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Identifying Effective E-Teaching and General Mathematical Teaching Profiles to Predict Student Mathematical Cognition and Affect

Mei-Shiu Chiu
Department of Education, National Chengchi University

The aim of this study was to identify the profiles of approaches to e-teaching and general teaching (g-teaching) and to explore the differences between the profiles in terms of student mathematical cognition and affect. Latent profile analysis (LPA) was applied to evaluate 3,978 Taiwanese 15-year-old students' perceived e-teaching and g-teaching behaviors (formative assessment, student orientation, and teacher direction) in mathematics classrooms. LPA identified four e/g-teaching profiles: parsimony, conservation, moderation, and liberal. Multivariate analysis of variance (MANOVA) and post hoc tests were used to examine profile differences in each element of cognition and affect; structural equation modeling (SEM) was used in latent constructs of cognition and affect. The combined MANOVA and SEM results indicated that moderation e/g-teaching benefits both cognition and affect, parsimony benefits cognition at the expense of affect, and both conservation and liberal benefit affect.

Keywords: e-teaching, latent profile analysis, mathematics affect, mathematics cognition, mathematics pedagogy

Corresponding author：Mei-Shiu Chiu，e-mail：meishiuchiu@gmail.com
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辨識可預測學生數學認知和情意的有效 E 化和一般數學教學法組合：潛在剖面分析法。
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辨識可預測學生數學認知和情意的有效 E 化和一般數學教學法組合

邱美秀
國立政治大學教育學系

本研究旨在辨識 E 化和一般數學教學法的組合類型，並探討所辨識出的教學組合類型在學生數學認知和情意上的差異情形。以潛在剖面分析（LPA）方法分析 3,978 名臺灣 15 歲學生在數學教室中的 E 化數學教學和三項一般性的數學教學法（形成性評量、學生導向和教師指導）。LPA 的結果辨識出四種 E 化與一般數學教學法組合：節約、保守、協調和自由使用 E 化與一般數學教學法的組合。接著，使用多變量變異數分析（MANOVA）和事後檢驗，來考驗四種教學法組合在學生各數學認知和情意細項內容上的差異，並且使用結構方程模式（SEM）考驗四種教學法組合在認知和情意二潛在構念上的差異。MANOVA 和 SEM 的分析結果顯示：協調的 E 化與一般數學教學法組合同時有益於學生認知和情意，節約的 E 化與一般數學教學組合有利認知但犧牲情意，保守和自由的 E 化與一般數學教學組合有利於情意。

關鍵詞：E 化教學、潛在剖面分析、數學情意、數學認知、數學教學法

通訊作者：邱美秀，e-mail：meishiuchiu@gmail.com
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Introduction

Information and communication technology (ICT) has gradually been incorporated into general teaching (g-teaching), resulting in "e-teaching" (González, 2012). The relationships between e- and g-teaching, however, remain vague. Both e- and g-teaching may include pedagogies or practices for traditional, lifelong, and connected learning (Blignaut, Hinostroza, Els, & Brun, 2010). Pedagogical knowledge can fully comprise technological pedagogical knowledge or technological pedagogical content knowledge (Chai, Koh, & Tsai, 2013). The term "blended teaching" (González, 2012) explicitly indicates the diverse practices of integrating e- and g-teaching in real educational settings.

Researchers have identified different approaches to integrating e- and g-teaching (termed "e/g-teaching" in this study). Innovative e/g-teaching cases (e.g., Tan & Tan, 2015) and survey studies (e.g., Sang, Valcke, van Braak, & Tondeur, 2010) have integrated e- and g-teaching on the basis of ideas or theories. Qualitative studies have categorized methods of using ICT in teaching (González, 2012). These studies have tended to define or group e/g-teaching in a predetermined categorical manner. The aim of the current study was to identify e/g-teaching profiles on the basis of student perceptions of real mathematics teaching by using latent profile analysis (LPA) (Fraley & Raftery, 2007). LPA is a person-centered clustering method that aims to maximize the most likely profiles of distinct meanings on the basis of empirical data. LPA can exceed the linear relationship between e/g-teaching and learning outcomes to identify nonlinear profiles likely to address differences in learning outcomes. Examples of nonlinear relationships between e- and g-teaching include teachers using both e- and g-teaching intensively (e.g., the constructivist approach; Park et al., 2015), using e- and g-teaching moderately (e.g., the balance approach; Tan & Tan, 2015), and using e-teaching for g-teaching (e.g., the traditional approach; Lan, Chang, & Chen, 2012).

After the patterns of mathematics teachers' e/g-teaching are identified, assessing how the patterns relate to students' cognitive and affective learning outcomes is essential. Mathematics teaching and national curricula both relate to and emphasize learning outcomes in both cognitive and affective aspects (Chiu, 2009; Chiu & Whitebread, 2011). Competent mathematics learners require both cognitive and affective dispositions, such as domain knowledge, meta-knowledge, heuristics methods, self-regulatory skills, and beliefs about self and mathematical learning (De Corte, 2004). The current study also devoted partial attention to ICT availability and socioeconomic status (SES), which may condition e/g-teaching profiles (Cuckle & Clarke, 2002). In summary, the purpose of this study included identifying profiles or patterns of mathematics teachers' e/g-teaching and assessing how the identified profiles interact with students' cognitive and affective learning outcomes, conditioned by students' ICT availability and SES.

Approaches to Integrating E- and G-Teaching

E/g-teaching profiles can be implied by past studies on approaches to integrating e- and g-teaching. Traditional and constructivist approaches are two extremes, and balance and theoretical approaches are mixed types of e/g-teaching, as shown in the following paragraphs.

The traditional, activating, or teacher-centred approach. This approach entails using ICT to present concepts, explain ideas, and lead discussion (Lan et al., 2012). Most teachers appear to focus on this traditional method of e-teaching (Blignaut et al., 2010; Louw, Brown, Muller, & Soudien, 2009; Smeets, 2005).

The constructivist, facilitating, or student-centred approach. This approach entails using ICT as a platform to transform teacher roles from dominant to parallel status (Park et al., 2015). Examples of this approach include collaborative creative writing (Vass, 2007) and use of Web 2.0 tools (Chai, Koh, Ho, & Tsai, 2012).

The balance approach. This approach entails using ICT as a tool to compensate for conventional g-teaching methods for distinct blocks of teaching sessions (Tan & Tan, 2015). For example, g-teaching (paper-and-pencil or concept development) is followed by e-teaching (ICT use for generalization or application).

The theoretical or pedagogical approach. E- and g-teaching can be fully integrated by existing higher-order conceptions of g-teaching. Examples of g-teaching conceptions include reflection (Leijen, Admiraal, Wildschut, & Robert-Jan Simons, 2008), learning theories, teacher knowledge (Benson & Brack, 2009), and learning models (e.g., cognition, action, and reflection) (Lan et al., 2012). This approach fully integrates e- and g-teaching, through which e-teaching has actually transformed existing g-teaching conceptions into innovative ones. (Nachmias, Mioduser, & Forkosh-Baruch, 2010; Tømte, Enochsson, Buskqvist, & Kårstein, 2015).

Relations between E/G-Teaching Profiles and Learning Outcomes

Student learning outcomes can be effectively promoted by both e- and g-teaching, such as collaborative learning in both face-to-face and online settings (Solimeno, Mebane, Tomai, & Francescato, 2008). Teachers tend to perceive ICT use as potentially benefiting student learning outcomes in the aspects or constructs of cognition (e.g., mathematics knowledge) and affect (e.g., motivation and collaborative skills) (Blignaut et al., 2010). If both e- and g-teaching can benefit students, the next question may be what e/g-teaching profiles are more effective than others in benefiting cognition and affect.

Cognition. Mathematical cognition for learners can be defined as applying mathematical knowledge and reasoning to study patterns and relationships (Burton, 1994). Mathematics education researchers have identified the cognitive activities involved in mathematical problem-solving. For example, mathematical problem-solving may include the procedures of understanding, planning, implementing, and reviewing (Polya, 1945, 1962) and addressing problems, thus reflecting on the experience, studying the process of resolving problems, and noticing the interaction between the experience and what is learned (Mason, Burton, & Stacey, 1996).

Successful mathematics cognitive activities can be measured as mathematics performance or achievements. Research has indicated that student achievements positively relate to teacher-centered g-teaching, such as reasoning orientation (Thorvaldsen, Vavik, & Salomon, 2012), direct instruction, and frequent test use to assess student learning, and negatively relate to rule orientation (Hinostroza, Labbé, Brun, & Matamala, 2011). The effects of e-teaching on achievement are perceived by teachers of low mathematics-ability classes but less often by those of high-ability ones (Thorvaldsen et al., 2012), who may nevertheless frequently employ e-teaching (Hinostroza et al., 2011). Positive relations between constructivist e-teaching and students' meaningful learning perceptions, achievements, and course satisfaction may not be guaranteed (Wurst, Smarkola, & Gaffney, 2008) without formative feedback (Espasa & Meneses, 2010). Therefore, formative assessment in teaching and learning processes may play a role in the effect of e/g-teaching on learning outcomes.

Affects. Mathematics affects are an indispensable part of mathematics cognitive activities (Gómez-Chaćon, 2000; Hannula, 2002). Mathematics affects include beliefs (e.g., I can competently solve problems), attitudes (e.g., I enjoy problem-solving), and emotions (e.g., mathematics is beautiful) (McLeod, 1992, 1994). Confidence-related mathematics beliefs (including self-efficacy) typically have high correlations with mathematics achievement (Chiu, 2012b; Grootenboer & Hemmings, 2007). E-teaching generally benefits student affects such as self-efficacy or confidence (Tan & Tan, 2015), interest, and engagement. Constructivist e-teaching (e.g., real-world settings, collaboration, and individual choices) can increase student interest in science (Wilson & Boldeman, 2012) and engagement (Rappa, Yip, & Baey, 2009). College teachers having multiple g-teaching concerns and using ICT for teaching tend to emphasize the roles of g-teaching in engaging students through ICT use (Webster & Son, 2015).

Relations Between E/G-Teaching Profiles and Conditions

Naturally, e-teaching at school is conditioned by school ICT availability (Cuckle & Clarke, 2002). Constructivist e-teaching further requires student ICT availability (Smeets, 2005). SES is potentially another condition, which generally has a positive relation with home ICT availability, ICT use quality, and achievement (Lee & Wu, 2012).

Research Questions

The literature review suggests that innovative and diverse e/g-teaching profiles may be identified on the basis of real context data by using nonlinear person-based modeling analysis. The identified profiles may address differences in learning outcomes in the explicit elements or latent constructs of cognition and affect through profile difference analysis partially considering conditions. Therefore, the objective of this study was to answer the following three research questions (RQs):

1. What are the profiles of mathematics e-teaching (ICT use) and g-teaching behaviors (formative assessment, student orientation, and teacher direction) perceived by students?
2. What are the differences between the identified profiles in the explicit elements of cognition (e.g., employing, formulating, and interpreting), affects (e.g., self-efficacy, interest, and engagement), and conditions (e.g., SES, home ICT availability, and school ICT availability)?
3. How do the identified profiles, conditioned by school ICT availability, predict differences in the latent constructs of cognition and affect?

Method

Data Source and Sample

This study used data on Taiwan from the main and ICT surveys of the Programme for International Student Assessment (PISA) in 2012 (Organisation for Economic Co-operation and Development [OECD], 2014b). The PISA started in 2000 and is a triennial international survey examining the achievement of 15-year-old students, principally in the fields of mathematics, science, and reading. PISA also collects self-report, contextual data from students, teachers, schools, parents, and national PISA administrators. PISA 2012 is the fifth survey focusing on mathematics.

The total Taiwan sample of PISA 2012 comprised 6,046 students. The four e/g-teaching measures used in this study (cf. the Measures section) included approximately 33.6% missing data, which prevented the use of LPA to identify e/g-teaching profiles (cf. the Data Analysis section). To handle the problem of missing data, multiple imputation procedures were attempted by using the mix package in R. However, the several imputed data sets generated unstable profile solutions, implying that different imputed data sets generated different profile solutions. Therefore, listwise deletion was used for the four e/g-teaching measures, which resulted in a total sample of 3,978 students in this study. Sampling weights were not used in this study because of the considerable amount of missing data and the use of listwise deletion. Accordingly, the findings of this study can only be explained as a phenomenon of the specific sample and cannot be generalized to the population.

The exact sample sizes for the other measures, as derived after the aforementioned listwise deletion, are presented in Table 1. Notably, the affective measures had small sample sizes because of missing data (Table 1), implying that some participating students did not fully complete the related affective measures in the survey. Medium correlations were observed between self-efficacy and mathematics cognitive measures (r = .63, .64, and .59), and these results are consistent with previous study findings revealing stable relationships between achievement- and confidence-related constructs (Chiu, 2012b; Grootenboer & Hemmings, 2007). Moreover, medium correlations were observed between self-efficacy and the other two affective measures (r = .43 and .48, respectively), implying relatively high differences between self-efficacy and the other two affective measures. This may result in lower factor loadings for either self-efficacy or the other two affective measures.

Measures

This study focused on 13 student measures obtained from the PISA 2012 database (OECD, 2014a, 2014b). These measures were grouped into four categories (e/g-teaching, cognition, affect, and condition). All 13 measures were derived from several items in the PISA data sets and rescaled using item response theory, with higher scores representing higher degrees in the meanings of these measures. Table 2 presents detailed information on the 13 measures, including measure names in this study; original labels in the PISA data set; item stems, sample items, and item numbers; measurement methods; OCED means, standard deviations (*SD*s), and internal reliability coefficients (Cronbach's alpha (α)); and Taiwan's α. Table 1 presents the means and *SD*s of the present Taiwan sample.

Data Analysis

The RQs were answered through statistical analysis using the software R Version 3.1.3 (R Core

Table 1

Descriptive Statistics and Correlations Between E/G-Teaching Behaviors, Cognition, Affects, and Conditions

	N	*Mean*	*SD*	*r*											
Measures				1	2	3	4	5	6	7	8	9	10	11	12
E/g-teaching behaviors															
1. ICT use	3978	-0.43	0.75												
2. Formative assessment	3978	-.10	.95	<u>.09</u>											
3. Student orientation	3978	.01	.98	<u>.13</u>	<u>.50</u>										
4. Teacher direction	3978	-.07	1.06	<u>.06</u>	<u>.68</u>	<u>.42</u>									
Cognition															
5. Employing	3978	547.38	107.12	<u>-.12</u>	-.01	<u>-.28</u>	.01								
6. Formulating	3978	577.25	134.29	<u>-.12</u>	-.02	<u>-.28</u>	-.01	<u>.95</u>							
7. Interpreting	3978	547.57	102.01	<u>-.12</u>	<u>-.05</u>	<u>-.31</u>	-.02	<u>.94</u>	<u>.92</u>						
Affects															
8. Self-efficacy	1980	.18	1.18	-.01	<u>.14</u>	<u>-.07</u>	<u>.13</u>	<u>.63</u>	<u>.64</u>	<u>.59</u>					
9. Interest	1981	.02	.96	<u>.10</u>	<u>.32</u>	<u>.13</u>	<u>.27</u>	<u>.32</u>	<u>.32</u>	<u>.26</u>	<u>.43</u>				
10. Engagement	1985	.07	.98	<u>.09</u>	<u>.27</u>	<u>.10</u>	<u>.19</u>	<u>.45</u>	<u>.43</u>	<u>.37</u>	<u>.48</u>	<u>.53</u>			
Conditions															
11. SES	3968	-.39	.84	<u>-.04</u>	<u>.06</u>	<u>-.07</u>	<u>.05</u>	<u>.43</u>	<u>.40</u>	<u>.38</u>	<u>.32</u>	<u>.11</u>	<u>.25</u>		
12. Home ICT availability	3976	-.35	.92	.03	<u>.09</u>	<u>.06</u>	<u>.04</u>	<u>.10</u>	<u>.10</u>	<u>.08</u>	<u>.15</u>	.01	<u>.11</u>	<u>.44</u>	
13. School ICT availability	3967	-.22	.82	<u>.08</u>	<u>.15</u>	<u>.11</u>	<u>.12</u>	.03	.03	.01	.04	<u>.07</u>	<u>.09</u>	<u>.08</u>	<u>.22</u>

Note. The underlined correlations (*r*s) are significant at $p = .05$.

Table 2

Detailed Descriptions of the 13 Measures

Measure name	PISA label	Item stem sample items (item numbers)	Measurement methods	OECD mean	OECD SD	OECD α	Taiwan mean	Taiwan SD	Taiwan α
E/g-teaching behaviors									
1. ICT use	Use of ICT in Mathematic Lessons	Within the last month, has a computer ever been used for the following purposes in your mathematics lessons? Drawing the graph of a function (such as y = 4x+6). (7 items)	3-point Likert scale: 1 = yes, students did this, 2 = yes, but only the teacher demonstrated this, 3 = no. (reverse coded)	-1.57	1.57	.91	-.43	.75	.95
2. Formative assessment	Teacher Behavior: Formative Assessment	How often do these things happen in your mathematics lessons? The teacher gives me feedback on my strengths and weaknesses in mathematics. (4 items)	4-point Likert scale: 1 = every lesson ~ 4 = never or hardly ever (reverse coded)	-.28	1.35	.76	-.10	.95	.74
3. Student orientation	Teacher Behavior: Student Orientation	(The same item stem as the above.) The teacher has us work in small groups to come up with joint solutions to a problem or task. (4 items)	(Same as the above)	-.98	1.06	.68	.01	.98	.69
4. Teacher direction	Teacher Behavior: Teacher-directed Instruction	(The same item stem as the above.) The teacher asks me or my classmates to present our thinking or reasoning at some length. (5 items)	(Same as the above)	.54	1.14	.73	-.07	1.06	.78
Cognitions									
5. Employing	Plausible value 1 in process subscale of Maths - Employ	(PISA 2012 released mathematics problems)	Cognitive performance test	493*	na	.91	547.38	107.12	.93
6. Formulating	Plausible value 1 in process subscale of Maths - Formulate	(PISA 2012 released mathematics problems)	Cognitive performance test	492*	na	.89	577.25	134.29	.93
7. Interpreting	Plausible value 1 in process subscale of Maths - Interpret	(PISA 2012 released mathematics problems)	Cognitive performance test	497*	na	.90	547.57	102.01	.90

(continued)

Table 2 (continued)

Measure name	PISA label	Item stem sample items (item numbers)	Measurement methods	OECD mean	OECD SD	OECD α	Taiwan mean	Taiwan SD	Taiwan α
Affects									
8. Self-efficacy	Mathematics Self-Efficacy	How confident do you feel about having to do the following mathematics tasks? Calculating how many square metres of tiles you need to cover a floor. (8 items)	4-point Likert scale: 1 = very confident ~ 4 = not at all confident (reverse coded)	1.15	1.50	.85	.18	1.18	.91
9. Interest	Mathematics Interest	Thinking about your views on mathematics: to what extent do you agree with the following statements? I enjoy reading about mathematics. (4 items)	4-point Likert scale: 1= strongly agree ~ 4 = strongly disagree (reverse coded)	-.82	2.93	.89	.02	.96	.91
10. Engagement	Mathematics Behavior	How often do you do the following things at school and outside of school? I do mathematics more than 2 hours a day outside of school. (8 items)	4-point Likert scale: 1 =always or almost always ~ 4 =never or rarely (reverse coded)	-1.55	1.12	.72	.07	.98	.76
Conditions									
11. SES	Index of economic, social and cultural status	(1) home possessions, (2) the highest parental occupation, and (3) the highest parental education. (3 items)	3 derived items, each z-standardized	-.22	.94	.65	-.39	.84	.69
12. Home ICT availability	ICT Availability at Home	Are any of these devices available for you to use at home? Desktop computer; portable laptop or notebook; Internet connection. (11 items)	3-point Likert scale: 1 = yes, and I use it, 2 = yes, but I don't use it, 3 = no (reverse coded)	.59	.76	.53	-.35	.92	.63
13. School ICT availability	ICT Availability at School	Are any of these devices available for you to use at school? Desktop computer; portable laptop or notebook; Internet connection. (7 items)	(Same as the above)	-.21	1.15	.65	-.22	.82	.59

Note. The OECD data with * were obtained from Figure I.2.37 in OECD (2014a) and the other OECD data and Taiwan's α were obtained from OECD (2014b). Taiwan's means and *SD*s were calculated on the basis of the final sample (n = 3978) used in this study. α = Cronbach's alpha (internal reliability coefficient); na = not available.

Team, http://www.R-project.org/). This study focused on answering the three RQs, but descriptive statistics and correlations (obtained by the psych and stats packages in R) facilitated a basic understanding of the measures and data structures.

RQ 1 was investigated through LPA, because all the 13 measures were continuous variables (Muthén & Muthén, 2012); the analysis was conducted using the mclust package in R. LPA can identify latent profiles with distinct meanings such as different SES levels (Chittleborough, Mittinty, Lawlor, & Lynch, 2014) and combinations of academic/cognitive, social/emotional, and behavioral risks (Wang & Peck, 2013). LPA is more efficient than conventional cluster analysis (Chiu, Douglas, & Li, 2009). A simulation study indicated that the mclust package in R tends to outperform Latent Gold® and the poLCA package in R, particularly for continuous measures (Haughton, Legrand, & Woolford, 2009). The mclust package applies a model-based clustering technique and uses higher Bayesian information criterion (BIC) values to represent more favorable profile number solutions. Notably, Mplus (Muthén & Muthén, 2012), another software package widely used by researchers for LPA, uses lower BIC values to represent more effective profile number solutions, because Mplus and mclust use different formulae for the BIC. A priori theories may also be used to determine proper profile numbers (Marsh, Lüdtke, Trautwein, & Morin, 2009). This means that profile names and numbers must be determined by considering existing research findings and educational practices in a society. For example, direct teaching and liberal teaching may be one of the dominant mathematics teaching profiles in Taiwan (Chiu, 2009; Chiu & Whitebread, 2011).

RQ 2 was answered through multivariate analysis of variance (MANOVA) for the categories of cognition, affect, and condition by using the base package in R. When MANOVA results showed significant differences, each element in the category was subjected to analysis of variance (ANOVA), followed by TukeyHSD post hoc tests using the base package. Subsequently, effect sizes (partial eta squared (η^2)) were obtained using the heplots, MASS, and car packages. According to Cohen (1988, p. 283), $.01 < \eta^2 < .06$ shows small effect sizes, $.06 < \eta^2 < .14$ medium effect sizes, and $\eta^2 > .14$ large effect sizes.

RQ 3 was answered through structural equation modeling (SEM) using the MASS, matrixcalc, and sem packages. The SEM technique used in this study focused on multiple-indicator/multiple-cause (MIMIC) analysis, because the models were aimed at examining profile differences (cf. Figure 2) (Hsu, Zhang, Kwok, Li, & Ju, 2011). Similar to MANOVA and ANOVA, MIMIC examines profile differences but additionally allows for measures with underlying latent constructs and conditions to be included in one model (Green & Thompson, 2006). The major criteria for determining model goodness of fit included (1) a root mean square error of approximation (RMSEA) lower than .10, (2) comparative fit index (CFI) higher than .90, and (3) nonnormed fit index (NNFI) higher than .90 (Hair, Black, Babin, & Anderson, 2010). Because of the large sample size in this study, the conventional criterion, a nonsignificant chi-square (χ^2), would be easily violated (Bollen & Long, 1993). Thus, χ^2 did not serve as the major criterion in this study.

Results

Profiles of Mathematics E/G-Teaching

The results of LPA involving the default testing of one to nine profiles by using the mclust package showed that seven profiles were the optimal solutions, as revealed by the highest BIC value (–29089.43) associated with the EEV (ellipsoidal, equal volume, and shape) model in Figure 1. Nevertheless, the seven-profile EEV solution generated indistinguishable means between the seven profiles and was difficult to interpret on the basis of theories or research findings. The three-, four-, and six-profile EEV solutions had relatively high BIC values (–32458.69, –32245.01, and –30807.00, respectively). The profile means of the three-, four-, and six-profile EEV solutions showed that the four-profile solution tended to be theoretically interpretable (Marsh et al., 2009) and was thus used for further analysis.

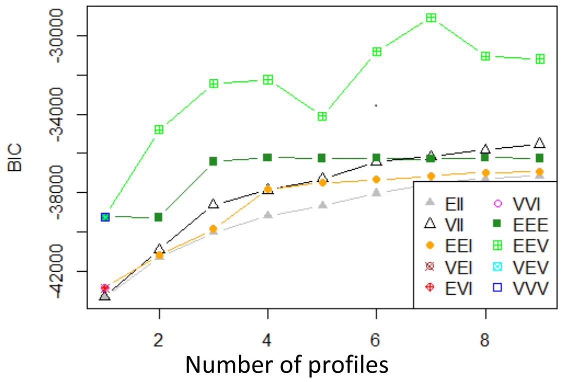

Figure 1 BIC values by number of profiles obtained through latent profile analysis. Multivariate mixture models used by the mclust package in R: EII = spherical, equal volume; VII = spherical, unequal volume; EEI = diagonal, equal volume and shape; VEI = diagonal, varying volume, equal shape; EVI = diagonal, equal volume, varying shape; VVI = diagonal, varying volume and shape; EEE = ellipsoidal, equal volume, shape, and orientation; EEV = ellipsoidal, equal volume and equal shape; VEV = ellipsoidal, equal shape; VVV = ellipsoidal, varying volume, shape, and orientation (Fraley, Raftery, & Scrucca, 2015, p. 28).

The MANOVA results showed that the four profiles differed in some e/g-teaching behaviors (Wilks = .22; $F_{(4,3973)}$ = 3386.60, p < .0005, η^2 = .77). The ANOVA and TukeyHSD post hoc test results indicated significant differences between the four profiles in the four e/g-teaching behaviors (Table 3). As shown by the last column in Table 3 for ICT use, students in Profiles C and D experienced more e-teaching than those in Profiles A and B (CD > AB); students in Profile D experienced more ICT use in teaching than those in Profile C (D > C). The same interpretation methods applied to formative assessment (BD > A; B > CD; D > C), student orientation (BD > A; B > CD; D > C), and teacher direction (BCD > A; B > CD). The differences between the profiles in the four e/g-teaching behaviors had medium to large effect sizes (η^2 = .08 for student orientation to .79 for ICT use). On the basis of these results, the profiles are designated and interpreted as follows.

Parsimony e/g-teaching (Profile A). The parsimony approach to e/g-teaching involves low e-teaching (ICT use) (*M* = –.77) and medium, below-average g-teaching (*M*s = –.22, –.11, and –.25 for formative assessment, student orientation, and teacher direction, respectively). In other words, parsimony teachers do not intensively use either e-teaching or g-teaching strategies in mathematics classrooms. Most students (75% = 2980/3978) experienced parsimony e/g-teaching.

Conservation e/g-teaching (Profile B). The major characteristic of conservation e/g-teaching is high degrees of g-teaching behaviors, with extremely high teacher direction (*M* = 2.55) and frequent use of formative assessment (*M* = 1.34) and student orientation (*M* = 1.10). However, conservation teachers seldom use ICT (*M* = -.76). Approximately 4% (=163/3978) of the students experienced conservation e/g-teaching.

Moderation e/g-teaching (Profile C). The moderation profile revealed medium degrees of e/g-teaching in all four behaviors, with ICT use as the highest (*M* = .52), followed by teacher direction, formative assessment, and student orientation (*M* = .11, –.09, and –.10, respectively). Approximately 9% (= 348/3978) of students experienced moderation e/g-teaching.

Liberal e/g-teaching (Profile D). The major characteristic of liberal e/g-teaching is intensive ICT use (*M* = 1.07) with emphasis on student orientation (*M* = .41) supplemented by formative assessment and teacher direction (*M*s = .18 and .03, respectively). Approximately 12% (= 487/3978) of the students experienced liberal e/g-teaching.

Profile Differences in Explicit Elements of Cognition, Affect, and Condition

The MANOVA results revealed that profile differences occurred in some cognitive elements (Wilks = .99; $F_{(3,3974)}$ = 14.00, p < .0005, η^2 = .01). In addition, the ANOVA results showed significant differences between the four profiles in all the three cognitive elements (Table 3). The TukeyHSD post hoc test results indicated that students who experienced Profiles A and C exhibited higher employing, formulating, and interpreting abilities in mathematics than did those who experienced Profiles B and D. The profile differences in the three cognitive elements had small effect sizes (η^2 = .02 for all three cognitive elements).

The MANOVA results showed some profile differences in the three affects (Wilks = .98; $F_{(3,1968)}$ = 14.55, p < .0005, η^2 = .02). Furthermore, the ANOVA and TukeyHSD post hoc test results revealed no profile difference in self-efficacy (η^2 = .00) but significant differences in interest (Profiles B, C, and D > Profile A; η^2 = .02) and engagement (Profile D > Profile A; η^2 = .01).

The MANOVA results showed some profile differences in the conditions (Wilks = .99; $F_{(3,3951)}$ = 18.03, p < .0005, η^2 = .01). Moreover, the ANOVA and TukeyHSD post hoc tests revealed no profile differences in SES and home ICT availability (η^2 = .00 for both) but a significant difference in school ICT availability (Profiles B, C, and D > Profile A; η^2 = .01). The results imply that profile differences may only be conditioned by school ICT availability, a result suggested in previous research (Cuckle & Clarke, 2002). Thus, the subsequent SEM analyses included only school ICT availability as the conditioning variable in the models.

Profile Differences Predicting Latent Cognition and Affect

SEM was applied to analyze six models (configured as Figure 2), with every two profiles being dummy coded to examine their differences in the latent constructs of cognition and affect; the two constructs were set to be correlated, a general phenomenon in mathematics education (Chiu, 2012a). The SEM results showed that the six models were acceptable, as indicated by all the NNFI and CFI values being higher than .90 and RMSEA values being equal to .10, except for the RMSEA value (= .11) of Model 5 (Table 4).

Table 3

Descriptive Statistics and Results of ANOVA and TukeyHSD Post Hoc Tests for the 4 Identified E/G-Teaching Profiles

	Profile A: Parsimony e/g-teaching			Profile B: Conservation e/g-teaching			Profile C: Moderation e/g-teaching			Profile D: Liberal e/g-teaching			ANOVA			TukeyHSD post hoc test
	N1	*Mean*	*SD*	*N2*	*Mean*	*SD*	*N3*	*Mean*	*SD*	*N4*	*Mean*	*SD*	$F_{(df1,df2)}$	*p*	η^2	$p < .05$
E/g-teaching behaviors																
ICT use	2980	-.77	.05	163	-.76	.09	348	.52	.35	487	1.07	.93	4960.00	<.0005	.79	CD>AB;D>C[*]
Formative assessment	2980	-.22	.89	163	1.34	.96	348	-.09	1.01	487	.18	.83	175.90	<.0005	.12	BD>A;B>CD;D>C
Student orientation	2980	-.11	.91	163	1.10	1.41	348	-.10	1.00	487	.41	.89	120.80	<.0005	.08	BD>A;B>CD;D>C
Teacher direction	2980	-.25	.89	163	2.55	.12	348	.11	1.05	487	.03	.98	507.50	<.0005	.28	BCD>A;B>CD
Cognitions																
Employing	2980	552.42	105.11	163	517.32	102.19	348	562.08	105.33	487	516.08	114.77	22.89	<.0005	.02	AC>BD
Formulating	2980	584.24	131.57	163	536.08	129.05	348	592.20	135.36	487	537.58	142.22	23.80	<.0005	.02	AC>BD
Interpreting	2980	553.17	99.60	163	512.22	97.07	348	560.97	103.24	487	515.58	108.78	28.05	<.0005	.02	AC>BD
Affects																
Self-efficacy	1480	.16	1.20	97	.36	1.28	172	.30	1.05	231	.13	1.07	1.70	1.70	.00	NS
Interest	1481	-.06	.94	98	.34	1.15	171	.20	.93	231	.26	.94	14.03	<.0005	.02	BCD>A
Engagement	1484	.01	.97	98	.17	1.10	172	.21	.94	231	.27	1.02	.01	.0002	.01	D>A
Conditions																
SES	2972	-.38	.82	162	-.39	.87	348	-.37	.87	486	-.48	.87	2.17	.09	.00	NS
Home ICT availability	2980	-.37	.90	162	-.22	.99	347	-.39	.85	487	-.26	1.03	3.092	.03	.00	NS
School ICT availability	2971	-.27	.81	163	-.10	.83	348	-.07	.77	485	-.05	.90	15.69	<.0005	.01	BCD>A

Note. [*]D > C = Profiles D > Profiles C (same interpretation methods applying to the others). Small effect size: $.01 < \eta^2 < .06$; medium effect size: $.06 < \eta^2 < .14$; large effect size: $\eta^2 > .14$ (Cohen, 1988, p. 283). $F_{(df1,df2)} = F_{(3,N1+N2+N3+N4-4)}$; df = degree of freedom. NS = not significant.

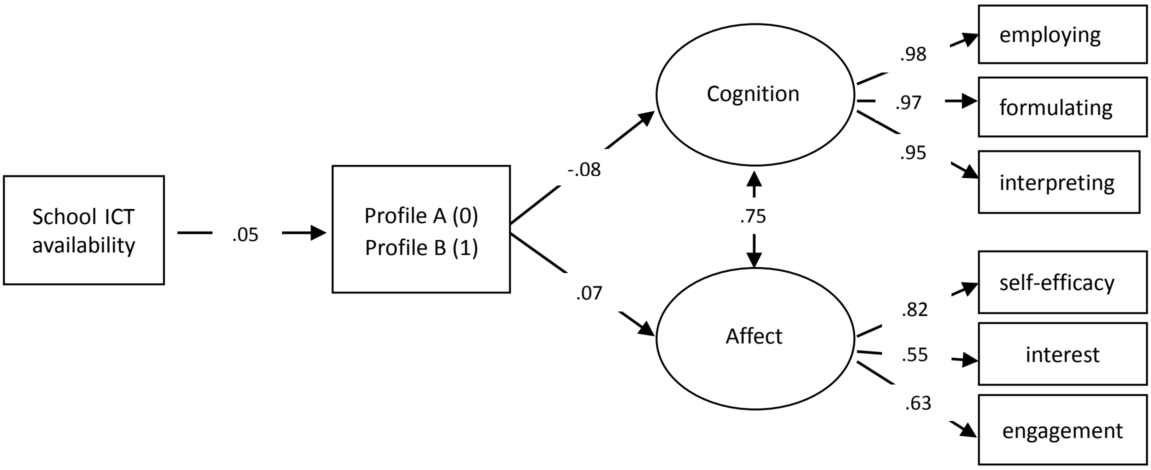

Figure 2 Structural model for the effects of profile differences on latent cognition and affect. Model 1 (Table 4) served as an example with Profile A coded as 0 and Profile B as 1. All the parameter estimates presented are significant at p = .05.

Table 4

Parameter Estimates Obtained by SEM

Relation \ Model	Model 1 Profile A(0) Profile B(1)	Model 2 Profile A(0) Profile C(1)	Model 3 Profile A(0) Profile D(1)	Model 4 Profile B(0) Profile C(1)	Model 5 Profile B(0) Profile D(1)	Model 6 Profile C(0) Profile D(1)
school ICT -> profiles	.05	.08	.09	.01	.02	.01
profiles -> cognition	-.08	.03	-.12	.21	.00	-.21
profiles -> affect	.07	.07	.06	-.03	-.07	-.04
cognition <-> affect	.75	.74	.75	.76	.74	.75
cognition ->employing	.98	.98	.98	.96	.98	.96
cognition ->formulating	.97	.97	.96	.95	.97	.95
cognition ->interpreting	.95	.95	.94	.93	.95	.93
affect -> self-efficacy	.82	.82	.81	.83	.83	.81
affect -> interest	.55	.55	.56	.54	.54	.55
affect -> engagement	.63	.63	.64	.62	.62	.64
Fit indexes						
χ^2	780.80	778.84	798.29	802.97	847.99	792.99
df	18	18	18	18	18	18
RMSEA	.10	.10	.10	.10	.11	.10
NNFI	.95	.95	.95	.95	.94	.95
CFI	.97	.97	.97	.97	.96	.97

Note. The underlined figures are significant at p = .05.

The factor loadings for cognition leading to employing, formulating, and interpreting (.93–.98) were large, and those for affect leading to self-efficacy, interest, and engagement (.54–.83) were acceptable (above .30; Costello & Osborne, 2005, p. 3). The two constructs (cognition and affect) were highly correlated (.74–.76), as suggested by previous research (Chiu, 2012b). These results suggest that SEM is suitable for examining profile differences because the six measures of cognition and affect have underlying constructs. SEM also allows for including school ICT availability as a condition. School ICT availability plays significant roles for models including Profile A (i.e., Models 1–3 in Table 4), with Profile A having less school ICT availability than Profiles B, C, and D (parameter estimates = .05, .08, and .09 respectively).

Both RQs 2 and 3 focused on the differences between the profiles in learning outcomes of cognition and affect, but RQ 2 focused on those in explicit elements and RQ 3 focused on those in latent elements. Table 5 presents a comparison of the answers to RQs 2 and 3. The answers to RQs 2 and 3 were the same in explicit and latent cognition (Profiles A and C > Profiles B and D), interest, latent affect (Profiles B, C, D > Profile A for both), and school ICT availability (Profiles B, C, and D > Profile A). The answers to RQs 2 and 3 differed only in affects, with Profile D having more engagement than Profile A but having less latent affect than Profiles B and C. One reason for the slightly unstable answers about affects may be that the factor loadings of the three affective elements were not as large as those of the three cognitive elements (Table 4).

Table 5 presents a comprehensive description of profile differences. The results were stable for cognition. Profiles A and C were determined to benefit cognitive learning outcomes more than Profiles B and D did. In affective learning outcomes, the profile differences were relatively unstable, which means that the four profiles performed slightly differently between different observed measures and the latent measure. Nevertheless, a general trend still occurred: Profile D was determined to benefit affect most, followed by Profiles B and C, and then Profile A. Profile differences in conditions were stable: the only difference occurred in school ICT availability. Detailed interpretations of the four profiles and their differences in learning outcomes are presented in the Discussion section.

Table 5

Test Results of Profile Differences in Cognition, Affect, and Condition Obtained by MANOVA and SEM

	MANOVA and related post hoc tests (Table 3)	SEM(Table 4)
Cognitions	na	AC>BD
Employing	AC>BD*	na
Formulating	AC>BD	na
Interpreting	AC>BD	na
Affects	na	BCD>A; BC>D
Self-efficacy	NS	na
Interest	BCD>A	na
Engagement	D>A	na
Conditions	na	na
SES	NS	na
Home ICT availability	NS	na
School ICT availability	BCD>A	BCD>A

Note. *AC > BD = Profiles A and C > Profiles B and D (same interpretation methods applying to the others); NS = not significant; na = not available.

Discussion

Four E/G-Teaching Profiles Addressing Differences in Learning Outcomes

In this study, the statistical method, LPA, identified four student-perceived profiles of e- and g-teaching behaviors in mathematics classrooms: parsimony, conservation, moderation, and liberal. The four identified profiles are context-based and partially mirror previous theories and findings, but they also provide new insights into approaches to integrating e- and g-teaching. Moderation e/g-teaching appears to be similar to the balance and pedagogical approaches; conservation e/g-teaching is similar to the traditional/activating/teacher-centered approach; liberal e/g-teaching is similar to the constructivist approach; and parsimony e/g-teaching has limited use of either e- or g-teaching pedagogies, which is not reported in the literature. The profiles further relate to learning outcomes in different degrees, as presented in descending order as follows.

Moderation e/g-teaching (Profile C). Moderation teaching often involves ICT use, and it also involves teacher direction but not at the expense of formative assessment and student orientation. Profile C is similar to the balance approach, in which e-teaching (or ICT) is used to compensate for g-teaching

(Tan & Tan, 2015), and is similar to the theoretical or pedagogical approach, in which the higher-order conception of g-teaching is fully integrated with e-teaching (Tømte et al., 2015). The moderation profile appears to be the most effective e/g-teaching profile in terms of its positive effects on both student cognition and affect among the four identified profiles (Tables 3–5). E-teaching increases not only student interest but also noise because of novel materials/tasks and collaborative works (Watts & Lloyd, 2004). ICT use may increase difficulty in teaching, and the difficulty may be reduced by high-quality teacher direction in design and management.

Parsimony e/g-teaching (Profile A). This approach, experienced by most students, combines slight use of e-teaching and slightly medium but below-average use of g-teaching in Taiwanese mathematics classrooms (Table 2). The parsimony profile benefits student cognition but may be at the expense of student affect, having the least affect among the four profiles (Table 5). The parsimony profile depicts mathematics teaching and learning to be serious and boring. Parsimony teachers have medium, below-average degrees of g-teaching, in addition to having the highest degree of student orientation, followed by formative assessment and teacher direction. Parsimony e/g-teaching may reflect Confucianism (emphasizing respectable teachers' serious roles) in Taiwanese society and recent constructivism (emphasizing student-centered teaching) in Taiwanese mathematics curricula (Chiu, 2011).

Conservation e/g-teaching (Profile B). Conservation teachers frequently engage in direction supplemented by formative assessment and student orientation. The conservation profile appears to partially reflect traditional/activating/teacher-centered approaches to e/g-teaching, in which e-teaching is seldom used or only for traditional purposes such as presenting materials (Lan et al., 2012). The conservation profile benefits affects but not cognition, a result different from previous research findings that high-quality g-teaching behaviors benefit cognition (Hinostroza et al., 2011; Thorvaldsen et al., 2012). One reason may be that effective g-teaching, which implies intense affective teacher–student relations, relates to affect (e.g., engagement) more than to cognition (e.g., achievements) (Roorda, Koomen, Spilt, & Oort, 2011).

Liberal e/g-teaching (Profile D). In a liberal classroom, class time is mostly allocated for teacher and student ICT use with high student orientation and medium, above-average formative assessment and teacher direction (Table 3). This profile appears to slightly reflect the constructivist approach to integrating e- and g-teaching (Park et al., 2015). The liberal profile benefits student interest, engagement, and latent affect (compared with Profile A), but its benefit to latent affect is slightly less than those of the moderation or conservation profiles (Table 5). The slight benefit of the liberal profile to affect, but not to cognition, is unsatisfactory because constructivist approaches to e-teaching can transform educational practices, which is advocated by scholars (e.g., Chai et al., 2012). ICT use in mathematics teaching requires teachers to extend their expertise from g-teaching to e/g-teaching, especially when teachers aim for a liberal e/g-teaching profile. Teachers with a liberal profile may need more professional development and support than those with the other three profiles. How to transform the liberal profile from benefiting only affect to benefiting both affect and cognition remains a concern for educators and future research.

Few Profile Differences in Conditions

Profile differences occur in school ICT availability, not in SES or home ICT availability (Table 3). Future research should consider other potential conditions that may play a role in e-teaching, such as digital learning materials, school management, and ICT technical support (Cuckle & Clarke, 2002; Shohel & Kirkwood, 2012; Somyürek, Atasoy, & Özdemir, 2009).

Only the parsimony profile was observed to involve low school ICT availability, which may partially explain the low ICT use revealed by the parsimony profile (Table 3). However, after being conditioned by school ICT availability, the parsimony profile was still observed to involve high student cognition and low affect (cf. Table 5 for comparison between the MANOVA and SEM solutions). The results regarding the conditioning effects of school ICT availability on cognition and affect imply that g-teaching behaviors play more roles in student learning outcomes than simple ICT use. ICT use in teaching may need to be closely linked to g-teaching for achieving traditional learning objectives of subject matters. Future research should validate this speculation.

Limitation and Suggestions for Education and Future Research

A limitation of this study is that the three affective measures appeared to perform differently, which may reduce the model fit to data because of measurement errors. In particular, self-efficacy acted differently from the other two affective measures (i.e., interest and engagement). The results show that self-efficacy exhibited higher correlations with cognitive measures than the other two affective measures did (Table 1). Furthermore, the profiles differed in interest and engagement but not in self-efficacy (Table 3). However, self-efficacy had a higher factor loading than interest and engagement did (Figure 2). All the results imply that different affective measures of mathematics may represent dissimilar constructs such as different beliefs, attitudes, and emotions (McLeod, 1992, 1994). Future research can investigate the diversity and complexity of affective constructs and their interaction with diverse cognitive measures and e- and g-teaching profiles.

The second limitation may be that the four e/g-teaching profiles were identified by statistical methods. Future research should investigate the validity of the four teaching profiles in real educational settings and interpret the identified four teaching profiles by using real cases in actual mathematics classrooms.

The four e/g-teaching profiles identified in this study and their interaction with student cognitive and affective learning outcomes may provide valuable suggestions for mathematics education practices. Moderation e/g-teaching, which is moderately open to using ICT and diverse general teaching methods, appears to benefit students most in both cognitive and affective mathematics learning outcomes. The results suggest that the comprehensive but moderate use of diverse teaching methods, including e-teaching, may be one of the most favorable choices for developing effective teaching for student learning outcomes. Future research should validate whether moderate e/g-teaching is superior to parsimony teaching in terms of affective learning outcomes and whether it is superior to both conservation teaching and liberal teaching in terms of cognitive learning outcomes.

Conclusion

The major contribution of this study is the use of LPA to identify student-perceived e/g-teaching profiles (latent nonlinear relationships between e- and g-teaching behaviors) that successfully demonstrate the differences in students' mathematics cognition and affect. First, the identified four e/g-teaching profiles contribute new knowledge to mathematics education research. The four e/g-teaching profiles identified in this study are outlined as follows: parsimony (low e-teaching and medium, below-average g-teaching), conservation (low e-teaching and high g-teaching, particularly in teacher direction), moderation (medium e-teaching and g-teaching), and liberal (high e-teaching and medium, above-average g-teaching of student orientation, formative assessment, and teacher direction, in descending order). The moderation profiles appear to be similar to the balance and pedagogical approaches and represent a thoughtful, considerate, and cautious use of e- and g-teaching. The conservation profile tends to reflect the traditional/activating/teacher-centered approaches to integrating e- and g-teaching, and the liberal profile reflects the constructivist/facilitating/student-centered approaches. The parsimony profile appears to be new in the literature and limited by school ICT availability.

Second, linking the identified teaching profiles with cognitive and affective learning outcomes provides practical implications for mathematics education. MANOVA and SEM were determined to generate similar results regarding the differences between the profiles in terms of learning outcomes;

however, MANOVA focused on elements and SEM focused on constructs of cognitive and affective outcomes. The moderation profile benefits both student cognition and affect. The parsimony profile benefits cognition but may harm affect. The two extreme profiles, conservation and liberal, benefit only affects. The literature tends to advocate constructivist e-teaching practices. However, the current study, based on data from a real educational setting, suggests that moderate ICT use with the merit of diverse g-teaching behaviors (in particular, teacher direction) may optimize student cognition and affect.

Finally, the successful use of LPA to identify distinct teaching profiles and the use of MANOVA and SEM to link teaching profiles with learning outcomes contribute a methodology to future research. Future educational research can use similar statistical methods to find context-based, effective teaching profiles for predicting diverse learning outcomes.

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