**Adaptability Among Science Teachers in Schools: A Multi-nation Examination of its Role in School Outcomes**

Rebecca J. Collie, Helena Granziera, Andrew J. Martin, Emma C. Burns

*School of Education, University of New South Wales, Sydney, Australia*

Andrew J. Holliman

*Department of Psychology and Human Development, UCL Institute of Education, London,*

*England*

Requests for further information about this investigation can be made to Dr. Rebecca J. Collie, School of Education, University of New South Wales, NSW 2052, AUSTRALIA. E-Mail: rebecca.collie@unsw.edu.au. Phone: +61 2 9385 9317. Fax: +61 2 9385 1946.

**Adaptability Among Science Teachers in Schools: A Multi-nation Examination of its Role**

**in School Outcomes**

**Abstract**

Adaptability helps teachers to navigate change, novelty, and uncertainty at work. We sought to extend understanding of adaptability by considering it at the school-level in 2,189 high schools across eight nations. We investigated whether two job demands (disruptive student behavior, student diversity) and a job resource (teacher collaboration) are associated with school-average teacher adaptability. We also examined the association that school-average teacher adaptability has with teacher self-efficacy and, in turn, student self-efficacy. Findings showed, for example, that greater school-average teacher adaptability was positively associated with teacher self-efficacy and, in turn, student self-efficacy. Findings were similar across the eight nations.

*Keywords:* teachers' adaptability; school-level; self-efficacy; secondary school; science; PISA, multi-nation

**Introduction**

Teaching is characterized by constant change. Teachers are expected to respond to the different and varying needs of students, incorporate novel professional learning into their instructional practices, and interact with new colleagues (Collie & Martin, 2016). Adaptability, or the capacity to regulate one's thoughts, feelings, and behaviors in response to changing, new, or uncertain situations (Martin, Nejad, Colmar, & Liem, 2012), has been identified as an important capability for teachers. Researchers have established that adaptability is a predictor of teachers' healthy functioning at work and positive academic outcomes among their students (e.g. Collie, Granziera, & Martin, 2018; Loughland & Alonzo, 2018; Parsons, 2012). However, research thus far has focused on individual teachers. Although highly informative, researchers have also identified the need to examine school-average phenomena (Konold & Cornell, 2015). Given the demonstrated benefits of adaptability among teachers, it is now important to examine its broader role at the school-level. School-average teacher adaptability refers to average levels of adaptability across a group of teachers. If school-average levels of adaptability are associated with important school-average teacher and student outcomes (e.g., self-efficacy), then it may be a salient area of focus for school-wide interventions. A focus on the school-level, then, has practical yields alongside important conceptual yields.

The aim of this study was to extend the knowledge of adaptability gained through studies on its role at the individual-level (e.g., Collie et al., 2018; Martin et al., 2012), by focusing on its role at the school-level. Importantly, our study focused on the subject of science. Science teachers are required to adapt, like teachers in other school subjects (e.g., lesson pacing, classroom management). In addition, science teachers must also make adjustments specific to their teaching domain—such as changes in technology and laboratory procedures, as well as

ongoing advances in knowledge that affect the curriculum. Given concerns about declines in

students' motivation in science worldwide (e.g., OECD, 2017) and identification that school-

level phenomena have a role to play in this (Burns, Martin, & Collie, 2019), we suggest it is also

important to examine factors that may be implicated in higher student motivation, such as

science teachers' adaptability.

Harnessing job demands-resources theory (Bakker & Demerouti, 2017) and using

science-focused data from eight OECD countries that participated in PISA 2015, we examined

school-average science teacher adaptability (as rated by students). In addition, we investigated

the extent to which three contextual school-average factors are associated with school-average

science teacher adaptability: school-average collaboration among science teachers; school-

average disruptive student behavior in science classes; and, student body diversity in terms of

language background, special needs, and socio-economic status. We also examined the extent to

which the contextual factors and teacher adaptability are associated with school-average science

teacher self-efficacy and, in turn, school-average student self-efficacy in science. Figure 1

demonstrates the model under examination. Given that we examined our model across eight

OECD countries, we also explored whether there were any major differences in how the factors

were associated cross-nationally.

**Teacher Adaptability**

As noted above, adaptability reflects the capacity to regulate thoughts, feelings, and

behaviors in response to changing, new, or uncertain situations (Martin et al., 2012). This is a

tripartite model comprising cognitive, behavioral, and emotional adaptability (Martin et al.,

2012). A growing body of work is showing the importance of teacher adaptability for positive

outcomes among both teachers and students. Adaptability is positively associated with teachers'

use of adaptive instructional practices in the classroom (Loughland & Alonzo, 2018), it is

negatively associated with teachers' disengagement (Collie et al., 2018), and it has been

indirectly associated with students' achievement (Collie & Martin, 2017).

Although the above research indicates the salience of adaptability at the individual-level,

the extent to which teacher adaptability plays a prominent role in school-average outcomes is an

empirical question that warrants attention. School-average teacher adaptability reflects the extent

to which there is a predominant tendency among teachers at a school to adjust their thoughts,

behaviors, and emotions to navigate change, uncertainty, and novelty at work. For example, high

levels of school-average teacher adaptability would reflect a predominant tendency among

teachers at the school to think through a variety of options, try out actions that differ from

previous efforts, or rein in feelings of frustration in response to a new situation in their teaching.

In contrast, low levels of school-average adaptability would reflect less inclination among

teachers to respond to novelty in these adaptive ways. Notably, we suggest this line of inquiry is

vital because it will extend current understanding from a teacher-focused knowledge-base to

include a broader school focus. To the extent that school-average teacher adaptability explains

significant variance in organization-level outcomes, interventions for teacher adaptability may

also be directed at the school-level.

In the current study, we focused specifically on school-average teacher adaptability for

science instruction. More precisely, we examined the extent to which teachers adjust their

instructional practices to meet students' learning needs in the science classroom (e.g., Parsons et

al., 2018). This can be considered a form of behavioral adaptability because it concerns the

behaviors and actions that teachers adapt. Loughland and Alonzo (2018) used a similar approach

in their observations of teachers and showed that when teachers were observed to use more

behavioral adaptability, this correlated with their self-reports of (cognitive, behavioral, and emotional) adaptability. In our study, we extend prior work by using another measure of behavioral adaptability: students' ratings of teachers' adaptability. We suggest such a focus is important because it provides targeted knowledge about how adaptability manifests (and is perceived by students) in the classroom.

In sum, the use of students' rating provides an important contribution given that prior studies on teacher adaptability have employed self-reports (e.g., Collie & Martin, 2017) or observations (e.g., Loughland & Alonzo, 2018) to measure adaptability. Moreover, prior studies on teacher adaptability have been limited to one country (e.g., Collie et al., 2018; Parsons, 2012). Research is thus needed to determine whether school-average teacher adaptability functions similarly across international contexts. Taken together, this investigation seeks to expand current knowledge of the role of teacher adaptability in several important ways.

**Conceptual Framework: Job Demands-Resources Theory**

Job demands-resources (JD-R) theory establishes that all jobs have specific contextual factors that facilitate or inhibit employee outcomes (Schaufeli & Bakker, 2004). Job demands are physical, psychological, organizational, or social elements of work that require physical or psychological exertion (e.g., high workload), and that are associated with physical and psychological costs and ill-health (e.g., burnout; Bakker & Demerouti, 2017). In contrast, job resources are physical, psychological, organizational, or social aspects of work that enable employees to achieve work-related goals and professional growth (e.g., social support; Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). Job resources are associated with positive outcomes (e.g., well-being, motivation; Skaalvik & Skaalvik, 2018). More recent iterations of JD-R theory have acknowledged that, in addition to job resources and demands, personal

resources are also important determinants of an employee's functioning at work (Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2007). Personal resources are malleable, personal capacities that reflect an individual's potential to influence the working environment, and like job resources, are associated with employee's positive outcomes (Schaufeli & Taris, 2014).

JD-R theory posits two processes that are relevant to the present research and that have been examined among a variety of professions and in many different countries (Bakker & Demerouti, 2017). The first process indicates that job and personal resources are associated with positive outcomes at work (viz. self-efficacy in the current study; Bakker & Demerouti, 2017). The second relevant process is that high levels of job resources also foster greater personal resources (e.g., adaptability; Bakker & Demerouti, 2017). In line with these established processes in JD-R theory, in our study we examined the association that teacher collaboration (a job resource) has with teacher adaptability (a personal resource), and the associations that both factors have with science teacher self-efficacy (see Figure 1).

In addition to these well-established processes from JD-R theory, we also investigated several additional processes that move beyond traditional conceptualizing. The first process is the potential link between job demands and personal resources. We suggest that a negative association between job demands and personal resources is possible given that high levels of job demands may lead to negative appraisals of one's capacities (McGonagle, Fisher, Barnes-Farrell, & Grosch, 2015). As such, in our study we examined the (negative) associations that disruptive student behavior and student diversity (job demands) have with teacher adaptability (a personal resource). Second, although JD-R theory does not typically consider job demands in relation to positive outcomes (however, see Bakker, Hakanen, Demerouti, & Xanthopoulou, 2007), researchers have shown that job demands are also negatively associated with desirable outcomes

among teachers (e.g., well-being; Skaalvik & Skaalvik, 2018). This is a process that deserves further empirical attention in schools, and one we examined by testing whether the two job demands are associated (negatively) with teacher self-efficacy (see Figure 1).

Taken together, we examined one job resource (school-average collaboration among science teachers), two job demands (disruptive student behavior in science classes, and student body diversity in terms of language background, special needs, and socio-economic status), and one personal resource (school-average science teacher adaptability). Although JD-R theory is a well-established approach for understanding individual-level employee functioning at work (Bakker & Demerouti, 2017), we posit that it can also be applied at a school-level. Indeed, Bakker and Demerouti (2017) highlight the need for research to examine the organization-level, which can reveal important knowledge about how an organization (i.e., school) is functioning as a whole. This broader focus can also provide important direction for intervention—and, in particular, it can reveal what job demands/resources and personal resources should form a focus in organization-wide intervention efforts.

Despite calls for researchers to examine JD-R theory at the organization-level (Bakker & Demerouti, 2017), only a handful of studies have done so and none appear to involve teachers. Moreover, although JD-R theory has been applied to understand employees' experiences in many nations across the globe, most research has involved examining only one country at a time (e.g., Collie et al., 2018). Given that there is increasing concern about the growing complexity of the teaching profession and the rising demands being placed upon teachers in many countries worldwide (e.g., Guerriero & Révai, 2017; OECD, 2019; UK Department for Education, 2018), cross-national research is now needed. In particular, it is important to examine the extent to which common resources and demands are implicated in teachers' outcomes in similar or

different ways across nations. Whereas differences will better highlight issues particular to each cultural context that can then be used to guide country-level policy and practice, similarities will be helpful for countries to know when they might be able to adopt processes and practices from other nations that have been successful. Furthermore, with the rise of international assessment and education recommendations, understanding what does and does not apply to particular contexts helps each country digest, interpret, and apply these international findings/guidelines from global bodies in more context-relevant ways.

**The Demands and Resources Under Examination and Their Hypothesized Associations**

In the previous section, we provided broad-level conceptual justification for our hypothesized model (see Figure 1) and the expected associations among factors guided by processes established within JD-R theory and empirical support. In the following sections, we bolster this with additional justifications related to the specific resources and demands that were examined in our study.

Various job resources and demands have been identified as salient in research among employees at the individual-level. Alongside our focus on teacher adaptability (a personal resource), we selected one job resource and two job demands that may also play a significant role at the school-level. The job resource, *teacher collaboration*, refers to the degree to which teachers can obtain assistance, advice, or encouragement from colleagues (Johnson, Stevens, & Zvoch, 2007). Turning to the job demands, *disruptive student behavior*, refers to student behaviors such as calling out, disturbing other students, disobedience, and aggression (Tsouloupas, Carson, Matthews, Grawitch, & Baber, 2010). *Student diversity* refers to students with different abilities, ethnicities, genders, social classes, cultures, and religions. Among these,

the current study focused on diversity in terms of language background, special needs, and socio-economic status.

**Linking job resources and job demands with teacher adaptability.** In the first part of our model (see Figure 1), we examined the extent to which teacher collaboration, disruptive student behavior, and student diversity are associated with teacher adaptability. Although previous research has not considered the link between teacher collaboration and adaptability at a school-level, it is possible to extrapolate from studies of individual teachers. For example, Thoonen, Sleegers, Peetsma, and Oort (2011) reported that with higher levels of teacher collaboration there is greater tolerance for uncertain situations (a core component of adaptability). Such teachers may therefore be more capable of demonstrating adaptability—though the extent to which this is evident at a school-level requires testing.

Turning to the job demands, in schools characterized by high levels of disruptive student behavior, the teaching staff as a whole may develop negative feelings and question their capacities, which may thwart their ability to meet students' learning needs (Kokkinos, 2007). Moreover, when a teaching staff is overrun in managing classrooms, this requires adaptability in classroom management, but likely leaves limited time for focusing on and adapting instruction (the focus in the current study). In addition, when there are very high levels of student diversity within a school, the teaching staff may also feel overwhelmed, lack confidence for meeting student needs (Goddard & Evans, 2018), and thus struggle to adapt effectively.

**Linking the resources and demands with teacher self-efficacy.** Another aim of the present study was to examine the extent to which teacher collaboration, disruptive student behavior, student diversity, and teacher adaptability are associated with teacher self-efficacy (see Figure 1). *Teacher self-efficacy* refers to teachers' beliefs in their ability to organize, plan, and

demonstrate behaviors that are required to achieve educational goals (Skaalvik & Skaalvik, 2010). A great deal of research worldwide has established the importance of teacher self-efficacy for a range of outcomes (e.g., Chong & Kong, 2012; Goddard & Goddard, 2001; Klassen & Chiu, 2010; Loughland & Alonzo, 2018). At the individual-level, teacher self-efficacy is linked with indicators of positive occupational and psychological functioning, such as teacher engagement and student achievement (Klassen & Chiu, 2010). At the school-level, teacher self-efficacy reflects the school-average levels of self-efficacy, and has been positively associated with higher student achievement (Goddard & Goddard, 2001). The extent to which similar relations occur with a wider range of resources and demands is needed to extend current understanding. At this point, it is important to delineate school-average self-efficacy (which focuses on an aggregated average of individuals' self-perceptions) from collective efficacy (which reflects individual judgements of the group's efficacy; e.g., Klassen, Usher, & Bong, 2010). We focused on self-efficacy rather than collective efficacy because we propose that adaptability is more closely associated with self-efficacy for one's own teaching, rather than shared beliefs about a larger group.

More precisely, we examined school-average science teacher self-efficacy and we investigated its associations with resources and demands. This positioning differs from prior research using JD-R theory where self-efficacy is typically considered a personal resource (e.g., Xanthopoulou et al., 2007). Notably, it is possible that teachers' self-efficacy still acts as a personal resource in our study; however, we wanted to focus on what other demands and resources lay a foundation for self-efficacy given it is an important outcome in itself. This ordering is supported by empirical work where self-efficacy has been established as an outcome of other job demands, job resources, and personal resources (e.g., Chang, 2013). Nonetheless, we

do acknowledge that longitudinal research is needed given it is possible that there are reciprocal effects involving self-efficacy and the other demands and resources.

Evidence for the associations involving teacher self-efficacy in our model (see Figure 1) stems from individual-level research and we extrapolate to the school-level in our hypotheses here. Starting with job resources, we propose that high levels of school-wide collaboration among science teachers likely fosters science teacher self-efficacy because it gives teachers access to a range of teaching strategies and different approaches to embed in their repertoire (e.g., Collie, Shapka, & Perry, 2012). Turning to job demands, high school-average disruptive student behavior can mean that teaching staff question their capacities, potentially negatively impacting school-average self-efficacy (e.g., Kokkinos, 2007). High school-average student diversity can mean that teaching staff feel overwhelmed and lack self-efficacy to best meet the needs of a wide variety of learners (e.g., Goddard & Evans, 2018). Finally, we propose that adaptability fosters mastery experiences (i.e., experiences of success)—which are a salient precursor of self-efficacy (Bandura, 1997)—because adaptability helps teachers to effectively navigate change and novelty in the classroom (Collie & Martin, 2016).

**Summary.** Taken together, we examined the direct associations that teacher collaboration, disruptive student behavior, and student diversity have with teacher adaptability, and the associations that all four factors have with teacher self-efficacy. We also examined whether teacher adaptability plays a significant role in linking the job resources/demands and teacher self-efficacy (i.e., via significant indirect associations). These hypothesized associations are supported by major tenets of JD-R theory, along with empirical evidence involving individual teachers (e.g., Kokkinos, 2007). However, the extent to which the hypothesized associations may be reflected at a whole-school level and among science teaching staff requires

attention, as does the role of such factors across different nations to see if such processes can be generalized.

**Student Self-efficacy as an Outcome of Teacher Self-efficacy at the School-level**

The final process examined in our model considers the association between school-average science teacher self-efficacy and student self-efficacy for learning science (see Figure 1). This part of our model moves beyond understanding from JD-R theory and is supported by conceptualizing from social cognitive theory (Bandura, 1997). Social cognitive theory (Bandura, 1997) states that self-efficacy is impacted by several factors including mastery experiences and vicarious experiences (i.e., learning from observing the efficacious behavior of others, such as a teacher or peers). Although no prior studies have appeared to consider the associations between these variables at a school-level, studies of individual teachers suggest that teachers who possess higher self-efficacy may facilitate learning environments that are more engaging, and may be better equipped to model and scaffold learning. Engaging learning environments, modeling, and scaffolding likely foster students' self-efficacy because these factors promote mastery and vicarious experiences (e.g., Bandura, 1997; Britner & Pajares, 2006). However, the empirical support for this relation has been mixed (e.g., Thoonen et al., 2011). Combined with the relative paucity of literature examining this nexus at the school-level or cross-nationally, mixed findings point to the need for further research in the area.

**The Role of Salient Covariates at the School-Level**

A number of extraneous factors may influence school-level factors and play a role in determining teacher- and student-level outcomes. For example, the National Center for Education Statistics (2018) reports that larger school sizes are associated with higher rates of disruptive student behavior. Teacher and student outcomes may similarly influence the

constructs examined in this study; however, the vast bulk of this prior work has been conducted at the student- or teacher-level. For instance, Klassen and Chiu (2010) demonstrated that teacher self-efficacy increases with years of teaching, then falls in later career teachers. Furthermore, Alrefaei (2015) reports that science and mathematics teachers who hold a bachelors' degree have higher self-efficacy compared to teachers who hold a master's degree. In terms of students, prior academic achievement may influence students' self-efficacy beliefs via the process of mastery experiences (Bandura, 1997). The range of variables that may influence the substantive constructs in the present study, and the conflicting findings described underscore the need to control for a number of structural and socio-demographic characteristics. Because such limited research has considered these relations at the school-level and among science teachers, we controlled for all of these variables in our examination.

### Study Overview

Using PISA data from eight OECD countries at the school-level, we examined the extent to which a job resource (science teacher collaboration) and two job demands (disruptive student behavior in science classes, student diversity) are associated with science teacher adaptability (a personal resource), the extent to which all factors are associated with science teacher self-efficacy and, in turn, student science self-efficacy. Figure 1 demonstrates the model under examination. In our analyses, we controlled for salient covariates, we also tested whether there were any major differences in how the factors were associated cross-nationally, we examined whether there were any indirect associations involving teacher adaptability, and we tested two alternative models.

Six research questions (RQ) guided the study:

1.    To what extent are teacher collaboration (positively), disruptive behavior

(negatively), and student diversity (negatively) associated with teacher adaptability

(while controlling for covariates)?

2.    To what extent are teacher collaboration (positively), disruptive behavior

(negatively), student diversity (negatively), and teacher adaptability (positively)

associated with science teacher self-efficacy (while controlling for covariates)?

3.    To what extent is science teacher self-efficacy positively associated with student self-

efficacy for learning science (while controlling for covariates)?

4.    To what extent do the findings of RQ1-3 differ across nations?

5.    To what extent does teacher adaptability play a role in linking teacher collaboration,

disruptive behavior, and student diversity with teacher self-efficacy via indirect

associations?

6.    To what extent does our hypothesized model offer greater explanatory power over

possible alternative models?

Based on JD-R theory and the literature cited above, we hypothesize that teacher

collaboration would be positively associated with teacher adaptability, whereas disruptive

behavior and student diversity would be negatively associated with teacher adaptability (e.g.,

Goddard & Evans, 2018; RQ 1). We expected that teacher collaboration and adaptability would

be positively associated with teacher self-efficacy, whereas the reverse would be true for

disruptive behavior and student diversity (e.g., Kokkinos, 2007; RQ 2). We hypothesized that

teacher self-efficacy would be positively associated with student self-efficacy (e.g., Britner &

Pajares, 2006; RQ 3). For RQs 4 and 5, we did not make hypotheses given that prior research has

not examined associations across countries, nor indirect effects. For our last research question,

we expected that our hypothesized model would be superior to the two alternative models given support from theory and prior empirical research (e.g., Bakker & Demerouti, 2017).

## Methods

### Participating Schools, Teachers, and Students

Data were drawn from 2,189 schools in eight OECD countries (comprising 14,182 science teachers and 57,131 students from those schools). These schools were selected based on three criteria: they (a) had principals who completed the 2015 PISA School Questionnaire, (b) had science teachers who completed the optional 2015 PISA Teacher Questionnaire, and (c) had students who completed the 2015 PISA Student Questionnaire. The countries examined were Australia (718 schools), Chile (188 schools), Czech Republic (341 schools), Germany (248 schools), South Korea (145 schools), Portugal (179 schools), Spain (199 schools), and the USA (171 schools); although Italy also met our inclusion criteria, it was excluded because there was systematic missing data on the teacher questionnaire.

For participating schools, the average school size was 919 ($SD = 631$) students, and the school-average class size was 26 ($SD = 6$) students. Almost two-thirds of the schools were government schools (65%; the remainder private/independent schools). On average, 15% of the students in these schools spoke a minority language at home, 11% had special needs, and 28% were from disadvantaged socio-economic backgrounds. The schools were located in villages (6%; less than 3,000 people), small towns (17%; 3,000 to 15,000 people), towns (27%; 15,000 to 100,000 people), cities (22%; 100,000 to 1 million people), and large cities (21%; over 1 million people). The majority (83%) of science teachers at these schools had achieved ISCED 5A level (bachelor's degree) or higher with a major in science. In the current study, there were on average 35 ($SD = 25$) students per school (cluster size).

The science teachers involved in the study were 57% female, had an average age of 44 ($SD = 11$) years, and an average teaching experience of 17 ($SD = 11$) years. The majority had a permanent contract (83%), with 16% of teachers on a fixed-term contract, and most were full-time teachers (84%). The students involved in the study were 50% female, with an average age of 16 ($SD = 0.29$) years, and 8% spoke a language at home that was different from the test language. The average socio-economic status using the Index of Economic, Social, and Cultural Status (ESCS) was -0.10 ($SD = 1.01$). This is an aggregated measure of parent education, parent occupation, and home possessions and has a mean of approximately zero for OECD countries ($SD = 1.00$). Students in our sample were thus slightly below average on ESCS.

**PISA Sampling Procedure**

In PISA, the sampling procedure endeavors to capture samples from each of the participating countries that are nationally representative. School selection involves identifying schools from across each nation that have students aged 15 years (the target age of PISA). Prior to selecting individual schools, each school is grouped based on school characteristics (strata) to improve the diversity of the sample, reduce selection bias, and reduce sampling variance (OECD, 2017). The second stage of sampling design involves student selection. Once schools have been selected, PISA-eligible students within those schools are randomly selected. In PISA, weights are used to adjust student and school scores (for full details about the weighting procedure, see OECD, 2017). At the student-level, weighted scores control for variations in cluster sizes across schools. At the school-level, weighted scores control for the variance in strata grouping and number of eligible student participants per school. These weights were employed in the current study (details below).

**Measures**

All substantive and covariate measures included in the present investigation were drawn from the 2015 PISA student, teacher, or school questionnaires (OECD, 2017). Given our investigation is focused on the school-level, and because classroom-level modeling was not possible (PISA does not provide data to link students with teachers), all variables were aggregated to the school-level in final modeling. All substantive factors were entered as aggregated mean scores to reduce the number of parameters relative to sample size.

**Job demands.** *Disruptive student behavior in science classes* was assessed with the "disciplinary climate in science classes" items in the student questionnaire (5 items; e.g., How often do these things happen in your <school science> lessons? "Students don't listen to what the teacher says," "There is noise and disorder"). Items were scored on a scale from 1 (Every lesson) to 4 (Never or hardly ever). The items were reverse coded for our analyses, such that a higher score represents greater prevalence of disruptive behavior. This scale demonstrated adequate variance at the school-level (intraclass correlation [ICC] = .15) and was reliable at the student-level ($\omega_h$ = .89) and school-level ($\omega_h$ = .98) using coefficient omega.[1]

*Student diversity* was assessed with three items from the school questionnaire that asked principals to estimate the percentage of students in the PISA test grade whose language spoken at home was different from the language of instruction, who had special needs, and who were from socio-economically disadvantaged backgrounds. We calculated the mean of these three percentages as an indication of school-average student diversity. We did not calculate reliability because we did not expect these three variables to reflect an underlying construct. Instead, they function as observed variables and together formed an average score reflecting diversity.

---

[1] For the student-level variables, coefficient omega was calculated from a multilevel confirmatory factor analysis (CFA) involving the four student-level variables: disruptive behavior, teacher adaptability, student self-efficacy, and the covariate student achievement. For the teacher-level variables, coefficient omega was calculated from a multilevel CFA involving the two teacher-level variables: teacher collaboration and teacher self-efficacy.

**Job resource.** *Science teacher collaboration* was assessed with items from the "science teacher collaboration" scale in the teacher questionnaire that asked science teachers about the extent to which they regularly collaborate on homework and assessment (4 items; e.g., "We exchange tasks for lessons and homework that cover a range of different levels of difficulty," "We discuss the criteria we use to grade written tests."). Items were scored on a scale from 1 (Strongly disagree) to 4 (Strongly agree). Reliability calculated from the individual items was adequate at the teacher-level ($\omega_h = .81$) and school-level ($\omega_h = .91$). This scale demonstrated adequate variance at the school-level (ICC = .24).

**Personal resource.** *Science teacher adaptability* was assessed with two items from the "adaption of instruction" scale of the student questionnaire that ask students about their science teachers' adaptability. The two items were "The teacher adapts the lesson to my class's needs and knowledge" and "The teacher changes the structure of the lesson on a topic that most students find difficult to understand." Together, these items reflect behavioral adaptability because they assess teachers' adaptations to their instruction in response to changing, new, or uncertain situations in the classroom (i.e., different student needs and abilities). The third item in the scale was excluded because it did not precisely reflect teacher adaptability, as per our operationalization (e.g., Martin et al., 2012). Instead, the third item more broadly tapped into instrumental support provided to students and may or may not have indicated teacher adaptability (i.e., "The teacher provides individual help when a student has difficulties understanding a topic or task"). Items were scored on a scale from 1 (Never or almost never) to 4 (Every lesson or almost every lesson). This scale was reliable at the student-level ($\omega_h = .76$) and school-level ($\omega_h = .93$), and demonstrated adequate variance at the school-level (ICC = .06).

**Self-efficacy outcomes.** *Science teacher self-efficacy* was assessed with items from the "self-efficacy for teaching science and science content" scales in the teacher questionnaire. These items ask teachers about their confidence regarding various science teaching tasks (4 items; e.g., To what extent can you do the following? "Assign tailored tasks to the weakest as well as to the best students," "Use a variety of assessment strategies") and science knowledge (4 items; e.g., To what extent can you do the following? "Explain a complex scientific concept to a fellow teacher," "Explain the links between biology, physics and chemistry"). Items were scored on a scale from 1 (Not at all) to 4 (To a large extent). In analyses, we created a mean score for each of the two subfactors and then used these two mean scores as indicators for a broader self-efficacy variable. Reliability for the broader self-efficacy variable was slightly below adequate at the teacher-level ($\omega_h = .64$), but adequate at the school-level ($\omega_h = .82$), which was our focus in the current study. This scale demonstrated adequate variance at the school-level (ICC = .17).

*Student self-efficacy* (for learning science) was assessed with the "science self-efficacy" items from the student questionnaire, which ask students about their confidence in performing various science-related tasks on their own. We created two subfactors reflecting self-efficacy to locate and interpret science knowledge (4 items; e.g., How easy do you think it would be for you to perform the following tasks on your own? "Recognize the science question that underlies a newspaper report on a health issue,") and self-efficacy to explain science to others (4 items; e.g., How easy do you think it would be for you to perform the following tasks on your own? "Predict how changes to an environment will affect the survival of certain species."). Items were scored on a scale from 1 (I could do this easily) to 4 (I couldn't do this). The items were reverse coded for our analyses, such that a higher score represents greater self-efficacy. In analyses, we created a mean score for each of the two subfactors and then used these two mean scores as indicators

for a broader self-efficacy variable. Adequate reliability was found for the broader self-efficacy variable at the student-level ($\omega_h = .89$) and school-level ($\omega_h = .94$), and the scale demonstrated adequate variance at the school-level (ICC = .05).

      **Covariates.** Five covariates were examined: school size, class size, teaching experience, science teacher educational qualification, and science achievement. *School size, class size*, and *teaching experience* were estimated as continuous variables. *Educational qualification* was a continuous measure representing the percentage of science teachers (compared with all science teachers) that had achieved ISCED 5A level (bachelor's degree) or higher, and that had a major in science. *Science achievement* was assessed via school-average plausible values for achievement in PISA. PISA produces multiple plausible values for each student's overall science score (for further details, see OECD, 2017). The plausible values, across all participating countries, have a mean of 500 (*SD* = 100), where scores higher than 500 indicate science achievement above the PISA 2015 average (OECD, 2017). In PISA 2015, 10 plausible scores are provided for each student (OECD, 2017). To accurately employ these scores, models are estimated 10 times each with a different plausible value (OECD, 2017). The estimates and *p*-values are then averaged and reported as the final estimates. To calculate reliability, a latent factor with all 10 plausible values as indicators was assessed. This scale was reliable at the student-level ($\omega_h = .99$) and school-level ($\omega_h = .99$), and there was adequate variance in this variable at the school-level (ICC = .32).

**Data Analysis**

      Preliminary analyses involved calculating reliability coefficients, means, standard deviations, skew, and kurtosis statistics for all substantive variables. Multilevel confirmatory factor analysis and measurement invariance tests were also run to provide additional

measurement support (see Supplementary Online Materials). Our main analyses involved

obtaining correlations, followed by path analysis. We used M*plus* 8.4 (Muthén & Muthén, 2017)

for all analyses. Robust maximum likelihood (MLR) was used as the method of estimation along

with country as the "cluster" variable. Given the modest number of schools per country relative

to estimated parameters at the school-level ($n \geq 145$ per country) and because we wanted to

compare results across countries, we conducted our main analyses with mean scores. Missing

data at the school-level were less than 1% for all variables (except student diversity, which was

27% missing) and were dealt with using the Full Information Maximum Likelihood defaults in

M*plus* (Dong & Peng, 2013). In PISA, weights are employed to ensure that sampling differences

do not have disproportionate influence on results. Student and teacher weight variables were

applied when aggregating to the school-level. The school weight variable was applied in

modeling described below. Models were run 10 times (for each plausible value) and the

estimates and *p*-values were averaged using M*plus* (via "type = imputation").

We obtained correlations between all variables—including all covariates and substantive

variables. Cohen's *d* effect sizes for the correlations are reported as follows: $r \geq .20$ is a small

effect, $r \geq .50$ is a medium effect, and $r \geq .80$ is a large effect. Then, we ran path analysis to

examine the structural paths between constructs (while controlling for shared variance). More

precisely, we examined the associations that school-average disruptive behavior, student

diversity, and science teacher collaboration have with school-average teacher adaptability, that

all constructs have with school-average teacher self-efficacy and, in turn, school-average student

self-efficacy (see Figure 1). School-average covariates served as controls for all constructs. To

interpret the beta estimates, we refer to effect sizes using Keith's (2015) guidelines: $\beta \geq .05$ is a

small effect, $\beta \geq .10$ is a medium effect, and $\beta \geq .25$ is a large effect (Keith, 2015). In presenting

benchmarks for effect sizes, Cohen (1988) provided them for use across disciplines, but also

encouraged researchers to use discipline-specific benchmarks when available. For this reason,

we chose to use Keith's benchmarks for interpreting our beta estimates as these were specifically

developed for the field of education based on prior research showing the practical results of

different effects.

We next compared the results across the countries. More precisely, we tested for any

differences in the significant substantive paths identified in the main analysis across countries

using two criteria. Paths were considered significantly different across groups when (a) the path

was significant in one group but not in the other group (or both significant but in opposite

directions), and (b) when the two paths were significantly different in strength from one another

using Wald tests of difference in M*plus* (and a Bonferroni correction). We also examined

indirect associations from the school-average job resources and demands to teacher or student

self-efficacy using non-parametric bootstrapping (1000 draws). Our aim was to determine the

extent to which school-average teacher adaptability plays a linking role in how the job

resources/demands are associated with school-average teacher or student self-efficacy. We also

examined teacher self-efficacy as a linking variable between the job resources/demands and

student self-efficacy. Finally, two alternative models were run to provide support for the

construct ordering in our hypothesized model. The alternative models involved changing the

ordering of the center constructs (adaptability and self-efficacy) and comparing indirect

associations with our hypothesized model to provide support for ordering.

## Results

Table 1 shows reliabilities and descriptive statistics for the whole sample. Reliabilities

were at appropriate levels. Multilevel confirmatory factor analysis and measurement invariance

tests provided further measurement support (see Supplementary Online Materials for details).

Table 2 shows the correlations among all variables. Here, we report all significant correlations among the substantive factors (all were large effect sizes as per Cohen's *d*). Starting with the associations involving school-average adaptability, this was negatively associated with school-average disruptive student behavior in science classes ($r = -.37$, $p < .001$), and positively associated with school-average student diversity ($r = .16$, $p < .001$), teacher self-efficacy ($r = .22$, $p < .001$), and student self-efficacy ($r = .29$, $p < .001$). In other associations, school-average disruptive behavior in science classes was negatively associated with school-average student self-efficacy ($r = -.25$, $p < .001$). School-average student diversity was negatively associated with school-average science teacher collaboration ($r = -.23$, $p < .001$). School-average teacher self-efficacy was positively associated with school-average student self-efficacy ($r = .21$, $p < .001$).

Turning to covariates, all findings are shown in Table 2. Only findings involving substantive variables and significant at $p < .001$ are discussed here. Schools with greater school-average teaching experience tended to have a less adaptable teaching staff ($r = -.19$) and greater teacher collaboration ($r = .13$). Larger schools tended to have less school-average student diversity ($r = -.15$). School-average science achievement was negatively associated with school-average disruptive behavior in science classes ($r = -.43$) and student diversity ($r = -.50$), and positively associated with student self-efficacy ($r = .35$).

**Path Analysis**

Table 3 shows the standardized beta estimates (significant and non-significant) and $R^2$ values. Figure 2 displays significant associations among the substantive factors. Results showed that school-average disruptive behavior in science classes was associated with lower school-average teacher adaptability ($\beta = -.40$, $p < .001$; large effect size). School-average teacher

adaptability was associated with higher school-average teacher self-efficacy ($\beta = .18$, $p < .001$; medium effect size). In turn, school-average teacher self-efficacy was associated with greater school-average student self-efficacy ($\beta = .08$, $p = .005$; small effect size). These associations were significant while controlling for covariates and shared variance.

Turning to the results involving covariates, only results at $p < .001$ are reported here (Table 3 shows all results). These findings are all medium to large effect sizes. Schools that had more experienced teachers tended to have greater school-average teacher collaboration among science teachers ($\beta = .11$), lower school-average teacher adaptability ($\beta = -.13$), lower school-average teacher self-efficacy ($\beta = -.18$), and lower school-average student self-efficacy ($\beta = -.14$). Schools with higher science achievement tended to have less disruptive behavior ($\beta = -.45$), less student diversity ($\beta = -.46$), and greater student self-efficacy ($\beta = .34$).

The cross-country comparisons were tested next. We compared structural paths across the two models using the two criteria noted in Methods. We tested 26 comparisons and no significant differences were evident (while taking into account a Bonferroni correction with an adjusted $p$-value of $< .002$; range of Wald (1) tests $= 0.10-5.71$, $ns$). We can conclude invariance in the paths across the countries. For indirect associations, there was a significant path involving disruptive behavior $\rightarrow$ teacher adaptability $\rightarrow$ teacher self-efficacy ($\beta = -.07$, $p = .028$; small effect size). This finding indicates that school-average teacher adaptability plays a role in linking disruptive behavior with teacher self-efficacy. Finally, our first alternative model involved testing job resources/demands $\rightarrow$ teacher self-efficacy $\rightarrow$ adaptability $\rightarrow$ student self-efficacy. Our second alternative model involved testing job resources/demands $\rightarrow$ teacher adaptability and teacher self-efficacy $\rightarrow$ student self-efficacy. In both of these models, there were fewer

significant direct associations between variables and no significant indirect associations.

Together, these alternative tests provide preliminary support for the hypothesized model.

## Discussion

The aim of the current study was to extend knowledge of teachers' adaptability by

examining the role it plays at the school-level among science teachers. We examined the extent

to which school-level resources and demands are associated with school-average science teacher

adaptability, whether all factors are associated with school-average science teacher self-efficacy

and, in turn, school-average student self-efficacy for science learning. Analyses showed that

schools with greater disruptive student behavior in science classes tended to have lower school-

average science teacher adaptability, schools with greater science teacher adaptability tended to

have greater school-average science teacher self-efficacy, and schools with greater school-

average science teacher self-efficacy tended to have greater school-average student science self-

efficacy. Importantly, these results occurred while controlling for the covariates—including

school-average achievement. Results also demonstrated that the paths in the model were similar

across the countries involved in the study. Taken together, the findings provide important

understanding about science teachers' adaptability at the school-level, and the role of school-

average factors in promoting positive teacher and student outcomes. Findings also highlight the

relevance of JD-R theory for examining school-level associations.

### Findings of Note

Results showed that schools with greater disruptive student behavior in science classes

tended to have lower school-average science teacher adaptability. This is the first time that a job

demand has been examined alongside adaptability and provides understanding of the conditions

in which school-average teacher adaptability may be thwarted. As noted earlier, personal

resources are malleable, personal capacities that reflect an individual's potential to influence the

working environment (Schaufeli & Taris, 2014). High job demands across a school likely mean

that the teaching staff has less control over the environment. More precisely, when there are high

levels of disruptive behavior in a school, teachers must collectively focus on maintaining order in

their classrooms (Arens, Morin, & Waterman, 2015). Although this undoubtedly requires teacher

adaptability, it is focused on adapting to manage students' behavior, leaving less time and fewer

opportunities for adapting instruction to meet students' learning needs. Collie and Martin (2020)

suggest there might be a critical point for adaptability after which there becomes too much

change, novelty, and uncertainty to effectively adjust. High levels of disruptive behavior may

mean that this critical point is reached more quickly regarding behavior management, leaving the

teaching staff struggling to adjust to novelty and uncertainty in students' learning needs. This

suggestion is supported by research linking disruptive student behavior with poorer instructional

quality (Hamre et al., 2013). An important avenue in future research is to specifically investigate

the existence of such a critical point.

The positive association between school-average teacher adaptability and teacher self-

efficacy likely occurred because when science teachers across a school are able to effectively

adjust to manage novelty or change in their teaching (i.e., adaptability), this helps the teaching

staff feel more effective in their work (e.g., through mastery experiences; Bandura, 1997). In

future, it will be important to ascertain whether this finding holds in longitudinal research and if

reciprocal relations are also evident (indeed, our alternative model provided some support for our

ordering, but additional research is needed; see Limitations for more on this).

Turning to the final part of the model, schools with greater science teacher self-efficacy

tended to have higher school-average student self-efficacy for learning science. This aligns with

prior research showing that school-average factors are salient for whole-school science outcomes (e.g., Burns et al., 2019), and with motivational theories establishing that social contexts—such as school—impact students' attitudes and beliefs towards learning (Ryan & Deci, 2017). This finding also adds clarity to prior mixed findings on the link between teacher and student self-efficacy at the individual-level (e.g., Thoonen et al., 2011). As per social cognitive theory (Bandura, 1997), it is possible that having more self-efficacious science teachers in a school helps facilitate learning environments that are more engaging and better equipped to model and scaffold learning for all students—thus, fostering school-average student self-efficacy through mastery and vicarious experiences (Britner & Pajares, 2006). More precisely, in schools where science teachers feel more confident in science, this likely helps school-average confidence in science among students too (Bandura, 1997).

In terms of comparing the findings cross-nationally, all model paths were consistent across the eight nations, indicating model invariance. This suggests that adaptability functions similarly and has an important role to play at the school-level across these various contexts. Moving forward, it will be important to extend this to additional (non-OECD) countries and to triangulate the findings with teachers' own ratings of their adaptability.

Turning to covariates, there was one significant association involving school-average teacher adaptability. Schools with less experienced teachers tended to have higher levels of school-average adaptability. This finding contrasts prior work (Collie et al., 2018; Collie & Martin, 2017), which found no significant relation between these variables at the teacher-level. However, research has shown that innovation can decrease as teachers gain experience (Thurlings, Evers, & Vermeulen, 2015). Moreover, research on students' adaptability has shown that older students are less adaptable (e.g., Martin, Nejad, Colmar, & Liem, 2013). Perhaps the

capacity to adapt is reduced as individuals develop or as mindsets, approaches, and strategies become more refined and solidified. Further research on this relation is needed.

**Implications for Practice, Research, and Theory**

The study has implications for practice at the school-level that are relevant to science teachers' workplace experiences and students' learning outcomes. First, the findings of this study indicate that there may well be merit in addressing school-average teacher adaptability. Collie and Martin (2016) recommend the use of self-assessment as a means to promote adaptability. Schools may be able to promote self-reflection by establishing professional learning communities in which science teachers reflect on an instance in which they adjusted their thoughts, behaviors, or emotions to manage a novel or uncertain situation, assess their response, and share this information with staff. In turn, these learning communities could discuss strategies that could be used in future situations of this nature. This reflection promotes self-awareness, which may encourage a school's teaching staff to focus on further reflecting upon and refining their adaptive practices. Other strategies such as peer mentoring and coaching may further promote self-reflection (see also Granziera, Collie, & Martin, 2019). Efforts that address student behavior at the school-level are also important. Initiatives such as school-wide social-emotional learning programs may involve developing students' social-emotional competence and building a positive school community (Weissberg, Durlak, Domitrovich, & Gullotta, 2015). School-wide policies regarding discipline are also implicated and have been shown to have varying effects on student behavior (Osher, Bear, Sprague, & Doyle, 2010).

The present study also demonstrates the importance of school-average teacher self-efficacy beliefs and their association with school-average student outcomes. As such, there may be merit in implementing staff-wide initiatives to enhance the self-efficacy of science teachers.

Posnanski (2002) advocates the implementation of relevant and meaningful professional learning which addresses the procedural and pedagogical issues that may undermine the self-efficacy of science teachers. Importantly, the present research demonstrates that such initiatives should not focus solely on individual outcomes; they should also focus on whole school capacity building. An important line of inquiry going forward is to examine the extent to which such intervention approaches impact school-average science teacher self-efficacy.

In terms of implications for theory, our study demonstrated that well-established individual-level processes in JD-R theory are also applicable to the school-level. Our study also provides mixed support for the additional processes that we hypothesized may be relevant among teachers. First, although we hypothesized that job demands may be associated with teacher self-efficacy, our results did not support this. However, this may reflect the variables under examination and further research with other job demands is needed to test this (e.g., see Skaalvik & Skaalvik, 2018). Second, we found support for the proposed negative association between school-average job demands (viz. disruptive behavior) and teachers' personal resources. This is one of the first studies to examine this association among teachers and thus additional research is needed to further examine it to see if it holds in relation to other job demands and personal resources. Together, these findings provide insights that advance understanding of the JD-R theory and its application among teachers.

**Limitations and Future Directions**

It is important to consider the limitations of the current study when interpreting the findings. First, although the use of PISA data comes with significant strengths (e.g., international and robust data, large sample sizes), it does have some constraints in terms of the variables that are available and the fact that it is not possible to link student and teacher data. In the current

study, our selection of variables was guided by JD-R theory and we focused on the school-level (as PISA allows linking students and teachers to the school). Nonetheless, going forward it will be important to examine these findings with additional theoretically appropriate variables and at the student-, teacher-, and school-level. In addition, we assessed behavioral adaptability with only two items. Examinations with more items that are better able to capture the complexity of adaptability are needed. Second, a strength of the current study is that we employed student reports of science teachers' adaptability and, in so doing, this is the first study using this approach (to the best of our knowledge). Moving forward, it will be important to augment this with research that employs students' and teachers' reports to see how these are similar (or different). Finally, we positioned self-efficacy as an outcome in the current modeling, which is different from some prior research using JD-R theory (e.g., Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009). The alternative models provided support for our ordering given that fewer direct associations and no indirect associations were significant. Nonetheless, longitudinal research is needed to test whether reciprocal associations are also possible (e.g., see Xanthopoulou et al., 2009).

### Conclusion

The aim of the current study was to develop knowledge about science teacher adaptability at the school-level and cross-nationally. Findings showed that schools with greater disruptive student behavior in science classes tended to have lower school-average science teacher adaptability. Schools with more adaptable science teachers tended to have greater school-average science teacher self-efficacy, and in turn, greater school-average student self-efficacy for science learning. Of note, the findings involving science teachers' adaptability were the same across the eight OECD countries examined. Taken together, the findings extend understanding of science

teacher adaptability, and its salience for teaching and learning outcomes at the school-level. The

findings also provide important evidence of the international relevance of teachers' adaptability.

**References**

Alrefaei, N.A. (2015). *Teachers' sense of efficacy: Examining the relationship of teacher efficacy and student achievement* (Doctoral dissertation). Retrieved from https://scholarworks.uark.edu/etd/1192

Arens, A. K., Morin, A. J. S., & Waterman, R. (2015). Relations between classroom disciplinary problems and student motivation: Achievement as a potential mediator? *Learning and Instruction, 39*, 184-193. http://dx.doi.org/10.1016/j.learninstruc.2015.07.001

Bakker, A. B., & Demerouti, E. (2017). Job demands-resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273-285. http://dx.doi.org/10.1037/ocp0000056

Bakker, A. B., Hakanen, J. J., Demerouti, E., & Xanthopoulou, D. (2007). Job resources boost work engagement, particularly when job demands are high. *Journal of Educational Psychology, 99*(2), 274-284. http://dx.doi.org/10.1037/0022-0663.99.2.274

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: Freeman.

Britner, S. L., & Pajares, F. (2006). Sources of science self-efficacy beliefs of middle school students. *Journal of Research in Science Teaching, 43*(5), 485-499. http://dx.doi.org/10.1002/tea.20131

Burns, E. C., Martin, A. J., & Collie, R. J. (2019). Examining the yields of growth feedback from science teachers and students' intrinsic valuing of science: Implications for student- and school-level science achievement. *Journal of Research in Science Teaching, 56*(8), 1060-1082. https://doi.org/10.1002/tea.21546

Chang, M. L. (2013). Toward a theoretical model to understand teacher emotions and teacher burnout in the context of student misbehavior: Appraisal, regulation, and coping. *Motivation and Emotion, 37*, 799-817. http://dx.doi.org/10.1007/s11031-012-9335-0

Chong, W. H., & Kong, C. A. (2012). Teacher collaborative learning and teacher self-efficacy: The case of lesson study. *The Journal of Experimental Education, 80*(3), 263-283. http://dx.doi.org/10.1080/00220973.2011.596854

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.

Collie, R. J., Granziera, H., & Martin, A. J. (2018). Teachers' perceived autonomy support and adaptability: An investigation employing the job demands-resources model as relevant to workplace exhaustion, disengagement, and commitment. *Teaching and Teacher Education, 74*, 125-136. https://doi.org/10.1016/j.tate.2018.04.015

Collie, R. J., & Martin, A. J. (2016). Adaptability: An important capacity for effective teachers. *Educational Practice and Theory, 38*(1), 27-39. http://dx.doi.org/10.7459/ept/38.1.03

Collie, R. J., & Martin, A. J. (2017). Teachers' sense of adaptability: Examining links with perceived autonomy support, teachers' psychological functioning, and students' numeracy achievement. *Learning and Individual Differences, 55*, 29-39. http://dx.doi.org/10.1016/j.lindif.2017.03.003

Collie, R.J., & Martin, A.J. (2020). *Adaptability: A social and emotional skill critical for (diverse) learners to navigate their ever-changing world.* Manuscript submitted for publication.

Collie, R. J., Shapka, J. D., & Perry, N. E. (2012). School climate and social–emotional learning: Predicting teacher stress, job satisfaction, and teaching efficacy. *Journal of Educational Psychology, 104*(4), 1189-1204. http://dx.doi.org/10.1037/a0029356

Demerouti, E., Bakker, A., Nachreiner, F., & Schaufeli, W. (2001). The job demands–resources model of burnout. *The Journal of Applied Psychology, 86*(3), 499-512. http://dx.doi.org/10.1037/0021-9010.86.3.499

Dong, Y., & Peng, C. J. (2013). Principled missing data methods for researchers. *SpringerPlus, 2*(1), 222. http://dx.doi.org/10.1186/2193-1801-2-222

Goddard, C., & Evans, D. (2018). Primary pre-service teachers' attitudes towards inclusion across the training years. *Australian Journal of Teacher Education, 43*(6), 122-142. http://dx.doi.org/10.14221/ajte.2018v43n6.8

Goddard, R. D., & Goddard, Y. L. (2001). A multilevel analysis of the relationship between teacher and collective efficacy in urban schools. *Teaching and Teacher Education, 17*(7), 807-818. http://dx.doi.org/10.1016/S0742-051X(01)00032-4

Granziera, H., Collie, R.J., & Martin, A.J. (2019). Adaptability: An important capacity to cultivate among pre-service teachers in teacher education programmes. *Psychology Teaching Review, 25*(1), 60-66.

Guerriero, S. & Révai, N. (2017). Knowledge-based teaching and the evolution of a profession. In S. Guerriero (Ed.), *Pedagogical knowledge and the changing nature of the teaching profession* (pp. 253-269). Paris, France: OECD Publishing. http://dx.doi.org/10.1787/9789264270695-en

Hamre, B. K., Pianta, R. C., Downer, J. T., DeCoster, J., Mashburn, A. J., Jones, S. M., Brown, J. L., Cappella, E., Atkins, M., Rivers, S. E., Brackett, M. A., & Hamagami, A. (2013).

Teaching through interactions: Testing a developmental framework of teacher effectiveness in over 4,000 classrooms. *The Elementary School Journal, 113*(4), 461-487. https://doi.org/10.1086/669616

Johnson, B., Stevens, J. J., & Zvoch, K. (2007). Teachers' perceptions of school climate. *Educational and Psychological Measurement, 67*(5), 833-844. http://dx.doi.org/10.1177/0013164406299102

Keith, T. Z. (2015). *Multiple regression and beyond: An introduction to multiple regression and structural equation modeling* (2nd ed.). New York, NY: Routledge.

Klassen, R. M., & Chiu, M. M. (2010). Effects on teachers' self-efficacy and job satisfaction. *Journal of Educational Psychology, 102*(3), 741-756. http://dx.doi.org/10.1037/a0019237

Klassen, R. M., Usher, E. L., & Bong, M. (2010). Teachers' collective efficacy, job satisfaction, and job stress in cross-cultural context. *Journal of Experimental Education, 78*(4), 464-486. http://dx.doi.org/10.1080/00220970903292975

Kokkinos, C. M. (2007). Job stressors, personality and burnout in primary school teachers. *British Journal of Educational Psychology, 77*, 229-243. http://dx.doi.org/10.1348/000709905X90344

Konold, T. R., & Cornell, D. (2015). Measurement and structural relations of an authoritative school climate model: A multi-level latent variable investigation. *Journal of School Psychology, 53*, 447-461. doi://dx.doi.org/10.1016/j.jsp.2015.09.001

Loughland, T., & Alonzo, D. (2018). Teacher adaptive practices: Examining links with teacher self-efficacy, perceived autonomy support and teachers' sense of adaptability. *Educational Practice and Theory, 40*(2), 55-70. https://doi.org/10.7459/ept/40.2.04

Martin, A. J., Nejad, H., Colmar, S., & Liem, G. A. D. (2012). Adaptability: Conceptual and

empirical perspectives on responses to change, novelty and uncertainty. *Australian Journal of Guidance and Counselling, 22*(1), 58-81. http://dx.doi.org/10.1017/jgc.2012.8

Martin, A. J., Nejad, H. G., Colmar, S., & Liem, G. A. D. (2013). Adaptability: How students' responses to uncertainty and novelty predict their academic and non-academic outcomes. *Journal of Educational Psychology, 105*(3), 728-746. http://dx.doi.org/10.1037/a0032794

McGonagle, A. K., Fisher, G. G., Barnes-Farrell, J. L., & Grosch, J. W. (2015). Individual and work factors related to perceived work ability and labor force outcomes. *The Journal of Applied Psychology, 100*(2), 376-398. http://dx.doi.org/10.1037/a0037974

Muthén, L. K., & B.O. Muthén. (2017). *Mplus user's guide* (7th ed.). Los Angeles, California: Muthén & Muthén.

National Center for Educational Statistics. (2018). *Indicators of school crime and safety - teachers' reports on school conditions.* Retrieved from https://nces.ed.gov/programs/crimeindicators/ind_12.asp

OECD (2017). *PISA 2015 Technical Report.* Paris, France: OECD.

OECD (2019). *Education Policy Outlook 2019: Working together to help students achieve their potential.* Retrieved from: https://doi.org/10.1787/2b8ad56e-en

Osher, D., Bear, G. G., Sprague, J. R., & Doyle, W. (2010). How can we improve school discipline? *Educational Researcher, 39*(1), 48-58. http://dx.doi.org/10.3102/0013189X09357618

Parsons, S. A. (2012). Adaptive teaching in literacy instruction. *Journal of Literacy Research, 44*(2), 149-170. http://dx.doi.org/10.1177/1086296X12440261

Parsons, S. A., Vaughn, M., Scales, R. Q., Gallagher, M. A., Parsons, A. W., Davis, S. G., . . .

Allen, M. (2018). Teachers' instructional adaptations: A research synthesis. *Review of*

*Educational Research, 88*(2), 205-242. http://dx.doi.org/10.3102/0034654317743198

Posnanski, T. J. (2002). Professional development programs for elementary science teachers: An

analysis of teacher self-efficacy beliefs and a professional development model. *Journal of*

*Science Teacher Education, 13*(3), 189-220. http://dx.doi.org/1016517100186

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in*

*motivation, development, and wellness.* New York, NY: Guilford Publications.

Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship

with burnout and engagement: A multi-sample study. *Journal of Organizational*

*Behavior, 25*(3), 293-315. http://dx.doi.org/10.1002/job.248

Schaufeli, W. B., & Taris, T. W. (2014). A critical review of the job demands-resources model:

Implications for improving work and health. In G. Bauer, & O. Hemming (Eds.), *Bridging*

*occupational, organizational and public health* (pp. 43-68). Dordrecht, Holland: Springer.

http://dx.doi.org/10.1007/978-94-007-5640-3_4

Skaalvik, S., & Skaalvik, E. M. (2010). Teacher self-efficacy and teacher burnout: A study of

relations. *Teaching and Teacher Education, 26*(4), 1059-1069.

http://dx.doi.org/10.1016/j.tate.2009.11.001

Skaalvik, E. M., & Skaalvik, S. (2018). Job demands and job resources as predictors of teacher

motivation and well-being. *Social Psychology of Education, 21*, 1251-1275.

https://doi.org/10.1007/s11218-018-9464-8

Thoonen, E. E. J., Sleegers, P. J. C., Oort, F. J., Peetsma, T. T. D., & Geijsel, F. (2011). How to

improve teaching practices: The role of teacher motivation, organizational factors, and

leadership practices. *Educational Administration Quarterly, 47*(3), 496-536.

http://dx.doi.org/10.1177/0013161X11400185

Thurlings, M., Evers, A., & Vermeulen, M. (2015). Toward a model of explaining teachers'

innovative behavior: A literature review. *Review of Educational Research, 85*(3), 430-471.

https://doi.org/10.3102/0034654314557949

Tsouloupas, C. N., Carson, R. L., Matthews, R., Grawitch, M. J., & Barber, L. K. (2010).

Exploring the association between teachers' perceived student misbehaviour and emotional

exhaustion: The importance of teacher efficacy beliefs and emotion regulation. *Educational

Psychology, 30*(2), 173-189. http://dx.doi.org/10.1080/01443410903494460

UK Department for Education (2018). *Making data work: Report of the teacher workload

advisory group*. Retrieved from https://www.gov.uk/government/groups/teacher-workload-

advisory-group

Weissberg, R. P., Durlak, J. A., Domitrovich, C. E., & Gullotta, T. P. (2015). Social and

emotional learning: Past, present, and future. In J. A. Durlak, R. P. Weissberg, & T. P.

Gullotta (Eds.), *Handbook of social and emotional learning: Research and practice* (pp. 3–

19). New York, NY: Guilford Press.

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2007). The role of

personal resources in the job demands-resources model. *International Journal of Stress

Management, 14*(2), 121-141. http://dx.doi.org/10.1037/1072-5245.14.2.121

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Reciprocal

relationships between job resources, personal resources, and work engagement. *Journal of

Vocational Behavior, 74*(3), 235-244. http://dx.doi.org/10.1016/j.jvb.2008.11.003
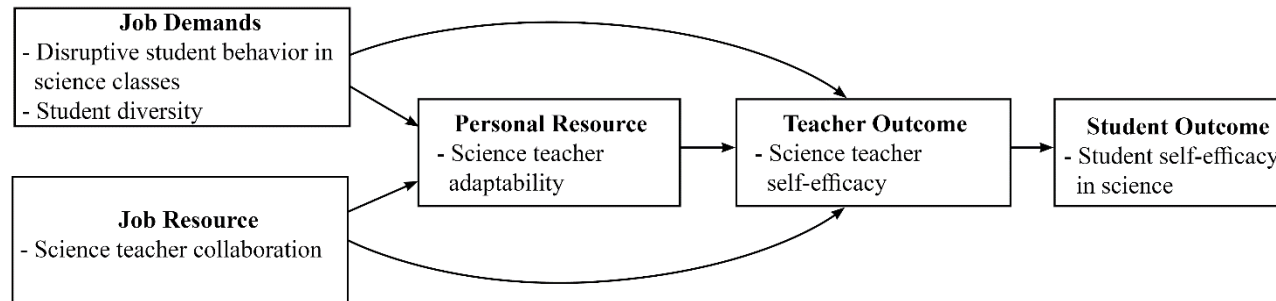
*Figure 1.* Hypothesized model showing associations between substantive factors. All factors are measured at the school-level (e.g., school-average teacher adaptability). Covariates (not shown) served as controls for all substantive factors.

Table 1

*Reliabilities and Weighted Descriptive Statistics at the School-Level*

| | School-level $\omega_h$ | M | SD | Skewness | Kurtosis |
|---|---|---|---|---|---|
| Student science achievement | .99 | 489.04 | 59.90 | -0.34 | 0.10 |
| Disruptive student behavior | .98 | 2.02 | 0.37 | 0.64 | 1.00 |
| Student diversity | — | 25.33 | 18.86 | 0.91 | 0.44 |
| Science teacher collaboration | .91 | 2.77 | 0.46 | 0.01 | -0.11 |
| Science teacher adaptability | .93 | 2.47 | 0.35 | 0.51 | 2.91 |
| Science teacher self-efficacy | .82 | 3.35 | 0.28 | -0.72 | 1.93 |
| Student science self-efficacy | .94 | 2.78 | 0.26 | -0.11 | 3.66 |

*Note.* School-level omegas reported here. For student- or teacher-level, see Measures. Although we report omegas at the school-level, the school-level variables were entered as mean scores. There is no omega for student diversity because this involved a mean score of three observed variables.

Table 2
*Correlations Among Constructs at the School-Level*

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. |
|---|---|---|---|---|---|---|---|---|---|---|
| *Covariates* | | | | | | | | | | |
| 1. School size | | | | | | | | | | |
| 2. Class size | .50*** | | | | | | | | | |
| 3. Teaching experience | .01 | .09** | | | | | | | | |
| 4. Qualifications of science teachers | .16*** | .07* | -.03 | | | | | | | |
| 5. Student science achievement | .15 | .09 | .09 | .11 | | | | | | |
| *Job demands* | | | | | | | | | | |
| 6. Disruptive student behavior | .02 | .13 | .06 | -.08* | -.43*** | | | | | |
| 7. Student diversity | -.15*** | -.22** | -.31* | -.07 | -.50*** | .04 | | | | |
| *Job resource* | | | | | | | | | | |
| 8. Teacher collaboration | .29** | .31** | .13*** | .12 | .11** | -.07 | -.23*** | | | |
| *Personal resource* | | | | | | | | | | |
| 9. Teacher adaptability | -.13 | -.21** | -.19*** | -.01 | .03 | -.37*** | .16*** | -.13 | | |
| *Motivation* | | | | | | | | | | |
| 10. Teacher self-efficacy | .02 | -.08 | -.20** | .09 | .25** | -.16 | -.05 | -.03 | .22*** | |
| *Outcome* | | | | | | | | | | |
| 11. Student self-efficacy | .01 | -.06 | -.13** | .22** | .35*** | -.25*** | -.04 | -.08 | .29*** | .21*** |

*$p < .05$, **$p < .01$, ***$p < .001$

Table 3

*Standardized Betas from Structural Equation Models at the School-Level*

| | Job demands | | Job resource | Personal resource | Motivation outcome | Student outcome |
|---|---|---|---|---|---|---|
| | Disruptive behavior | Student diversity | Teacher collaboration | Teacher adaptability | Teacher self-efficacy | Student self-efficacy |
| *Covariates* | | | | | | |
| School size | 0.02 | 0.01 | 0.17** | -0.04 | 0.03 | -0.06 |
| Class size | 0.16** | -0.16** | 0.21** | -0.09* | -0.08 | -0.06 |
| Teaching experience | 0.08** | -0.26** | 0.11*** | -0.13*** | -0.18*** | -0.14*** |
| Qualifications of science teachers | -0.05 | -0.02 | 0.08 | -0.01 | 0.06 | 0.19 |
| Science achievement | -0.45*** | -0.46*** | 0.05 | -0.09 | 0.28** | 0.34*** |
| *Job demands* | | | | | | |
| Disruptive behavior | | | | -0.40*** | 0.05 | — |
| Student diversity | | | | 0.05 | -0.01 | — |
| *Job resource* | | | | | | |
| Teacher collaboration | | | | -0.09 | 0.01 | — |
| *Personal resource* | | | | | | |
| Teacher adaptability | | | | | 0.18*** | — |
| *Motivation* | | | | | | |
| Teacher self-efficacy | | | | | | 0.08** |
| $R^2$ | 23% | 35% | 14% | 21% | 15% | 21% |

*Note.* All factors are school-average variables. Dashes represent associations that were not tested as part of the hypothesized model.

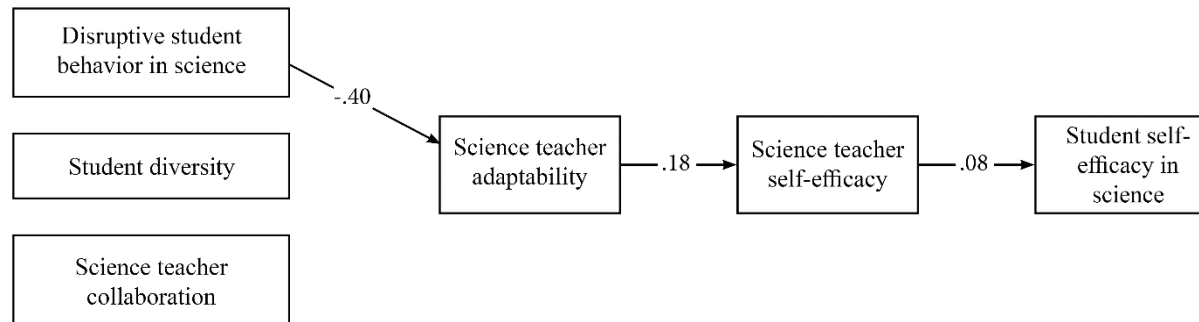$p < .05$, ** $p < .01$, *** $p < .001$.

*Figure 2.* Final model showing associations among all factors. All paths shown were significant at *p* < .05. Covariates (not shown) served as controls for all factors. Table 3 shows standardized beta estimates (including with covariates).

**Supplementary Online Materials**

**for**

**Adaptability Among Science Teachers in Schools: A Multi-nation Examination of its**

**Role in School Outcomes**

**Multilevel Confirmatory Factor Analysis**

Although it is not possible to match students with teachers in PISA 2015 data, it is

possible to match students and teachers with schools. Thus, to provide additional

measurement support for the variables under examination in our study, we ran one multilevel

confirmatory factor analysis (CFA) involving the student-rated variables and another

multilevel CFA (ML-CFA) involving the teacher-rated variables (we did not run a CFA for

the school-level variables because these were all observed; i.e., non-latent). In these models,

the student or teacher weight was applied at Level 1 (L1) and the school weight was applied

at Level 2 (L2).

The ML-CFA involving the student variables included (student-reported) teacher

adaptability, disruptive behavior, student self-efficacy for science, and student achievement

(covariate). The fit was adequate: $\chi^2(309) = 1997.74$, $p < .001$, RMSEA = .010, CFI = .99,

TLI = .99. The ML-CFA involving the teacher variables included science teacher

collaboration and teacher self-efficacy. The fit was adequate: $\chi^2(20) = 37.21$, $p < .001$,

RMSEA = .008, CFI = .99, TLI = .99.

Next, we ran invariance tests with multigroup ML-CFA to check that the items

functioned similarly across countries. We included all student-rated variables in the student

model and all teacher-rated variables in the teacher model (we did not run separate ML-CFAs

for each scale because several of the instruments contained fewer than 4 items, meaning there

was inadequate degrees of freedom to calculate and compare fit indices). Four models with

progressively more cross-country parameter constraints were run: configural (all parameters freed across countries), metric (loadings constrained across countries), scalar (loadings and intercepts constrained across countries), and latent variance-covariance (loading, intercepts, variances, and covariances constrained across countries). For both the student-focused and teacher-focused tests, invariance was supported given that changes in RMSEA across the models of .015 or less and changes in CFI of .01 or less were observed (Chen, 2007; Cheung & Rensvold, 2002). Table S1 shows the fit indices for all measurement invariance tests.

Table S1

*Fit Indices from Measurement Invariant Tests Involving Students and Teachers*

|  | Student-level | | | Teacher-level | | |
|---|---|---|---|---|---|---|
|  | RMSEA | CFI | TLI | RMSEA | CFI | TLI |
| Configural model | .031 | .98 | .97 | .035 | .98 | .97 |
| Metric model | .031 | .97 | .97 | .036 | .97 | .97 |
| Scalar model | .030 | .97 | .97 | .032 | .98 | .97 |
| Variance-covariance model | .027 | .97 | .98 | .027 | .97 | .97 |