized at three levels: Student, parent/family, and school (OECD, 2013). The sampled survey data are collected using various questionnaires that are specifically designed for the students, their parents, and the schools. However, due to the complexity of the data, very few studies have examined these variables simultaneously to explore patterns and relationships with student digital problem-solving performance. This is mainly due to the lack of versatile methodologies and tools available to analyze the immense computer-generated log file data. In PISA 2012 DPS, students’ problem-solving behavioral processes are documented in the task-specific log files, including *response time*, *number of clicks*, *content of clicks*, *access sequences*, and so on (OECD, 2014b). This crude, disordered data needs to be pre-processed before usage in data analyses packages.

### **Educational Data Mining of Big Data Using CART**

Knowledge Discovery in Database (KDD), often called data mining, is a technique of discovering patterns of knowledge from very large quantities of data — *big data* (Han, Kamber, & Pei, 2011). Big data have five primary features commonly referred to as the 5Vs: Volume, variety, velocity, value, and veracity (Chiou, 2015; De Mauro, Greco, & Grimaldi, 2015). Big datasets include vast amounts of data collected from various sources and updated speedily. This data must be readily explored with proper tools to obtain veracious and valuable information for model building and decision making. Bousbia and Belamri (2014) proposed an educational data mining application process (see Figure 2), which is based on the models of Sachin and Vijay (2012), and Romero and Ventura (2013).

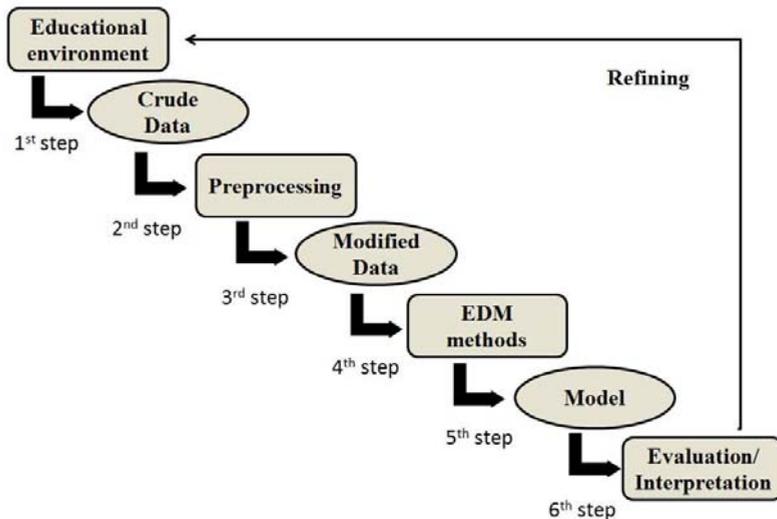


Figure 2. The educational data mining application process (Adapted from: Bousbia & Belamri, 2014, p. 12)

The educational data mining application process is a stepwise process. The first step is to collect the crude data from the educational environment, the forms of which are often disorganized numbers and words. Hence, preprocessing into well-organized data, recognizable by statistical software, is required. However, it still cannot be used and must be modified further into several analyzable *task-specific* indicators (e.g., those of TRAFFIC examined in this study in accordance with the task design and the associated coding guide). Then, researchers can use these indicators to conduct data mining with appropriate analytical tools to discern noteworthy patterns and even models inherent in the data. Finally, researchers need to evaluate and interpret the analytical results. The outcomes of the EDM will be used to improve the educational environment. The PISA 2012 DPS log files can be downloaded at OECD's official PISA website. It is somewhat organized data which should be modified into analyzable indicators for the mining of reliable and valuable knowledge (i.e., the 4<sup>th</sup> step of the process in Figure 2).

In recent years, the number of published research articles related to educational data mining has increased, mainly focusing on behavior modeling, performance modeling, and student assessment (Peña-Ayala, 2014; Romero &

Ventura, 2007, 2010). For example, Sanzana, Garrido and Poblete (2015) used the data mining technique of Classification and Regression Tree (CART) to examine students' academic performance in mathematics. Similarly, Alivernini and Manganelli (2015) studied students' science performance across the 25 countries participating in PISA 2006, again using CART as a data-mining tool.

In the research literature, some researchers have attempted to use the big data generated by computer delivery platforms to explore students' problem-solving competence. For instance, Lee (2015) transformed the data collected from an interactive computer testing system into analyzable indicators: Number of times of opportunities to learn, correction duration time, error duration time, and number of hint requests. In another study which used the same database as the present study, Greiff et al. (2015) examined the PISA 2012 DPS log files to explore students' problem-solving competence across the 43 participating economies. The researchers found that students' problem-solving performance is related to whether the sampled students have applied the optimal strategy called "Vary-One-Thing-at-A-Time" (i.e., VOTAT) in the problem-solving process. Of note is that the analysis methodologies used in these pioneer studies can only explore a very limited number of variables. If we want to study the question of what variables and indicators affect students' problem-solving performance, we should seek to use data mining techniques that can deal with the substantial and chaotic big data with relative ease.

The aim of the present study is to find out what variables (student, parent/family, and school) and task-specific indicators (problem-solving process variables pertaining to a selected problem-solving task: TRAFFIC) may affect students' problem-solving performance. The data is drawn from the PISA 2012 DPS database, and the analyses are based on the educational data mining technique CART to be elucidated in the ensuing sections of this paper.

## **Methodology**

### **Data Source and Participants**

The participants are 2,651 fifteen-year-old *high-performing problem-solving experts* and *low-performing problem-solving novices* who have responded to the TRAFFIC problem task coming from the top ten high-

performing economies in the PISA 2012 DPS. The participants comprise 1,075 students from seven Eastern economies (i.e., Singapore, Korea, Japan, Macao, Hong Kong, Shanghai, and Taiwan) and 1,576 students from three Western economies (Canada, Australia, and Finland). Because the performance of students in these top ten economies has more referential and learning value than other PISA 2012 participating economies, and the number of students in the top ten high-performing Eastern and Western economies who have responded to the TRAFFIC problem task are of comparable magnitudes (i.e., 1,075 compared to 1,576 student log files to be analyzed), the sample sizes are sufficient to conduct the EDM procedure from a big data perspective.

In PISA 2012, each student was randomly assigned one of the 24 digital test forms containing clusters of problem-solving, mathematics and/or reading test units delivered on computer-based platforms, which took students approximately 40 minutes to complete. Hence, no sampled student has the chance to respond to all 16 digital problem tasks (test units), and depending on the test form assigned, a typical student has the chance to respond to 2-5 problem tasks during the 40 minute test session.

As a trial study, based on the contents of the four PISA 2012 DPS released problem tasks from which the student log files are available for public scrutiny, a good start is to select a digital problem-solving task (or its sub-task such as TRAFFIC examined in this study; see Figure 3 for the item stimulus and the four-option multiple-choice question) that is capable of exhibiting the most basic feature of the digital problem-solving processes, i.e., *there is an optimal problem-solving path as envisaged in the test design and the associated coding guides.*

According to PISA 2012 DPS framework (OECD, 2013), TRAFFIC requires students to demonstrate their abilities in planning and executing, which are two of the four key steps of the problem-solving process (i.e., *understanding, planning, executing, and evaluating*). According to the description of the competence of a *level 5* or *6* student in the PISA 2012 DPS, the ability to discern the optimal strategy to solve a problem is the key characteristic of a high-performing problem-solving expert. Hence, this study chooses problem tasks with a problem-solving strategy to find the optimal solution path, with the conviction that it is thereby possible to classify experts and novices to the greatest extent.

**TRAFFIC**

Here is a map of a system of roads that links the suburbs within a city. The map shows the travel time in minutes at 7:00 am on each section of road. You can add a road to your route by clicking on it. Clicking on a road highlights the road and adds the time to the **Total Time** box. You can remove a road from your route by clicking on it again. You can use the **RESET** button to remove all roads from your route.

**Total Time:** 0 minutes

**RESET**

**Question 1: TRAFFIC CP007Q01**

Pepe is at Sakharov and wants to travel to Emerald. He wants to complete his trip as quickly as possible. What is the shortest time for his trip?

- 20 minutes
- 21 minutes
- 24 minutes
- 28 minutes

Figure 3. PISA 2012 digital problem-solving task: TRAFFIC (Source: <http://erasq.acer.edu.au/>)

In a nutshell, computer-generated log files of TRAFFIC, as well as student responses in the student, parent, and school questionnaires, form the corpus of data analyzed in this study.

In TRAFFIC, examinees need to click the lines connecting locations to select the roads, and then the computer will calculate the total travelling time in minutes. The examinee may choose many possible paths, e.g., Sakharov-Market-Silver-Emerald, the total travelling time of which is 21 minutes. This study analyzes all six possible paths with a total travelling time less than 30 minutes. The shortest route is Sakharov-Market-Park-Unity-Emerald, which requires 20 minutes travelling time.

Every behavioral step of the examinee is documented in computer-generated log files. The TRAFFIC log file contains seven distinct columns: Country, School ID, Student ID, Event (student's behavior), Time (how many

seconds duration), Event-number (the number of steps), and Event-value (changes visualized on the screen). The present study compiled and explored four task-specific indicators from the log files of TRAFFIC: (1) *Response time for solving a problem task*, (2) *Total number of steps for solving a problem task*, (3) *Discovery of the possible paths of the problem task (Yes/No)*, and (4) *Discovery of the optimal solution path of the problem task (Yes/No)*. These four indicators are the outcomes at the step 4 of the EDM application process (see Figure 2).

### **Variables**

In this study, the dependent variable of CART is a dichotomous variable (*Problem-solving expert* versus *Problem-solving novice*). The two groups of students are classified by problem-solving proficiency levels, which are delineated from the students' PISA 2012 digital problem-solving scores. A problem-solving expert is a student with a high proficiency level above 4; and the problem-solving novice is a student with a low proficiency level below 2. The independent variables of CART are data collected from questionnaires at the student, parent/family, and school levels (see Table 1). For details of these variables, readers are encouraged to consult the *PISA 2012 Assessment and Analytical Framework* (OECD, 2013) and the *PISA 2012 Technical Report* (OECD, 2014b). Among these 91 variables listed, four are task-specific indicator variables of TRAFFIC that are extracted and organized from the digital problem-solving log files.

### **Method**

This study employed the EDM technique CART to analyze the large number of variables and big data. A traditional classification and regression method can hardly analyze a large quantity of variables with complex relationships amongst variables simultaneously. However, CART, as a frequently-used method of data mining, can manage complex big data. It has several advantages compared with other classification and regression methods. Firstly, CART can analyze hundreds of independent variables, nominal, ordinal or continuous, which belong to different levels of measurement. Secondly, no assumption is made regarding the underlying distribution of the

Table 1  
*Selected Variables from the PISA 2012 Database for Addressing the Research Question*

Variable type	Classification	Variable label
Personal	Student background	Gender
		Grade repetition in earlier grades
Environment	Family background	Index of economic, social and cultural status
		Immigration status
		Family structure
		Wealth
		Cultural possessions
	Parent background	Home educational resources
		Educational level of father
		Educational level of mother
		Highest parental education in years
		Highest educational level of parents
	Classroom & instruction	Highest parental occupational status
		Teacher behavior: formative assessment
		Teacher behavior: student orientation
Teacher behavior: teacher-directed instruction		
Teacher support		
Disciplinary climate		
Ability grouping for mathematics classes		
Mathematics teacher's classroom management		
Mathematics teacher's support		
Schooling & staffing conditions of school	Cognitive activation in mathematics lessons	
	Teacher student relations	
	Teacher focus	
	Teacher participation/autonomy	
	Teacher morale	
	Class size	
	Extracurricular creative activities at school	
	Mathematics extracurricular activities at school	
	Mathematics extension course types offered	
	Quality of physical infrastructure	
	Quality of school educational resources	
	Proportion of girls at school	
	Proportion of certified teachers	
Proportion of mathematics teachers		
Proportion of teachers with university degrees		
Mathematics teacher-student ratio		
Student-teacher ratio		
Student-related factors affecting school climate		
Teacher-related factors affecting school climate		
Shortage of teaching staff		

(continued)

Variable type	Classification	Variable label
	School policy & leadership	Public or private School autonomy School ownership Total school enrollment School selectivity/student admission policies Use of assessment Framing and communicating the school's goals and curricular development Instructional leadership Promoting instructional improvements and professional development Teacher participation in leadership Index of school responsibility for resource allocation Index of school responsibility for curriculum and assessment
	ICT availability	Limitations of the computer as a tool for school learning ICT availability at school Ratio of computers for education and number of students Ratio of computers connected to the web and number of computers Computer as a tool for school learning ICT availability at home ICT resources ICT entertainment use ICT use at home for school-related tasks Time of computer use (minutes) Use of ICT in mathematic lessons Use of ICT at school
Knowledge	Disciplinary knowledge	Familiarity with mathematical concepts
	Experiences & learning time	Experience with applied mathematics tasks at school Experience with pure mathematics tasks at school Test language learning time (minutes per week) Mathematics learning time (minutes per week) Science learning time (minutes per week) Out-of-school study time
Skills	Task-specific variables from the log files of problem task TRAFFIC	Response time for solving a problem task Total number of steps for solving a problem task Discovery of the possible paths of the problem task (Yes/No) Discovery of the optimal solution path of the problem task (Yes/No)

(continued)

Variable type	Classification	Variable label
Attitudes	Schooling/Problem-solving attitudes	Openness for problem solving Perseverance Attitude towards school: Learning outcomes Attitude towards school: Learning activities
	Mathematics learning dispositions	Mathematics behavior Mathematics intentions Instrumental motivation for mathematics Mathematics interest Mathematics work ethics Subjective norms in mathematics
Beliefs	Schooling	Sense of belonging to school
	Mathematics learning dispositions	Mathematics anxiety Attributions to failure in mathematics Mathematics self-efficacy Mathematics self-concept

assumed values of the independent variables. Thirdly, the analyses are not affected by multi-collinearity between independent variables. Fourthly, CART uses sophisticated methods to compensate for missing data. Lastly, the results are relatively simple for non-statisticians to interpret (Allore, Tinetti, Araujo, Hardy, & Peduzzi, 2005; Breiman, Friedman, Olshen, & Stone, 1998; Lewis, 2000; Strobl, Malley, & Tutz, 2009).

The Gini index is the statistical criterion for CART to terminate the iterative partitioning process. The stopping principle underlying the index is to reduce the impurity of the target sample (the *parent node*) by dividing the subjects into two subgroups (the *children nodes*) based on a certain independent variable (Strobl, Boulesteix, & Augustin, 2007). A minor impurity means great homogeneity of the subgroups. In the case of this study, a maximally pure node will only consist of students who are problem-solving experts, or only students who are problem-solving novices. The independent variable which can produce the most homogeneous children nodes is automatically selected by CART as the most influential partitioning variable. Subsequently, each child node will be divided into two subgroups by the same means. At this step, the child node turns into a parent node, and the newly-produced subgroups become children nodes. With the continuation of

the partition process, the students are progressively classified into smaller yet more homogeneous sub-groups. The process continues until the reduction of the impurity becomes lower than a predetermined criterion (Gini index  $< .001$ ), or the number of students in the subgroup is lower than a certain threshold (set at 50 in this study) (Strobl et al., 2009).

The tree models, one for the problem-solving expert and novice students of the seven Eastern economies (1,075 students), and the other for the three Western economies (1,576 students) who have responded to the TRAFFIC problem-solving task, were developed on a *training sample* that was randomly selected from the whole sample, with a sampling fraction of 60%. The results were subsequently validated on a *test sample*, which was randomly selected from the whole sample with a sampling fraction of 40%. Finally, the accuracy of the two tree models was estimated using cross-validation techniques (Breiman et al., 1998).

## Results

Figure 4 shows the classification tree produced by CART exploring the problem-solving model of TRAFFIC for the problem-solving expert and novice students of the seven high-performing Eastern economies. It has 5 terminal nodes (subgroups): Node 4, node 5, node 6, node 7, and node 8. Students in node 4 and node 6 are predicted as problem-solving experts; whereas students in node 5, node 7, and node 8 are predicted as problem-solving novices. The overall percentage of correct prediction is 86%.

Amongst the 91 variables analyzed by CART, the most important factor is the problem-solving strategy of finding the optimal solution path to the destination. If student finds the optimal solution, the probability to be a problem-solving expert goes up from 70.9% to 87.5% (node 2). However, if the student does not have the ability to find the optimal solution, the probability of becoming a problem-solving expert decreases drastically from 70.9% to 27.3% (node 1).

Mathematics self-efficacy is also an important factor for students of the top-performing Eastern economies. In the literature, the term *self-efficacy* is used to describe an individual's belief that through one's actions, one can

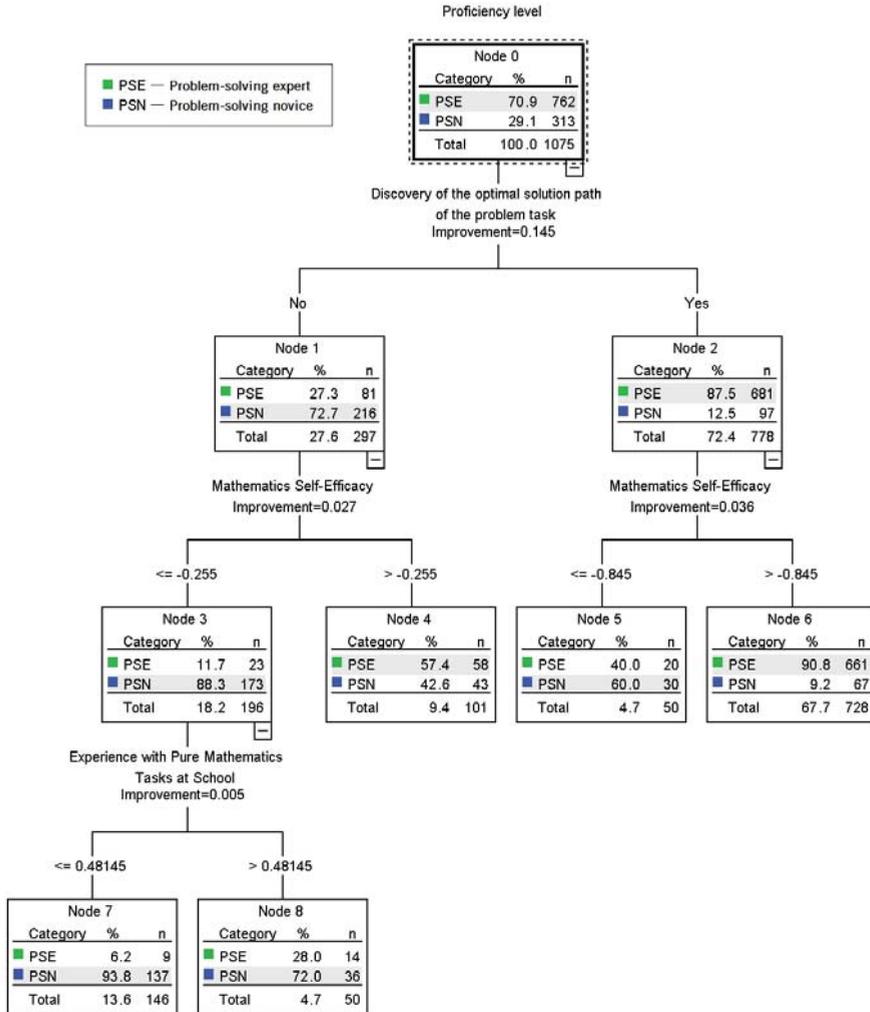


Figure 4. Results of the CART analysis of the Eastern economies

produce desired effects. This in turn is a powerful incentive to persevere in the face of difficulties (Bandura, 1977a). Mathematics self-efficacy refers to an individual's conviction that one can successfully perform mathematics tasks at designated levels of performance (Schunk, 1991). In the PISA study, mathematics self-efficacy assessed students' confidence about performing the following mathematics tasks: Solving an equation like  $3x + 5 = 17$ ; calculating

how much cheaper a TV would be after a 30% discount; understanding graphs presented in newspapers; and so on. For students who have the problem-solving strategy to find the optimal solution path (on the right-hand side of the classification tree), and if mathematics self-efficacy is higher than  $-0.845$  (at the 20<sup>th</sup> percentile of the construct), the percentage of problem-solving experts goes up from 87.5% to 90.8% (node 6); and if mathematics self-efficacy is equal or lower than  $-0.845$ , the percentage of problem-solving experts decreases drastically from 87.5% to 40.0% (node 5). For students who do not have the problem-solving strategy to find the optimal path (on the left-hand side of the tree), and if mathematics self-efficacy is higher than  $-0.255$  (at the 60<sup>th</sup> percentile), the percentage of problem-solving experts increases visibly from 27.3% to 57.4% (node 4); and if mathematics self-efficacy is equal or lower than  $-0.255$ , the percentage of problem-solving experts decreases from 27.3% to 11.7% (node 3).

However, the percentage of problem-solving experts in node 3 can be improved by having more student experiences with pure mathematics tasks at school. This factor inquires about the frequency of student experiences with pure mathematics tasks such as  $6x^2 + 5 = 29$  at school. If the score of the factor is higher than 0.481 (at the 40<sup>th</sup> percentile), the percentage of problem-solving experts increases from 11.7% to 28.0% (node 8); but if it is equal or lower than 0.481, the percentage of problem-solving experts decreases from 11.7% to 6.2% (node 7).

Figure 5 shows the classification tree of the problem-solving model of TRAFFIC for the problem-solving expert and novice students of the three top-performing Western economies. This tree has 6 terminal nodes (subgroups): Node 3, node 5, node 6, node 7, node 9 and node 10. Students in node 6 and node 10 will be predicted as problem-solving experts; while students in node 3, node 5, node 7 and node 9 will be predicted as problem-solving novices. The overall percentage of correct prediction is 87%.

Amongst the 91 variables analyzed by CART, the most important factor is mathematics self-efficacy. If an individual's mathematics self-efficacy is higher than 0.145 (at the 60<sup>th</sup> percentile of the construct), the percentage of problem-solving experts increases visibly from 43.7% to 77.8% (node 2); and if students' mathematics self-efficacy is equal or lower than 0.145, the percentage of problem-solving experts decreases from 43.7% to 17.7% (node 1).

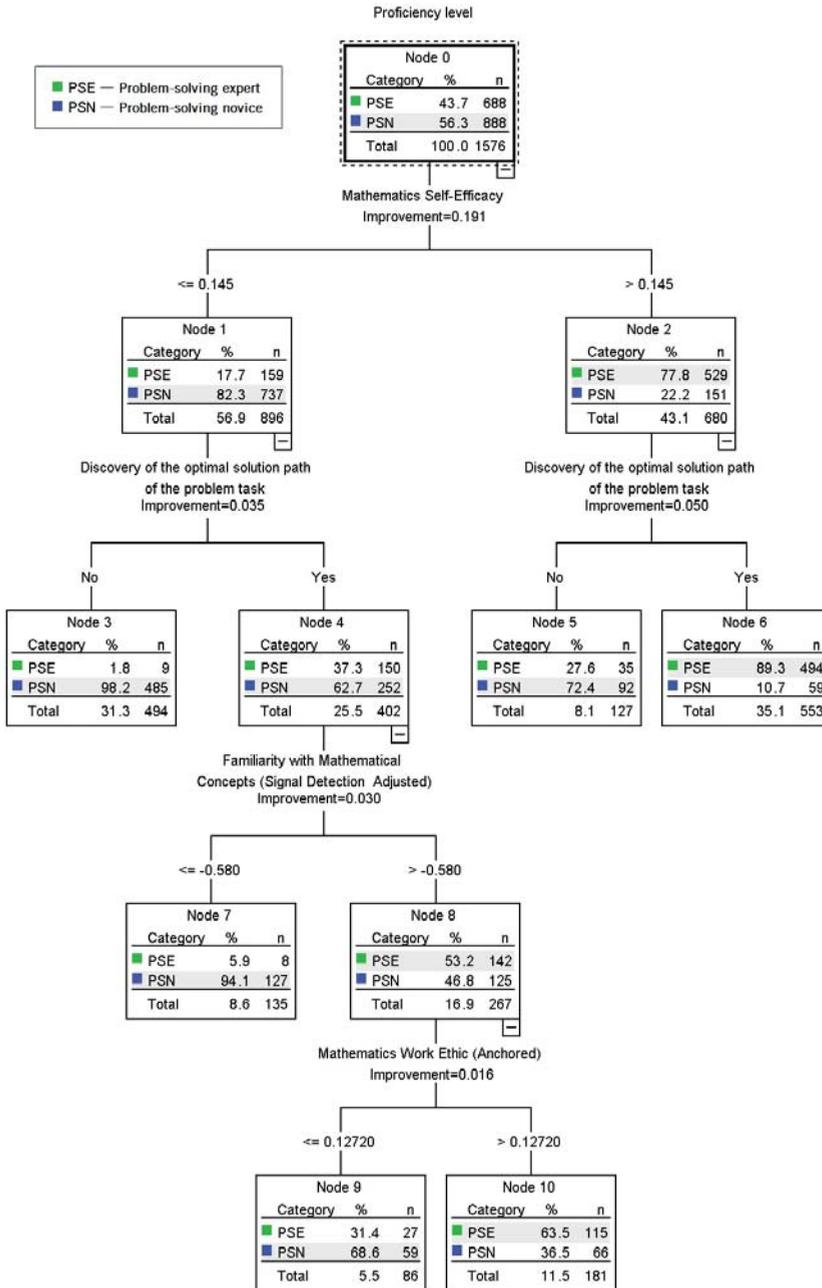


Figure 5. Results of the CART analysis of the Western economies

The second important factor analyzed by CART is the strategy of finding the optimal solution path to the destination. For students whose mathematics self-efficacy is higher than 0.145 (on the right-hand side of the tree), and if one has the ability to conceive the optimal solution, the probability to be a problem-solving expert increases a bit from 77.8% to 89.3% (node 6); but if one does not have the ability to find the optimal solution path, the probability to be a problem-solving expert decreases noticeably from 77.8% to 27.6% (node 5). Likewise, for students whose mathematics self-efficacy is equal or lower than 0.145 (on the left-hand side of the tree), if one has the ability to find the optimal solution path, the probability to be a problem-solving expert increases from 17.7% to 37.3% (node 4); but if one does not have the ability to find the optimal solution path, the probability to be a problem-solving expert decreases from 17.7% to a near-zero 1.8% (node 3).

Nevertheless, the percentage of problem-solving experts on the left branch can be improved. For students in node 4, if they are familiar with mathematical concepts such as *exponential function*, *divisor*, or *linear equation*, i.e., with score higher than  $-0.58$  (at the 30<sup>th</sup> percentile), the probability of being problem-solving experts increases noticeably from 37.3% to 53.2% (node 8); but if they are not familiar with mathematical concepts, i.e., with score equal or lower than  $-0.58$ , the probability of being problem-solving experts decreases visibly from 37.3% to 5.9% (node 7).

Furthermore, for students in node 8, having a higher mathematics work ethics can also improve the percentage of problem-solving experts. In PISA 2012, mathematics work ethics refers to the extent with which students agree with the following statements: *I work hard on my mathematics homework*; *I study hard for mathematics quizzes*; *I pay attention in mathematics class*; *I keep my mathematics work well organized*; and so on. For students in node 8, if the score of mathematics work ethics is higher than 0.127 (at the 40<sup>th</sup> percentile), the probability of their being problem-solving experts goes up a bit from 53.2% to 63.5% (node 10); but if the score of mathematics work ethics is equal to or lower than 0.127, the probability of their being problem-solving experts decreases from 53.2% to 31.4% (node 9).

Comparing the two problem-solving tree models of TRAFFIC between Eastern and Western economies, we can observe that: (1) the factors having the strongest influence classifying whether a student is a problem-solving

expert or a problem-solving novice in both Eastern and Western economies are essentially at the student-level; (2) The strategy of finding the optimal solution path has the strongest influence on classifying whether a student is a problem-solving expert or a problem-solving novice in the seven top-performing Eastern economies; however, the most important factor in classifying a student as a problem-solving expert or a problem-solving novice is mathematics self-efficacy in the three high-performing Western economies; (3) Besides the two factors of finding the optimal solution path and mathematics self-efficacy, students' problem-solving proficiency is also affected by student experiences with pure mathematics tasks at school in the Eastern economies, and by familiarity with mathematical concepts, as well as mathematics work ethics, in the Western economies.

## Discussions

### **Factors Classifying Whether a Student is a Problem-Solving Expert or Novice in High-Performing Eastern and Western Economies**

This study adopted an exploratory approach to find out the most important factors that classify whether a student is a problem-solving expert or a problem-solving novice, respectively, in the top ten high-performing Eastern and Western economies. The factors identified can be classified into three categories: (1) knowledge (i.e., *experience with pure mathematics tasks at school, familiarity with mathematical concepts*); (2) problem-solving skills (i.e., *discovery of the optimal solution path of the problem task*); (3) attitudes and beliefs (i.e., *mathematics self-efficacy, mathematics work ethics*). Student problem-solving competence is affected by factors listed in these three categories, whether in Eastern or Western economies. All listed factors are student-level factors.

Students' knowledge, skills, attitudes and beliefs have significant bearings on their problem-solving competence. Many researchers assert that disciplinary knowledge plays an important role in solving problems (Brand-Gruwel et al., 2005; Elio & Scharf, 1990; Mayer, 1998). The study results of Brand-Gruwel et al. (2005) reveal that problem-solving experts activate their prior knowledge more often than problem-solving novices,

which is consistent with the findings of the present study. Students who are familiar with disciplinary knowledge, or have more experience with tasks related to this knowledge, will have a greater possibility to become a problem-solving expert.

Additionally, researchers have found that the crucial difference between problem-solving experts and novices are how they organize knowledge (Chi, Feltovich, & Glaser, 1981; Larkin, McDermott, D. P. Simon, & H. A. Simon, 1980) and how they use knowledge during problem solving (Elio & Scharf, 1990). Amongst the many problem-solving skills, the ability to find the optimal solution path is especially essential for an individual to become a problem-solving expert (Slack & Stewart, 1990). Based on the log file data of a problem-solving task other than TRAFFIC in PISA 2012 DPS, Greiff et al. (2015) found that students' problem-solving performance is related to whether or not they have applied the optimal strategy of VOTAT. In retrospect, three decades ago, Smith and Good (1984) identified 32 problem-solving strategies that problem-solving experts and novices used differently. For instance, the researchers observed that successful problem solvers tend to break the problem into smaller parts, and then solve the parts step by step; compare the work done in various parts of the problem for consistency; and then consider one variable at a time, and so on.

The present study finds that attitude plays a substantial role in classifying one's level of problem-solving proficiency. *The Framework of Singapore School Mathematics Curriculum*, devised by one of the high-performing Eastern economies examined in the present study, suggests that attitudes toward mathematical problem-solving include beliefs, interests, appreciation, confidence, and perseverance (Kaur & Har, 2009). Additionally, according to Aiken (1980), attitude is a learned predisposition to respond positively or negatively to certain objects, situations, concepts, or persons. Mandler (1989) has further argued that a negative attitude is the result of frequent failures, or interruptions of planned actions when solving mathematical problems. Repeated emotional reactions result in the development of a relatively permanent schema about mathematics, which will affect the formation of a student's mathematics self-efficacy. Hence, one's mathematics self-efficacy is very important when one is engaged in solving a mathematical problem, such

as the TRAFFIC problem in this study. Finally, Nicolaidou and Philippou's study (2003) showed that attitudes and self-efficacy correlate to predict achievement in problem-solving; moreover, self-efficacy is a more powerful predictor than attitude.

In PISA 2012, mathematics work ethics refers to how hardworking and conscientious a student is while learning mathematics. Most people believe hard work, or learning conscientiously, is one of the most important factors to improve one's performance. In the research literature, hard work and conscientious learning do have some positive influence on one's academic performance. In Poropat's (2009) research, academic performance was found to correlate positively and significantly with conscientiousness. Likewise, the results of Cooper, Robinson, and Patall (2006) found generally consistent evidence for a positive influence of homework on achievement. Nevertheless, no research has yet proven that work ethics is the most important factor classifying whether a student is high-performing or low-performing. In this study, mathematics work ethics is found to affect students' level of problem-solving proficiency, but not as much as mathematics self-efficacy, problem-solving strategies, or familiarity with mathematical concepts.

### **Relative Importance of Factors Identified Between Eastern and Western Economies**

In both Eastern and Western economies, whether a student is a problem-solving expert or a novice is affected by one's possession of disciplinary knowledge, task-specific problem-solving skills, and favorable student attitudes and beliefs. However, differences still exist between students of Eastern and Western economies:

- (1) Possession of task-specific problem-solving skills is the most important factor in the Eastern economies, while the exhibition of mathematics self-efficacy is the most important factor in the Western economies. This may be due to cultural differences in classroom practices of the Eastern and Western educational systems — schools in Eastern economies focus more on knowledge acquisition and skills training, whereas schools in Western economies put more emphasis on student cognitive and psychological development. Eastern students, especially those associated

with the *Confucian heritage culture*, have been reported to have a stronger preference for high-level and meaning-based learning strategies. They also have more time to discuss problem-solving strategies in class than Western students (Biggs, 1994). These help students perform better when solving problems.

Klassen (2004) reviewed several studies comparing students' self-efficacy between Eastern and Western countries, and found that for the most part, Eastern students' self-efficacy is lower than Western students. Moreover, self-efficacy is shown to be a strong predictor of student performance in Western, but not in Eastern education systems. This finding is consistent with the findings of the present study.

- (2) Mathematics work ethics affects a student's level of problem-solving proficiency in the Western economies more than in Eastern economies. A plausible explanation to this unexpected finding is that students in the Eastern economies generally are quite hard-working, and are accustomed to attribute their success to effort, whereas students in the Western economies tend to attribute their success to ability (Biggs, 1994; Hess & Azuma, 1991). Because most of the students of the high-performing Eastern economies are generally hard-working, the factor of mathematics work ethics does not stand out to be a decisive factor to classify problem-solving experts and novices in the present study. For the students of the high-performing Western economies, although students can increase self-efficacy and hence performance by believing that academic success hinges upon confidence in one's own ability, their problem-solving performance can also be improved considerably by adopting a *growth mindset* of which hard work and conscientiousness are essential components (Boaler, 2013; Dweck, 2006).

## **Conclusions and Recommendations**

Based on the PISA 2012 digital problem-solving assessment log files, as well as responses to the student, parent and school questionnaires, the present study used the data mining technique of classification and regression tree (CART) to discern which factors classify whether a student is a high-performing problem-solving expert or low-performing novice in the two

groups of students of the top ten high-performing Eastern and Western economies. The results showed that: (1) in the seven Eastern economies, amongst the 91 variables under examination, three factors that are found to have major influence in determining students' problem-solving proficiency levels are: *Discovery of the optimal solution path of the problem task*, *Mathematics self-efficacy*, and *Experience with pure mathematics tasks at school*; (2) in the three Western economies, the factors which have influence in classifying students' problem-solving proficiency levels are: *Mathematics self-efficacy*, *Discovery of the optimal solution path of the problem task*, *Familiarity with mathematical concepts*, and *Mathematics work ethics*. All of the factors identified are student-level variables.

With regard to the factors identified, there are some subtle differences between the high-performing Eastern and Western economies. Firstly, *Discovery of the optimal solution path of the problem task* has the strongest influence in classifying whether a student is a problem-solving expert or a problem-solving novice in the Eastern economies, while *Mathematics self-efficacy* has a greater influence in the Western economies. In addition, besides the factors of *Discovery of the optimal solution path of the problem task*, and *Mathematics self-efficacy*, student problem-solving proficiency is also affected by *Experience with pure mathematics tasks at school* in Eastern economies, and *Familiarity with mathematical concepts* and *Mathematics work ethics* in Western economies. The implication is that teachers should design problem-based learning based on these findings, with due attention paid to helping students organize and acquire essential knowledge, learn the task-specific problem-solving strategies, and develop self-efficacy and work ethics purposefully.

Educators have long argued that the traditional mode of teaching with a focus on knowledge acquisition is not beneficial for students to develop integrative competence, such as the digital problem-solving competence in this study (Blank, 1982). One viable approach for contemporary teaching is to emphasize the cultivation of students' positive learning attitudes and beliefs. According to the results of this study, teachers should not only focus on disciplinary knowledge and skills, but also attitudes and beliefs. In the Eastern cultural context, enhancing students' task-specific problem-solving skills is more effective in raising student problem-solving competence, while in the

Western cultural context, helping students to develop self-efficacy is more efficient to improve student problem-solving ability. Increasing student mathematics work ethics also has a moderate positive effect on student problem-solving performance in the high-performing Western economies.

Among the many factors related to student attitudes and beliefs, self-efficacy is confirmed in this study to have the strongest influence on students' digital problem-solving competence. Therefore, how can teachers develop students' self-efficacy? According to Bandura's (1977b) social learning theory, an individual's self-efficacy may come from four main informational sources: (1) An individual's performance accomplishment provides the most influential efficacy because it is based on personal mastery experiences; (2) vicarious experiences of observing others succeed through their efforts; (3) verbal persuasions in order to cope with circumstances successfully; and (4) states of physiological arousal from which people judge their level of anxiety and vulnerability to stress. In school environments, teachers can provide more opportunities for students to master problem-solving tasks that are appropriately set at their ability levels. Collaborative learning is also an effective way to help students gain successful experience from others, and meanwhile develop their own self-efficacy.

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