Mindfulness and Connection Training During Preservice Teacher Education Reduces Early Career Teacher Attrition Four Years Later

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Abstract

Early career teacher attrition disrupts school continuity, precludes many of those who leave from achieving expertise, and drains economic resources from school systems. In a longitudinal cluster randomized controlled trial ($k = 8$, $n = 98$), we examined the impact of a 9-week meditation-based intervention on undergraduate preservice teachers' rates of attrition from teaching approximately 4 years later. The odds of attrition among intervention group participants 3 years into their teaching careers were significantly reduced by at least 77.0% regardless of modeling approach (Odds ratios = 0.13–0.23, $p\text{s} \leq .013$) compared to teacher education as usual controls. In benefit-cost analyses, we estimated that for every \$1 spent on the intervention, hiring districts saved \$3.43 in replacement teacher costs. Additional research is required to replicate the core finding of reduced attrition and understand the pathways through which the intervention caused these reductions.

Keywords: Mindfulness, Teacher education; Teacher attrition; Teacher retention; Benefit-cost analysis

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Introduction

Approximately 3.7 million public school teachers educate over 56 million children in American schools (U.S. Department of Education, 2021). Teachers explain more variance in student outcomes than any other school-based factor (Koedel et al., 2015) which places teachers at the center of many policies to improve student outcomes. Although improving teacher quality and longevity, especially through the first few years on the job, have been focal policy concerns, the rate at which teachers leave the profession (i.e., attrition rate) has not declined over the last 20 years (Ingersoll et al., 2018). With predictions of substantial retirements among the aging teacher corps (García & Weiss, 2020) and many teachers now contemplating leaving teaching earlier than planned (Walker, 2022), the importance of keeping teachers in the profession has become amplified by growing concerns about shortages of qualified teachers (Dee & Goldhaber, 2017). If provisions within undergraduate teacher education could help reduce attrition rates and keep early career teachers in the workforce longer, many of the challenges schools face related to finding effective and qualified teachers, which are substantial, could be preempted.

Improving teacher quality and longevity are interrelated concerns. Most teacher improvements in effectiveness occur during the first few years on the job (Papay & Kraft, 2015). Around 44% of teachers leave the profession within their first 5 years, or approximately 8%–10% per year, on average (Ingersoll et al., 2018). At any given time, a considerable proportion of America's teaching corps is comprised of new, inexperienced teachers learning on the job who are likely to leave and be replaced by new, inexperienced teachers (Henry et al., 2011). Early career attrition could act as a beneficial natural sorting mechanism (Adnot et al., 2017), but research suggests that high levels of staff attrition have pervasive detrimental effects that negatively affect the achievement of all students and not only students placed with a new or inexperienced teacher (Ronfeldt et al., 2013; Sorensen & Ladd, 2020).

Early career teacher attrition also contributes to systematic educational inequities. Teacher attrition rates are substantially higher in schools serving high proportions of economically disadvantaged students (Ingersoll et al., 2018; Sorensen & Ladd, 2020). Accordingly, students from lower income backgrounds may be more likely to experience less effective teachers (Goldhaber et al., 2015). These same students are more likely to attend schools with fewer resources. Consequently, already under-resourced schools are forced to allocate a greater share of limited resources to teacher recruitment and training, magnifying the negative consequences of teacher attrition.

Replacing teachers is also expensive. In inflation adjusted 2022 dollars, the estimated costs to districts of recruiting, hiring, and training a teacher range from $6,838.79 in low-cost St. Lucie County School District, Florida (Shockley et al., 2006) to $22,631.06 in urban Milwaukee, Wisconsin (Barnes et al., 2007). However, these estimates likely underestimate the real costs because they do not account for lost human capital or the likelihood that a departing more experienced teacher will be replaced by a new, less experienced and ineffective one (Simon & Johnson, 2015).

Developing and testing interventions intended to reduce early career teacher attrition is an integral part of the field of school psychology. In addition to the economic returns of reduced early career attrition, the potential for increased teacher longevity to improve teaching quality, teacher-student relationships, and the overall classroom and school climates is substantial. Alongside these improvements, we would expect attendant gains in student learning and healthy development. Furthermore, because rates of attrition are higher in lower resource schools, reducing early career teacher attrition has the potential to particularly improve educational outcomes for students in low resource schools,

Individual and Structural Predictors of Teacher Attrition

The causes of teacher attrition are complex. To date, most research and policy has focused on structural rather than individual factors. Research has established that work conditions are associated with teacher attrition and turnover (i.e., moving from one school to another while continuing as a teacher; Johnson, 2012; Simon & Johnson, 2015). More specifically, (a) school resources (e.g., quality of facilities, materials); (b) well-organized, collegial and supportive schools; and (c) schools that articulate high expectations for students have each been associated with teacher longevity and performance (Borman & Dowling, 2008; Johnson et al., 2012; Kraft et al., 2016; Simon & Johnson, 2015).

Although robust to potential confounding variables, the magnitude of associations between these structural characteristics and teacher attrition are small. For example, Kraft et al. (2016) estimated that a standard deviation increase in teacher perceptions of school leadership quality reduced teacher attrition from around 15.1% per year to about 13.4%. Associations between perceived administrative support and teacher longevity are of a similar magnitude (Boyd et al., 2011; Nguyen et al., 2020; Wynn et al., 2007). Other structural factors, including principal turnover and hiring and onboarding practices are also associated with teacher attrition. For instance, principal turnover is associated with a 2%–3% relative increase in teacher turnover (DeMatthews et al., 2022). Late hiring (i.e., hiring closer to the beginning of or during a school year) was associated with large increases in the likelihood of leaving (around 200%; Jones et al., 2011). However, none of these studies tested the causal effect on attrition of manipulating through intervention the variable of interest (e.g., increasing perceptions of school leadership quality).

Attempts to reduce teacher attrition have also focused on structural reforms. Recent examples include early career induction programs, merit pay systems, and reforming hiring practices (Nguyen et al., 2020). Some of these reforms have shown limited promise. For example, in a meta-analysis, merit pay programs reduced attrition by 1.6 percentage points (Nguyen et al., 2020). Teacher preparation programs that include immersive classroom experiences and focus on student achievement are associated with lower rates of attrition than traditional teacher education programs, but at a small magnitude (Pearson $r = -.136$; Latham & Vogt, 2007). It is important to consider that these effects do not account for potential selection bias (i.e., candidate teachers selecting more intensive programs may be different to begin with) among several possible confounders. Still, results like these are one reason current standards in teacher education emphasize “clinical” experiences.

Early career teacher attrition rates have remained steady for at least the last 2 decades despite an accumulating understanding of the structural predictors of teacher career outcomes (Goldhaber & Theobald, 2022; Ingersoll, 2001; Ingersoll et al., 2018). Given the inherent challenges in implementing structural reforms and the modest associations between these factors and teacher attrition, it is surprising that more attention has not been directed towards individual teacher characteristics and attrition. To the extent that teacher characteristics have been studied, the focus has been on variables like credentialing, licensure scores, educational attainment, and demographics (Borman & Dowling, 2008; Nguyen et al., 2020).

Research that has estimated associations between teacher mindsets (i.e., belief structures), skills, and dispositions and attrition have indicated that these characteristics may be promising avenues for further research. For instance, new teachers who report higher levels of the personality trait conscientiousness are less likely to attrite, as are new teachers who believe that they were well prepared by their undergraduate program for teaching (DeAngelis et al., 2013; Kim et al., 2019). Higher conscientiousness also predicts classroom organization, which is an indicator of effective instruction (Baier et al., 2019) that new teachers often struggle with and report as a major stressor; poorer classroom organization contributes to early career attrition (Greenberg et al., 2014).

Beyond personality traits, teacher self-efficacy (i.e., the belief in one's ability to carry out the job of teaching) has been associated at a moderate magnitude with teaching effectiveness (r = 0.28; Klassen & Tze, 2014). *Grit*, or a teacher's passion and perseverance to achieve their goals, was associated with reduced mid-year attrition (standardized mean difference [SMD] = 0.79) and increased effectiveness as assessed by a metric of student learning (SMDs = 0.42–0.45; Duckworth et al., 2009). In two other studies (i.e., Aldrup et al., 2018; Klusmann et al., 2008), higher levels of teacher adaptive self-regulation, defined as high levels of engagement and resilience, were associated with improved student perceptions of instructional quality and teacher reported well-being, which in turn were related to higher quality student-teacher relationships. This may help explain why teachers whose teaching quality was rated more highly upon career entry are less likely to attrite (Vagi et al., 2019); such teachers may have an easier time transitioning to the full-time responsibilities of professional teaching, thereby reducing a central cause of stress that makes early career attrition more likely.

In contrast, elevated symptoms of distress are associated with the intention to leave and career attrition in teachers (Hirshberg et al., 2023; Ingersoll et al., 2018; Ryan et al., 2017). Strengthening characteristics associated with improved instruction and reduced attrition while reducing characteristics associated with poorer instruction and increased rates of attrition are logical approaches to the problem that have received little attention (Jennings & Greenberg, 2009).

Meditation Interventions and Stress

Teaching has long been characterized as a high stress, high emotion profession (Hargreaves, 1998; Kyriacou & Sutcliffe, 1978). Teachers have reported high levels of stress, anxiety, and depressive symptoms, often at rates higher than comparable general population adults (Hirshberg et al., 2023; Kush et al., 2022). Meditation-based interventions (MBIs), commonly described as stress reduction programs (Kabat-Zinn, 1982), effectively reduce stress and increase self-regulation (Goldberg et al., 2021).

Folkman and Lazarus' Transactional Model of Stress and Coping (Folkman & Lazarus, 1988; Lazarus & Folkman, 1984) presents stress as a two-stage process. In the first stage, individuals determine, often automatically, whether a situation poses a challenge to their well-being (i.e., is potentially stressful). After a situation has been appraised as potentially stressful, in the second stage of coping, individuals activate, again often without conscious deliberation, a strategy to manage the perceived stress. Coping strategies can range from deliberative reappraisal to avoidance or denial.

Both appraisal and coping processes offer potential levers for intervention. For example, changing a teacher's mindset from the belief that they do not have the capacity to work with difficult student interactions to a growth mindset in which they believe they can learn to navigate any circumstance may fundamentally alter appraisal and coping mechanisms (Hirshberg et al., 2022). Instead of challenging classroom situations eliciting dread or avoidance, such a change in mindset may result in these situations being appraised as opportunities to grow or they may elicit adaptive coping strategies that help resolve the difficulty. In a positive cascade, successfully navigating challenging situations might strengthen self-efficacy beliefs, which in turn could positively affect future appraisals and coping.

MBIs are thought to affect appraisal processes and strengthen adaptive coping responses to stress (Dahl et al., 2020; Hirshberg et al., 2022; Roeser et al., 2012). Meditation is an umbrella term that includes many types of contemplative practice, of which mindfulness meditation is the most ubiquitous. The multifaceted skill of mindfulness is defined as paying attention, on purpose, to present moment experience with an attitude of non-judgment or acceptance (Kabat-Zinn, 2013). Like all forms of meditation, mindfulness practices are intended to strengthen the skill of mindfulness through repetition. For example, during the mindfulness practice of *breath awareness* one rests attention on the breath while maintaining a background monitoring awareness. If the mind wanders from the breath, one is instructed to gently bring it back to the breath. The act of resting attention on the breath is said to strengthen the skill of *focused attention*, the act of monitoring is said to strengthen *meta-awareness*, and the act of gently bringing the mind back without judgment or reactivity is said to strengthen *equanimity* or *acceptance* (Dahl et al., 2020). Loving-kindness meditation, another form of practice common in MBIs and mindfulness interventions (Dahl et al., 2015; Hirshberg et al., 2018), intends to increase feelings of goodwill, warmth, and generosity to others by repeatedly bringing others to mind and sending warm wishes and goodwill to them.

MBI research with teachers has found positive effects on mindfulness, stress, burnout, anxiety, depression, and well-being (Hirshberg et al., 2022; Jennings et al., 2017; Roeser et al., 2013). Placed within the Transactional Model of Stress and Coping (Folkman & Lazarus, 1988; Lazarus & Folkman, 1984), mindfulness can be understood as an adaptive form of self-regulatory coping. For example, Roeser et al. (2013) found that assignment to an 11-week mindfulness intervention significantly increased mindfulness at post-intervention compared to the wait-list control group and improvements in mindfulness fully mediated follow-up reductions in occupational stress and burnout. Similarly, in a large study of educators ($N = 662$), Hirshberg et al. (2024) reported that assignment to a 4-week smartphone-based MBI resulted in significant increases in mindfulness that mediated 33.3% of the intervention's effect on follow-up distress (i.e., an aggregate of stress, anxiety, and depressive symptoms).

Although most MBI research has focused on coping processes, some data indicate that appraisal processes are also affected by MBIs. Hirshberg et al. (2022, 2024) conducted their study with educators during the early part of the COVID-19 pandemic when students attended school remotely and most people were isolated at home. Yet the educators assigned to the MBI reported significant reductions in loneliness despite continued social isolation, indicating that their appraisals had changed even as life conditions had not.

Although more research is needed, it is easy to imagine how reducing a teacher's propensity to appraise situations as stressful and/or increasing their ability to respond to stress adaptively might benefit their teaching, their students, and career longevity. In Figure 1, we propose a theory of change that illustrates the complementary effects that integrating MBI training into preservice teacher education is proposed to have on learning to teach, well-being and distal outcomes such as student achievement and career longevity.

An Integrative Model for Teacher Education

Figure 1 presents an integrative model of teacher education in which standard teacher education is augmented with high-quality MBI. We argue that standard teacher education is primarily focused on the development of teaching-relevant knowledge (e.g., curricular, pedagogical, pedagogical content knowledge). To the extent that teacher education programs emphasize clinical aspects of training such as practicum, these programs may also systematically seek to develop skill in teaching relevant practices (e.g., effective classroom management practices). However, in Figure 1 we locate a set of qualities as antecedent to what is labeled as effective teaching or enactment. We argue that these antecedents are comprised of the individual teacher-level mindsets, which are skills and dispositions, that when combined with relevant teacher-related knowledge form the foundation of effective teaching and career persistence.

Critically, teacher mindsets, skills, and dispositions are malleable (Choi & Lee, 2020; Dahl et al., 2020; Malinauskas, 2017). As already noted, higher levels of teacher self-efficacy are not only associated with teacher effectiveness, but also with higher levels of student academic adjustment and teacher occupational satisfaction and well-being (Zee & Koomen, 2016). Higher levels of teacher growth mindset moderate, among other outcomes, the benefits of students' growth mindsets on achievement (Yeager et al., 2022). Skills such as mindfulness or adaptive self-regulation and adjacent personality facets like conscientiousness are also malleable, with increases in skills associated with a reduced likelihood of attrition and improved mental health and well-being (Hirshberg et al., 2022; Klusmann et al., 2008; Roberts et al., 2017; Saks et al., 2022). Similarly, teacher dispositions (e.g., the tendency toward enjoyment) have been associated with higher levels of student enjoyment, whereas a tendency towards anger has been associated with lower student-teacher relationship quality and mediating the effect of poor student-teacher dynamics on teacher emotional exhaustion (Frenzel et al., 2009; Taxer et al., 2019).

MBIs are privileged in the integrative model because high-quality MBIs are theorized to strengthen healthy mindsets, skills, and dispositions (Dahl et al., 2020 Vago & Silbersweig, 2012). Enhancing positive mindsets while systematically strengthening skills and positive dispositions is theoretically important for maximal impact and sustained benefit. For example, although previously low-achieving students disproportionately benefit from interventions that increase their growth mindset (Yeager et al., 2019), these students are likely to continue to suffer from a skills gap as a consequence of their previous low achievement. An intervention that not only improves mindsets but also provides systematic strengthening of skills and dispositions (through practice) may provide optimal opportunities for learning and growth. The growth mindset that skills and dispositions such as attention, emotion regulation, acceptance, and well-being can be strengthened through practice is central to MBIs, with practice-based skill and disposition strengthening understood to be the primary mechanisms of sustained benefit (Dahl et al., 2020; Hirshberg et al., 2024; Mind et al., 2012; Roeser et al., 2013; Vago & Silbersweig, 2012).

The Present Study

Results from the portion of this study conducted during preservice teacher (PST) education (i.e., pre, post, and 6-month follow-up assessments) were consistent with the integrative model. Specifically, participants assigned to the MBI made significant improvements on standardized observer ratings of their classroom teaching (Hirshberg et al., 2020) and demonstrated reduced automatic race bias towards Black child faces on Black/White Child Implicit Association Test – a measure associated with inequitable teaching practices (Hirshberg et al., 2022b). Although MBIs appear well suited to strengthen individual-level factors associated with early career attrition, to our knowledge, no research has yet evaluated this possibility. In the present study, we examined this gap in the literature by following participants for 3 years after graduating from the PST program (i.e., 4 years post-assignment) to assess intervention effects on early career attrition. We selected 3 years of follow-up because attrition rates are elevated in the first years of teaching and most on the job learning also occurs during this period. This study aimed to advance teacher education research by preregistering[1] the study design and measures, employing a causal design (i.e., a cluster randomized controlled trial), applying multiple robustness tests to the data, and contextualizing the results in a benefit-cost analysis (BCA). We hypothesized that assignment to the intervention during PST education would predict significantly reduced odds of attrition 3 years into participants' professional teaching careers.

Method

Participants

Participants (n = 98) were recruited from an undergraduate elementary PST education program at a large research university in the United States. The elementary education program consists of four licensing areas, including (a) Early Childhood – English as a second language, (b) Middle childhood/Early adolescent – English as second language, (c) Middle childhood/Early adolescent – Special education, and (d) Middle childhood/Early adolescent – Content focused minor. Licensing areas operate as cohorts, with approximately 24 students moving through the 2-year PST sequence together. The PST program includes course and clinical work (e.g., student teaching) and concludes with an undergraduate degree in education and teaching licensure.

Two cohorts from each licensing area participated in the study (i.e., eight cohorts in total). Approximately 56% of eligible PSTs consented to become research participants. Females (n = 95, 96.94%) were the largest number of participants; 84 participants (85.71%) were Caucasian/White. About 5% of participants self-reported as Hispanic (n = 5), 4.08% as Asian (n = 4), 3.06% as African American (n = 3), and two participants self-reported as mixed or other

[1] https://clinicaltrials.gov/study/NCT02544412

race not reported (2.04%). The average participant age was 21.99 years (*SD* = 0.68). The sample's race/ethnicity and gender distributions were representative of the demographics of the partnering PST program (i.e., around 94% female, 85% White). Two participants from each group did not become teachers and thus could not attrite, reducing the analytical sample to 94 (n_{control} = 39 control, $n_{\text{intervention}}$ = 55).

In the primary analyses we report on all randomly assigned participants who entered into professional teaching (i.e., intention-to-treat sample [ITT]; $k = 8$; $N = 94$; $n_{\text{control}} = 39$, $n_{\text{intervention}} = 55$). In the sensitivity analyses, we report on a reduced sample after removing one control cohort for violating study protocols ($n = 88$, k = 7; $n_{\text{control}} = 31$, $n_{\text{intervention}} = 57$). This cohort was recruited into and an unknown number of participants took part in a yoga-based training that included mindfulness meditation elements, exposing this cohort active intervention components.

Power Analysis

Study sample size was based on an *a priori* power analysis indicating that to detect treatment effects of Cohen's $d \geq 0.60$ on mindfulness and race bias (Kang et al., 2014; Roeser et al., 2013), which were two primary outcomes of the parent trial, a sample of 100 would be sufficient assuming $\alpha = 0.05$ and power (1- β error probability) = 0.80.

Study Design

This study was designed as a longitudinal cluster randomized controlled trial conducted over the final year of undergraduate PST education, with 3 years of follow-up. Primary outcomes from the PST education study phase included mindfulness, race bias, and teaching observation scores (Hirshberg et al., 2020, 2022b). The primary endpoint of this study was career attrition assessed 3 years after graduating from the program (i.e., 4 years after random assignment).

As indicated in the logic model presented in Figure 1, the intervention was designed to be integrated into PST education to the greatest degree possible. Faculty in the PST program unanimously voted to allot 30 min of the weekly 2.5-hr cohort seminar class as intervention time for intervention cohorts. Depending on intervention cohorts' schedules, the 30 min of seminar time allotted to the MBI occurred at the beginning or end of the seminar with the additional 60 min occurring contiguously. All PSTs in intervention cohorts participated in the 30 min of the MBI held during seminar and were able to participate in the contiguous 60 min of intervention, but only research participants were expected to. During the final semester of undergraduate PST education (semester after intervention), intervention cohorts participated in 15–20 min "booster sessions" once per month. Control group contamination was guarded against by the cohort nature of the program, agreements with the PST program to not allow participating cohorts to be recruited into other related research, and through conversations with cohort leaders about the importance of an unexposed control group to the study design. Over four consecutive semesters (Fall 2015–Spring 2017), the two cohorts entering their final year in the PST program were recruited into the study (eight total; see Figure 2 and Supplementary Materials Figure S1 [CONSORT Diagram]).

Study assessments were conducted before random assignment (i.e., pre-test), at the end of the intervention (i.e., post-test, at the end of the first semester of participation), and at the end of the second semester of participation just before graduation (i.e., an approximately 6-month follow-up). For 3 years each October after graduating, we emailed participants a survey invitation asking about employment, stress, burnout, and occupational well-being. We report on the primary endpoint of these assessments, which was whether participants were teaching at the Year 3 follow-up.

We block randomized by licensure track to ensure that one cohort from each licensure track was assigned to intervention and the other to control. This design controlled for the possibility that licensure tracks enrolled PSTs with different characteristics, systematically affected PSTs differently, or systematically produced different occupational outcomes that might bias estimates. For example, special education teachers tend to have higher rates of career attrition than other certification areas (Billingsley & Bettini, 2019). Block randomizing by licensure area ensured that one dual certification (i.e., Early Education and Special Education) licensing cohort was assigned to intervention and the other to control.

It is possible that the timing at which cohorts enrolled into the study was associated with exogenous factors that could bias estimates of attrition. The final long-term follow-up for the last two cohorts to enroll occurred in October 2020 thru December of 2021, the first full COVID-19 pandemic school year. If these cohorts were assigned to the same condition, it is possible that estimates of attrition would be biased by pandemic effects on career decisions. The block random number sequence generated prior to study onset was balanced across time (i.e., each semester the same number of cohorts were assigned to treatment and control), ensuring that any time effects were controlled and did not bias treatment effect estimates.

Participants were kept blind to their cohort's assignment until after pre-testing was completed. However, it is possible that intra-cohort dynamics affected the propensity to enroll in the study. Rates of enrollment differed between the cohort with the highest (84%) and lowest (18.2%) rates of enrollment. Differential rates of enrollment are a particular concern for the dual certification (i.e., Early Education and Special Education) cohorts because, as noted, special education teachers are known to attrite at higher rates than other teachers. However, the dual certification cohort assigned to intervention was three times as large as the control dual certification cohort (n =12 vs. n = 4), suggesting that if differential rates of enrollment between these cohorts biased estimates, we would expect a downward bias of intervention effects.

Participants were compensated $145 for completing pre-, post-, and the initial follow-up assessments. An additional $15 was provided upon completion of each longitudinal follow-up (maximum of $190). The University of Wisconsin Madison Institutional Review Board approved all materials and procedures. Data and code used in this manuscript are available at https://osf.io/a5pvz/.

Measures

The primary outcome, coded as 0 (*Yes*) or 1 (*No*), was whether participants were teaching at the Year 3 long-term follow-up. We used self-reported employment on the Year 3 survey and public employment data from the Wisconsin Department of Public Instruction to confirm self-reported data and populate employment data for Year 3 long-term survey non-responders. We gathered employment status on all participants at the Year 1 and Year 3 long-term surveys.

Intervention implementation fidelity was assessed in multiple ways. The same three instructors co-taught all four implementations to ensure consistency and the curriculum was manualized. Each week instructors were provided with a checklist of the core content intended for that session. Completed checklists were compared post study. The same guided audio meditations were provided to all intervention participants, weekly reports on outside of class meditation practice were collected from intervention participants, and attendance at intervention sessions was recorded. Full adherence was communicated to participants as attending eight or more of the nine possible intervention sessions, attending both 4-hr intensives, and daily practice of between 5–20 min during the intervention semester. Each week participants completed practice logs that were provided to the study on a weekly basis.

Data Analysis

Using Welch's *t*-tests and chi-square tests, we first checked for between-group balance on the wide range of observed variables collected at pre-test. Using a Fisher's exact test, we compared rates of entry into teaching between the groups. Participants who never taught (n = 4; n_{control} = 2, $n_{\text{intervention}}$ = 2) could not attrite and were removed from subsequent analyses (final analytic sample n = 94). Attrition estimates could also be biased by differential rates of school turnover between the groups. This concern is particularly salient for benefit-cost estimates because the school where the teacher left incurs the same hiring costs whether a teacher leaves the profession or goes to another school. Using a Fisher's exact test, we compared turnover rates between the groups. Finally, urban schools serving high proportions of low-income students have consistently higher rates of turnover and attrition than suburban schools (Boyd et al., 2011). Therefore, it was important to examine patterns of employment at Year 1. We constructed a three-level categorical variable (school type) for the type of school participants worked in in their first year of professional teaching. Urban schools serving a high proportion of free and reduced lunch program students were the reference category. Relatively affluent suburban schools and a combination of rural, parochial, foreign, and other types of schools made up the second and third categories, respectively. We tested for differences in school type at Year 1 and controlled for this variable in attrition analyses.

There are multiple ways to analyze longitudinal data and different analytic approaches can produce substantively different estimates. Steegen et al. (2016) suggested that all reasonable analyses should be estimated and reported in what they called a multiverse approach. If estimates are consistent, results can be said to be robust to modeling approach. If estimates vary widely the results are not robust and should be interpreted with caution. The clustered nature of these data (e.g., participants within cohorts), the relatively small number of cohorts, and the fact that randomization occurred at the cohort level combined presented potential modeling challenges. We therefore applied a multiverse approach to test the robustness of estimates across different modeling approaches.

We estimated and report in the Results two generalized hierarchal linear models (HLMs) appropriate to the study design, with one using maximum likelihood and the other Bayesian estimation. We fit three additional models: (a) a Firth's bias-reduced likelihood regression that adjusts for bias in logistic regression with rare outcome events, such as attrition in these data (Firth, 1993), but does not account for clustering; (b) a likelihood regression model with clustered standard errors; and (c) a Fisher's exact test because it addresses concerns about statistical inferences from asymptotic *p*-values in relatively small sample sizes by using the true distribution (Bind & Rubin, 2020). These latter three models, reported in the Supplementary Materials, produced substantively similar estimates to the HLMs.

Generalized Hierarchal Linear Model. We first fit a generalized HLM in which participants were nested within cohort and attrition at Year 3 was regressed onto group (i.e., control or intervention) and the school type covariate, which by design (cluster randomized trial) is an appropriate method for these data. The mixed HLM can be written as:

$$\mathrm{Y_{ij}} = \beta_0 + \beta_1 * \mathrm{GROUP_j} + \beta_2 * \mathrm{Y1.Schooltype_{ij}} + \mathrm{u_{0j}} + \mathrm{r_{ij}}$$

where Y_{ij} is the probability of attrition for participant i in cohort j at Year 3, β_0 reflects the average attrition rate in the control condition controlling for Year 1 school type, β_1 represents the effect of assignment to the intervention (reference = control), controlling for Year 1 school type, β_2 is the effect of Year 1 school type, with random effects u_{0j} (level-2 [cohort] intercept residual) and r_{ij} (level-1 [participant] residual).

Beta-Binomial Bayesian Hierarchal Linear Model. Because debate remains regarding the minimum number of level-2 units required for HLM using maximum likelihood estimation (Huang, 2018), we fit an analogous HLM using Bayesian estimation in which posterior estimates are always hypothetically possible and can produce stable estimates for clusters with smaller sample sizes (Hox et al., 2012). In addition, an informative beta prior was calculated using historical rates of average teacher attrition 3 years into teaching (i.e., 22%) with 95% confidence that < 40% of new teachers would not be teaching after 3 years (Goldhaber & Theobald, 2022; Ingersoll et al., 2018).

The Bayesian HLM can be written identically to the first HLM, with results interpreted as the probability of model estimates of centrality, and the random intercept u_{0j} thought of as a prior distribution informed by the data. The high-density interval (HDI; i.e., credible interval) takes the place of the frequentist confidence interval. The HDI can be interpreted as the 95% probability that the population estimate falls within the lower and upper estimates of the HDI. The region of practical equivalence (ROPE) is the percentage of parameter estimates that fall within the null region. Kruschke (2018) suggested that when no parameter estimates from the HDI fall within the ROPE, this pattern can be interpreted similarly to rejecting the null hypothesis. As a beta-binomial model, the range of the ROPE was set to -0.18, 0.18 (Makowski et al., 2019). As an additional indication of effect significance, we report the probability of direction, which reflects confidence in the direction of an effect. In this case, the probability that assignment to the intervention resulted in lower rates of attrition. A probability over 95% corresponds approximately to a two-sided p-value < .05. Prior to running 6000 Markov chain Monte Carlo iterations, 1500 warm-up runs were estimated.

Additional Sensitivity Analyses. We re-estimated both HLMs with the impacted control cohort removed. Results from a Firth's bias reduced likelihood model, a logistic regression with clustered standard errors, and a Fisher's exact test are reported in Supplementary Materials Table S1.

Benefit-Cost Analysis. Ideally, we would have framed the BCA to incorporate four key components: societal, school district, student achievement, and teacher well-being. Estimating societal impacts of reduced teacher attrition is difficult as we are not aware of a clear metric to base such an analysis on. Student achievement effects are estimable, but participants in this study went on to work in more than 40 districts throughout the state of Wisconsin, making obtaining student data infeasible. We designed the study so that returns in terms of teacher well-being were theoretically estimable, but follow-up survey completion was around 50%, limiting confidence in those data. Thus, we framed the BCA around school districts. Following Society for Prevention Research standards for BCAs (Crowley et al., 2018), intervention costs were estimated with the ingredients method in which all costs associated with program implementation are included and added, providing a comprehensive cost estimate (Belfield et al., 2018). Whenever possible, ingredient costs were specific to the region of the United States where this research occurred (Table 1). All costs and benefits were inflation adjusted to 2022 dollars.

Because MBI training is supplemental to PST education, we did not model fixed costs such as the cost of running a PST education cohort (e.g., facilities and administrative costs), as they are assumed by PST education. All total costs for MBI training are variable costs with fixed costs set to \$0. We first calculated the lower and upper bounds for total costs (Table 1; lower bound = sum of Items 1–10, upper bound = sum of Items 1–14). Both lower and upper cost bounds are likely overestimated for several reasons. First, we included instructor training costs even though no training costs were incurred in this study; instructors were selected because of their existing expertise. That said, we included instructor costs in the lower bound because they are a reasonable anticipated cost in a future implementation. Second, we included instructor training as a variable cost even though once trained, an instructor could implement many intervention sessions, reducing the per session cost. Third, we based costs on three instructors per implementation. However, MBIs are frequently taught by one instructor, which would reduce instructor training costs and fees, combined among the largest costs, by two thirds. Finally, as an opportunity cost we included 8 hr of participant lost earning potential (at $15 per hour; line item 14 in Table 1) due to intervention “intensive” attendance on weekends, even though many PSTs may not work during these hours. We set the weekly hour of intervention contiguous to cohort seminar time with an opportunity cost of $0 (line item 13 in Table 1) because participants’ schedules made it impossible to work during these times. We also did not include time spent during cohort seminar on intervention as an opportunity cost because we predicted that it would improve teaching outcomes (i.e., would be a benefit).

The marginal cost of adding a PST to the intervention is equal to the change in total cost divided by the change in the number of PSTs. As the number of treated PSTs increases, marginal costs decrease up to the maximum PSTs per intervention implementation (i.e., n = 25). From Table 1, the marginal costs are calculated by dividing the lower and upper cost bounds (CB) by the intention-to-treat sample (ITT; intervention n = 55) that is equal to $939.15 per PST ($834.70, $1,043.61). This approach is prudent because, as noted, cost estimates are conservative and because the intervention was actually provided to all PSTs in cohorts assigned to the MBI (n = 84), not only study participants. Per cohort marginal costs were calculated by dividing the lower and upper bound cost estimates by four ($11,477.13, $14,349.63), which was the total number of intervention cohorts.

To estimate benefits (i.e., savings to districts due to reduced attrition) we first needed to estimate the costs school districts incur from teacher attrition. We used Shockley et al.'s (2006; \$6,838.79 in 2022 dollars) and Barnes et al.'s (2007; \$22,631.06 in 2022 dollars) teacher recruitment, hiring, and training cost estimates as the lower and upper bound teacher attrition costs, respectively. We assumed that the observed Year 3 attrition rate in the control group (23.08%), which is consistent with estimates of teacher attrition within the first years of professional teaching (Goldhaber & Theobald, 2022; Gray & Taie, 2015; Guthery & Bailes, 2022; Ingersoll et al., 2018), was the expected attrition rate for the intervention group. To calculate the expected intervention group Year 3 attrition count, we multiplied the intervention group ITT sample that entered teaching (n = 55) by the control group attrition rate (23.08%) for an expected intervention attrition count at Year 3 of 12.69. The difference between the intervention group's expected Year 3 attrition count (n = 12.69) and observed Year 3 attrition count (n = 2) was 10.69. The lower and upper bounds of observed intervention benefit were calculated by multiplying 10.69 by Shockley et al.'s (2006) and Barnes et al.'s (2007) teacher replacement cost estimates. Because intervention implementation costs are valid for up to 25 PSTs, we followed the same procedure in simulation analyses in which the intervention and control groups were each set to 100, representing the benefits of the intervention in the maximally efficient context. Point estimates are the average of lower and upper bounds.

The net present value (NPV) subtracts from intervention-related savings in attrition costs (i.e., benefits) from the costs of the intervention. We calculated the NPV for the comprehensive variable costs and separately for the comprehensive plus potential variable intervention costs, for the ITT sample and the simulated analysis. The benefit-cost ratio (BCR) is calculated by dividing intervention benefits by costs, which we calculated for comprehensive variable and comprehensive plus potential variable intervention cost estimates in ITT and simulated samples.

All data analysis was conducted in R statistical software (R Core Team, 2021). See Supplementary Materials Table S2 for a full list of R packages.

Intervention

A detailed description of the intervention, as well as a sample lesson, can be found in the Supplementary Materials. The 9-week training was based on Mindfulness-Based Stress Reduction (Kabat-Zinn, 1982) and a traditional Tibetan Buddhist structure to mind training. Over the course of one semester, the intervention consisted of weekly 1.5-hr classes along with two 4-hr intensive practice days (21.5 hr total). During the following semester, intervention cohorts followed a prescribed sequence of 15-min weekly practices implemented during seminar. Mindfulness practices included breath awareness, body scan (i.e., scanning of body sensations), sound practice (i.e., using sounds as the anchor for attention), walking meditation, and mindful movement. Connection practices included generating feelings of warmth and well-wishing for oneself and others and contemplation on the caring intention to teach. Intervention participants were asked to spend 10–20 min each day on a mindfulness or connection practice.

The same three instructors implemented all intervention waves. All instructors were White and female identifying between the ages of 35 and 50 years. All instructors had formal training in teaching mindfulness (i.e., range = 56–250 hr), had extensive meditation teaching and practice experience (5–20 years of each), and were current or former classroom teachers.

Results

For the wide range of measures collected at baseline, we observed no evidence for group differences (Supplementary Materials Table S1). There was no evidence that Year 1 school type differed between the groups (Fisher's exact test $p = .590$). On the subset of participants for whom we had Year 1 and Year 3 school type data, there was no evidence that rates of turnover (i.e., changing schools/districts but remaining in teaching) were different between the groups (Fisher's exact test $p = .265$). Turnover was descriptively higher in the control group (control = 54%, intervention = 40%).

Intervention Implementation Fidelity and Adherence

Over 95% of intervention content was delivered during the intended session and there was > 95% consistency between implementations according to contemporaneous instructor notes. All but one cohort, due to external disruptions, adhered to the weekly practice schedule over the initial follow-up during PST education. Approximately 68% of (39/57) of intervention participants reached prescribed criteria for full class attendance (i.e., 8/9 classes and both intensive sessions). Eighty-eight percent of intervention participants attended at least one extended practice session. On average, participants reported 13.94 min of meditation practice per day ($SD = 9.47$).

Teacher Attrition

Of the participants who became teachers (94/98, 95.92%), nine out of 39 control (23.08%) and two out of 55 intervention (3.36%) PSTs had left by Year 3 (Figure 3).

Model 1: Generalized Hierarchal Linear Model

Full results of Models 1 and 2 are presented in Table 1. Assignment to the intervention predicted an 87.1% decrease in the odds of attrition at professional Year 3 compared to teacher education as usual control (Odds ration [*OR*] = 0.13 95% CI [0.03, 0.65], $p = .013$), controlling for Year 1 school type. Differences in Year 1 school type (e.g., urban low SES vs. suburban affluent) did not significantly predict attrition at Year 3 (all contrast *p*s > .400). Results from this model were caveated by a singularity warning suggesting that the random effects structure was too complex for the data. One likely explanation was that the clustering (i.e., cohorts) explained very little outcome variance (i.e., attrition rates by intervention cohort were 0.0%, 10.5%, 0.0%, and 0.0%).

Model 2: Beta-Binomial Bayesian Hierarchal Linear Model

Assignment to the intervention predicted a 77.1% decrease in the odds of attrition at professional Year 3 compared to teacher education as usual control (95% High Density Interval [HDI[[0.09, 0.57]), controlling for Year 1 school type, with 0.0% of samples falling inside the ROPE. In other words, there was a 95% probability that the population attrition rate for intervention participants fell within the credible interval (0.09, 0.57) and the posterior distributions of attrition rates between the control and intervention groups were not equivalent (i.e., 0.0% of samples in the ROPE). The probability that the intervention led to reduced attrition relative to the control group was 99.93% (i.e., probability of direction).

Sensitivity Analyses

Results from models removing the affected control cohort were equivalent to ITT analyses (Table 1) as were additional modeling strategies (see Supplementary Materials).

Benefit-Cost Analysis

We frame our BCA from the perspective of school districts that must recruit, hire, and train new teachers. The ingredients list is provided in Table 1 and all BCA results in Table 3. In ITT benefit-cost analyses, the districts that hired intervention PSTs saved through reduced attrition $157,516 ($73,107, $241,926) for a per teacher savings of $2,863.93 ($1,282.58, $4,244.32). The actual cost of the intervention was $45,909 or $834.71 per ITT participant. The NPV was $111,607 (CB: $27,198, $196,017) or $1,958.02 (CB: $494.51, $3,563.95) per ITT participant. The benefit-cost ratio was 3.43 (CB: 1.59, 5.27). Thus, for every dollar invested in the intervention, districts saved between $1.59 and $5.27 in expected replacement teacher costs over 3 years. In a balanced design with 100 participants per group, the predicted per participant NPV and benefit-cost ratio based on variable costs were \$2,405.38 (\$870.37, \$3,940.39) and 6.24 (2.90, 9.58), respectively.

Discussion

Early career teacher attrition disrupts school continuity, precludes many of those who leave from reaching their potential effectiveness as teachers, and drains limited economic resources from school districts. Moreover, because urban and high-poverty schools experience greater turnover, teacher attrition may contribute to inequitable educational opportunities for minoritized students. Today, many teachers are considering leaving the profession early and fewer potential teachers are entering the profession (Walker, 2022). We report that assignment to a 9-week mindfulness and connection intervention partially integrated into undergraduate PST education reduced the odds of attrition at the crucial Year 3 juncture by 77%–87% relative to control group teachers who received the same PST education but not the MBI. This effect was not the result of differences in the types of schools intervention and control participants worked in immediately after graduating from the PST program or higher rates of school turnover (i.e., moving from a low resource to high resource school) during professional teaching in the intervention group.

Lower odds of attrition among intervention PSTs were also not the result of unexpectedly high attrition rates in the teacher education as usual control group. Consistent with population estimates of early career attrition (e.g., Ingersoll et al., 2018), 23.08% of the participants in the control group who had entered professional teaching had left by Year 3. Thus, the intervention effect on attrition was the result of significantly lower than expected rates of attrition in the intervention group. Of the 55 intervention group participants who became teachers, only two

(3.64%) had left in their first 3 years on the job. This 3-year attrition rate is less than half of the historical *yearly* teacher attrition rate among new teachers (Goldhaber & Theobald, 2022; Ingersoll et al., 2018).

In three of the four intervention cohorts, no participants had left teaching at the study endpoint. The highest 3-year attrition rate in an intervention cohort (10.53%) was less than half of control group or equivalent historical attrition rates. Intervention cohorts' rates of attrition were in all cases lower than control group cohort attrition rates and expected attrition rates based on historical trends (see Figure 3). The exception, surprisingly, was in the Early Education and Special Education licensure track. Special education teachers generally have higher rates of attrition than other categories of teachers, but no intervention or control participants from this licensure track had left teaching at study endpoint. However, the control special education cohort had the lowest study enrollment (n = 4, 18%), making it plausible that the PSTs who enrolled in the study were different from many cohort PSTs who chose not to participate.

All statistical models estimated large magnitude, statistically significant effects of the intervention on attrition (see Table 1 and Supplementary Materials). The consistency of the estimated intervention effect adds confidence that estimates were not artifacts of the modeling approach. Even in the most conservative model, the Bayesian HLM with informative priors estimated large magnitude intervention reductions in attrition (77.0%) with high probability.

Although these data present causal evidence that assignment to the intervention led to reduced rates of attrition, the mechanism through which this effect occurred remains unknown. Researchers who study MBIs with in-service teachers have mostly asserted that the primary pathway of benefit is reduced stress through improved coping (e.g., Jennings & Greenberg, 2009; Roeser et al., 2012). Teacher stress and burnout are consistently reduced following high quality MBIs (Jennings et al., 2017; Roeser et al., 2013), but it is less clear that this is the case for PSTs (Hirshberg et al., 2020; Hue & Lau, 2015). This may be because PSTs are not (yet) experiencing as much distress and burnout as in-service teachers. When viewed as a preventive intervention, it is possible that integrating this MBI within PST education led to better prepared teachers who adapted more easily to the profession, thereby experiencing less stress and reducing the likelihood attrition. Consistent with this interpretation and our logic model of change (Figure 1), observers rated intervention PSTs as showing greater improvement in classroom behaviors at the end of PST education (Hirshberg et al., 2020). Replicating the primary effect of reduced attrition and testing hypothesized mechanisms leading to reduced attrition are needed to understand the policy implications of these results, including, for example, whether integrating MBIs into PST education is warranted.

In benefit-cost analyses, we estimated that districts that hired PSTs assigned to the intervention saved, after deducting intervention implementation costs, a combined total of $157,516 during the 3 years of study follow-up, or $1,282.58 to $4,244.32 per teacher in low and high-cost areas, respectively. Based on our conservative calculations, every dollar invested in the intervention resulted in average savings to districts of $3.43 ($1.59, $5.27). Simulating a maximally efficient implementation approach where all 25 PSTs in a cohort receive the intervention, we estimated that every dollar invested in the intervention would save districts $6.24 ($2.90, $9.58).

Although caution is warranted before drawing broad generalizations, it is important to contextualize these results within the current teacher labor market and the lack of causal research on strategies that reduce attrition. Many districts are facing a shortage of qualified teachers (Peyton et al., 2021; Wiggan et al., 2021). The U.S. Department of Education (2021) expected

357,000 teachers to be hired for the 2022–2023 school year. If half of these new hires received this MBI and we assume equivalent effects on attrition, using variable cost estimates, by 2026 districts nationwide would save $228,940,530 to $757,611,120. The 77%–87% causal reductions in attrition associated with the MBI in this study are even more notable when placed within what is known through observational research about the factors associated with attrition. For example, a standard deviation increase in teacher perceptions of leadership quality were associated with about 11% reductions in teacher attrition (Kraft et al., 2016).

It is reasonable to assume that the true population intervention effect was overestimated. Effect size estimates tend to become smaller as trials scale up (e.g., Sims et al., 2023) and are often more heterogenous than apparent in trials with relatively homogenous samples, a salient concern here as our sample was not representative of all PSTs nationwide. Relatively small reductions in early career attrition can still result in significant benefits. In high teacher replacement cost areas, for instance, just a 2% reduction in the attrition rate over 3 years produces a positive benefit-cost ratio using estimates from the simulated balanced groups of 100 analyses. This means that for districts where costs are high, such as in many urban districts, the intervention would confer economic returns even if its efficacy was reduced by 80%.

Of course, the financial benefits districts enjoy when teachers stay on the job is only part of the story. Families, students, and schools benefit as well. For example, students benefit from a teacher’s accrued on-the-job learning (Bastian, 2013), lower staff turnover is associated with improved school climate and staff morale, both of which are associated with improved student outcomes (Thapa et al., 2013), and families’ connections to teachers might improve because of reduced attrition (Kwon et al., 2020). Rather than viewing MBIs as orthogonal or parallel to teacher education, they might more appropriately be viewed as synergistic with or possibly even integral to optimal PST and therefore school outcomes.

The results of this study are germane to the field of school psychology in terms of identifying interventions that have the potential to positively impact the school and classroom environment through teacher retention. Although not directly tested in this study, a major cause of educator attrition is burnout, which negatively impacts teachers' well-being, as well as the quality of their relationships with students. Similar mindfulness-based interventions have been shown in other research to improve both teacher and student well-being. Mitigating teacher attrition means that teachers can become seasoned in the profession and to be present and available to establish supportive relationships with students. This in turn is expected to have a positive impact on student learning and well-being, a hypothesis that can be tested in future research to further expand the science and practice of school psychology.

Limitations

There are several important limitations to note. The sample was relatively small, which combined with the frequency of attrition, makes replicating these results in a larger sample of PSTs essential. Relatedly, this study sampled from a PST program at a large research university that educates a relatively homogenous population of PSTs. It is not clear whether these results will translate across different PSTs (e.g., race, gender, age) or different teacher certification contexts. Some potential opportunity costs were assessed via self-report (e.g., practice time logs). Although the method applied avoided some of the potential biases associated with retrospective reports on behaviors by regularly collecting practice reports (i.e., weekly), the accuracy of these data is unknown. Finally, this study estimated the causal effect of assignment to the MBI during PST education on career attrition 4 years later (i.e., the direct effect of intervention on teacher attrition in Figure 1) but we were not able to examine the mechanisms leading to this effect (i.e., skill development and enactment as mediators in Figure 1). Understanding mechanisms of action is important for multiple reasons, including that this knowledge may support intervention optimization and inform future policy.

Conclusion

Time is precious and in short supply in many PST programs. The perception some PST educators may have of an opportunity cost in MBIs, in the form of taking time away from traditional PST educational or other relevant experiences, may render them *de facto* poorly received. For research evidence to be taken up, it must reflect the realities of PST programs and of professional teaching. At a time when more teachers are considering leaving teaching (Walker, 2022) and many report high levels of distress (Hirshberg et al., 2023; Kush et al., 2022), rather than viewing MBIs as secondary to the purposes of teacher education, these data suggest that they may support its core purpose: Educating effective teachers who stay in the profession.

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Table 1

Ingredients Table

Ingredient			**Cost (2022 US Dollars)**			
	Quantity	**Unit Cost**	**Total**	**Per PST (ITT)**	**Per PST (n = 100)**	**Per Cohort**
1. Art supplies	4	$56.85	$227.40	$4.13	$2.27	$56.85
2. 3-ring binders	8	$3.68	$29.44	$0.54	$0.29	$7.36
3. Paperback books	4	$6.91	$27.64	$0.50	$0.28	$6.91
4. Durable goods (paper)	4	$168.80	$675.20	$12.28	$6.75	$168.80
5. Dry erase markers	4	$8.24	$32.96	$0.60	$0.33	$8.24
6. Food	4	$259.20	$960.00	$17.45	$9.60	$240.00
7. Index cards	500	$4.67	$18.68	$0.34	$0.19	$4.67
8. Paper copies	200	$0.13	$26.20	$0.48	$0.26	$6.55
9. Instructor Training	3	$7,649	$22,947	$417.22	$229.47	$5,736.75
10. Instructor compensation	12	$1,747	$20,964.00	$381.16	$209.64	$5,241.00
Lower Bound			***$45,908.52***	$834.70	$459.09	$11,477.13
Potential Costs not Incurred						
11. Facilities Rental	44	$100/half day	$4,400.00	$80.00	$44.00	$1,100.00
12. Administrator	112	$62.23/hr	$6,970.00	$126.73	$69.70	$1,742.50
13. Opportunity cost of other activities in lieu of MBI during PST education	9	$0 per hr	$0	$0	$0	$0.00
14. Opportunity cost of weekend retreat hours	8	$15 per hr	$120	$2.18	$1.20	$30.00
Upper Bound			***$57,398.52***	$1,043.61	$573.99	$14,349.63

Note. PST = Preservice teacher; ITT = Intention-to-treat sample. Costs are ingredient estimates from Columbia University's *E$timator* tool or actual costs incurred, wherever possible, benchmarked to regional prices. Ingredient 9 (i.e., Instructor Training) is the estimated cost to train one intervention instructor based on the following assumptions: (a) A minimum of 56 hr (1 week) of retreat style teacher training in meditation ($3,579; Brown University, n.d.), (b) A minimum of 3 years of regular meditation practice ($0), (c) At least 2 meditation retreats of 1 week or longer (i.e., > 100 hours of retreat; $2,030 per retreat), and (d) prior classroom teacher experience ($0, prerequisite experience). Ingredient 10 (i.e., Instructor Compensation) was the amount of money paid to each instructor for each training (3 instructors x 4 implementations = 12). Per PST (*n* = 100) costs reflect maximally efficient estimates because up to this number of participants (i.e., 25 per cohort; 100 total), no additional costs are required. Lower bounds are based on the costs incurred. Upper bounds are based on the cost incurred plus additional costs that might be required in future implementations.

Table 2

Estimates from Maximum Likelihood and Bayesian Hierarchal Linear Models of Attrition

Variable	Model Odds ratio [Confidence/Credible Interval]	
	HLM	**Bayesian HLM**
Intervention	0.13* [0.03, 0.65]	0.23^ [0.09, 0.57], ROPE = 0.0%
School Suburban	1.02 [0.12, 8.51]	0.32 [0.13, 0.78]
School Other	2.03 [0.36, 11.40]	0.32 [0.12, 0.77]
Sample size	$K = 8$, $n = 94$	$K = 8$, $n = 94$
Sensitivity Analyses		
Intervention	0.12* [0.02, 0.65]	0.24^ [0.09, 0.61], ROPE=0.0%
School Suburban	0.92 [0.05, 16.9]	0.27 [0.11, 0.66]
School Other	4.42 [0.47, 41.80]	0.27 [0.10, 0.68]
Sample size	$K = 7$, $n = 88$	$K = 7$, $n = 88$

Note. HLM = Hierarchal linear modeling; CI = Confidence interval; ROPE = Region of practical significance in Bayesian statistics. In Bayesian HLM, CI stands for credible interval or the 95% high density interval. The practical significance of an effect can be ascertained by the percentage of the ROPE that fall within the CI, with no samples falling within the ROPE equivalent to evidence suggesting that the null should be rejected.

*$p < .05$. **$p < .01$. ***$p < .001$. ^reject the null hypothesis in Bayesian models.

Table 3

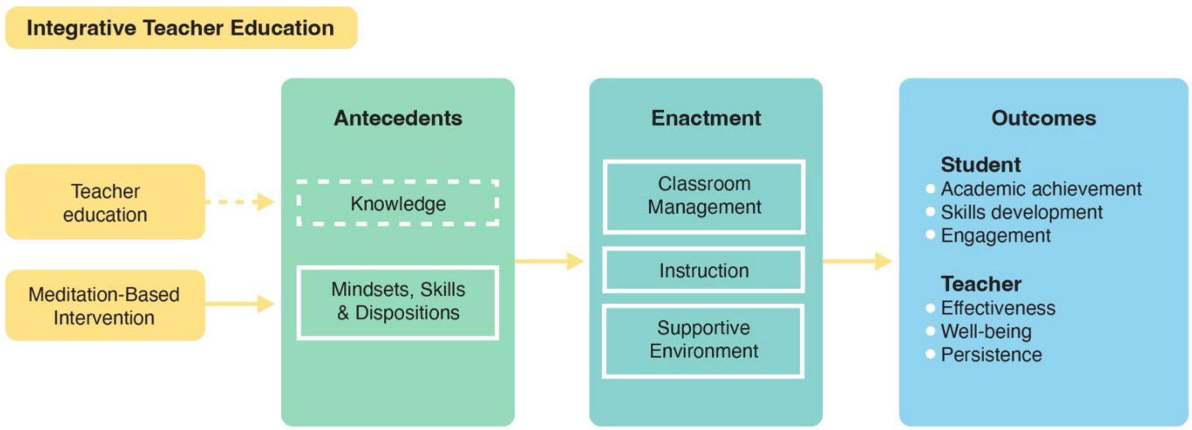
Intervention Benefits and Costs: Analyses of Intention-to-Treat Sample and Balanced Groups of 100 Preservice Teachers

Panel A: Intention to Treat Sample Intervention Benefits and Costs						
	A	B	C	D	E	F
Program	Attrition Count (*n*)	Expected Attrition Count (*n*)	Expected Minus Actual Attrition Costs	Intervention Costs	NPV	BCR
Teacher Education + MBI (*n* = 55)	2	12.69	$157,516 ($73,107–$241,926)	Lower bound cost (LB) $45,909	$111,607 ($27,198–$196,017)	3.43 (1.59–5.27)
				Upper bound cost (UB) $57,399	$100,117 ($15,708–$184,527)	2.72 (1.27–4.22)
Teacher Education As Usual (*n* = 39)	9	9	$0	–	–	–
Panel B: Simulated Intervention Benefits and Costs for Balanced Groups of 100 Preservice Teachers						
	G	H	I	D	J	K
Program	Attrition Count (*n*)	Attrition Costs	Intervention Reductions in Attrition Costs	Intervention Costs	NPV	BCR
Teacher Education + MBI (*n* = 100)	3.64	$53,635 ($24,893, $82,377)	$286,447 ($132,946, $439,948)	LB $45,909	$240,538 ($87,037–$394,039)	6.24 (2.90, 9.58)
				UB $57,399	$229,048 ($75,547–$382,549)	4.99 (2.32, 7.67)
Teacher Education As Usual (*n* = 100)	23.08	$340,082 ($115,784, $522,325)	–	–	–	–

Note. ITT = Intention-to-treat sample; NPV = Net Present Value or the benefits minus the actual costs (i.e., E = C minus D); BCR = Benefit-cost ratio or the benefits divided by the costs (NPV [C]÷Intervention costs [D]); Attrition Count (*n*) = Observed number of participants no longer teaching at Year 3 follow-up; Expected Attrition Count (*n*) = Intervention group sample size times control group attrition rate (23.08%); Expected Minus Actual Attrition Costs = Low-cost area teacher replacement costs of $6,838.79 (Shockley et al., 2006, × 10.69 = $73,107). High-cost area teacher replacement costs of $22,631.06 (Barnes et al., 2007, × 10.69 = $241,926). The point estimate is the mean of these two values. Intervention cost lower and upper bounds are the actual costs incurred and the costs incurred plus possible future costs, respectively (Table 1). Panel B follows the same calculations but based on a simulated scenario in which intervention and control participants each have samples of 100.

Figure 1

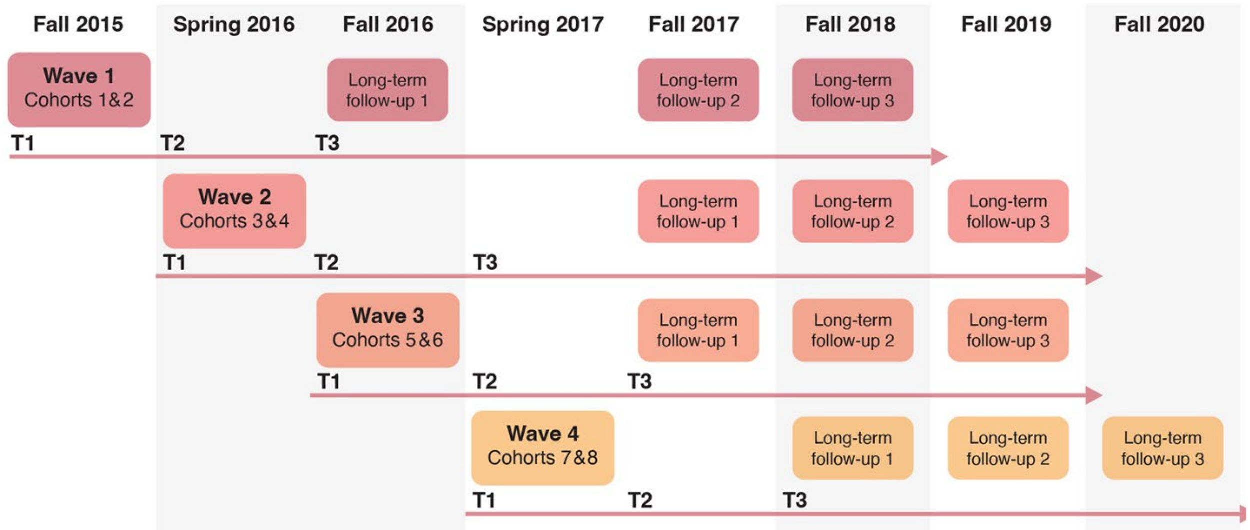
An Integrative Model of Teacher Education



Note. The model assumes that current teacher education primarily educates teaching relevant knowledge, but that in addition, mindsets, skills, and dispositions are required to learn to be an effective teacher. Consequently, the model proposes integrating current teacher education with high-quality meditation-based interventions to strengthen the teaching of the knowledge, mindsets, skills, and dispositions that allow teachers to enact effective classroom practices. These, in turn, are predictive of positive student and teacher outcomes.

Figure 2

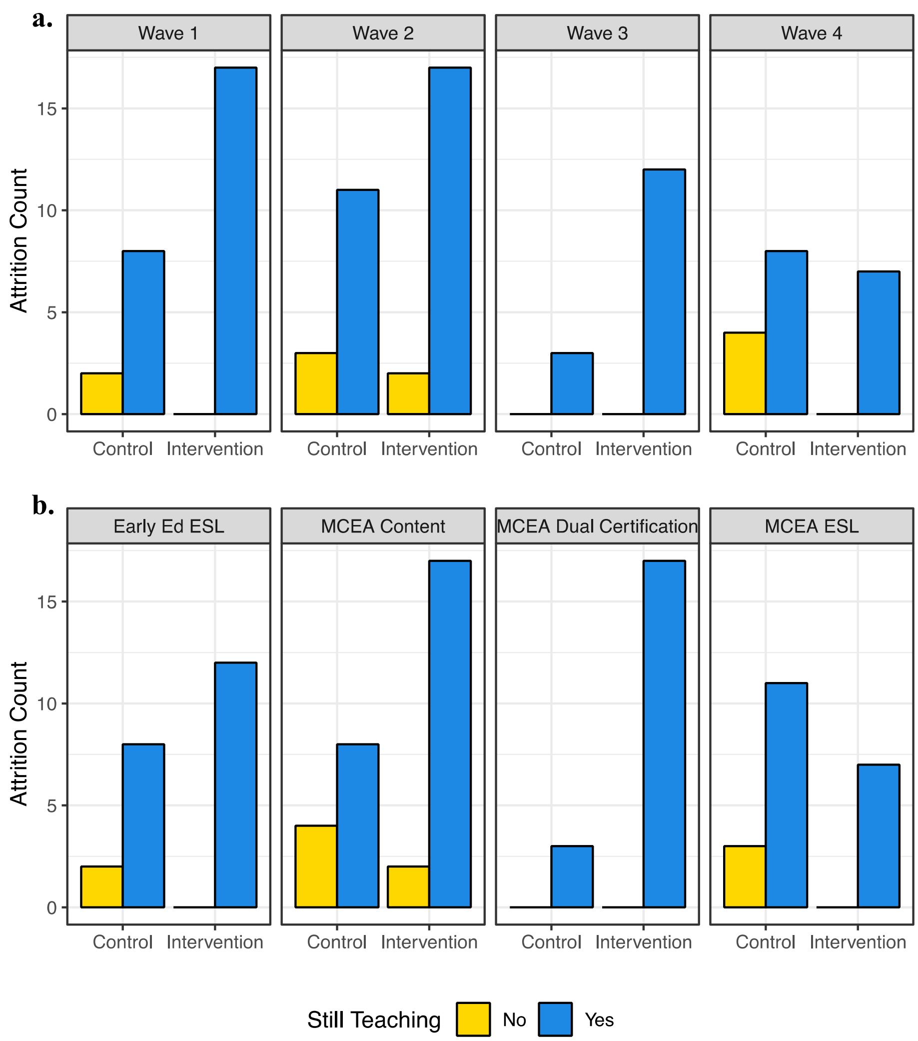
Study Timeline and Overview



Note. T1 = Pre-test prior to random assignment; T2 = Post-intervention assessment; T3 = Follow-up coinciding with the end of the PST education program and graduation from college. Long-term follow-ups were conducted in November/December each year for 3 years following graduation from the PST education program.

Figure 3

Attrition Counts in Intervention and Control Cohorts by Study Wave and Cohort Type



Note. Early Ed ESL = Early Education English as Second Language; MCEA = Middle Childhood Early Adolescence; Content = Content area licensure; Dual Certification = Content and Special Education licensure; ESL = English as Second Language licensure. Figure 1a illustrates number of control and intervention teacher participants attrition/persistence in teaching at the Year 3 follow-up (i.e., 4 years after random assignment) by study wave. Figure 1b illustrates number of control and intervention teacher participants attrition/persistence in teaching at Year 3 by licensure track.

Supplementary Materials

Figure S1

CONSORT Diagram

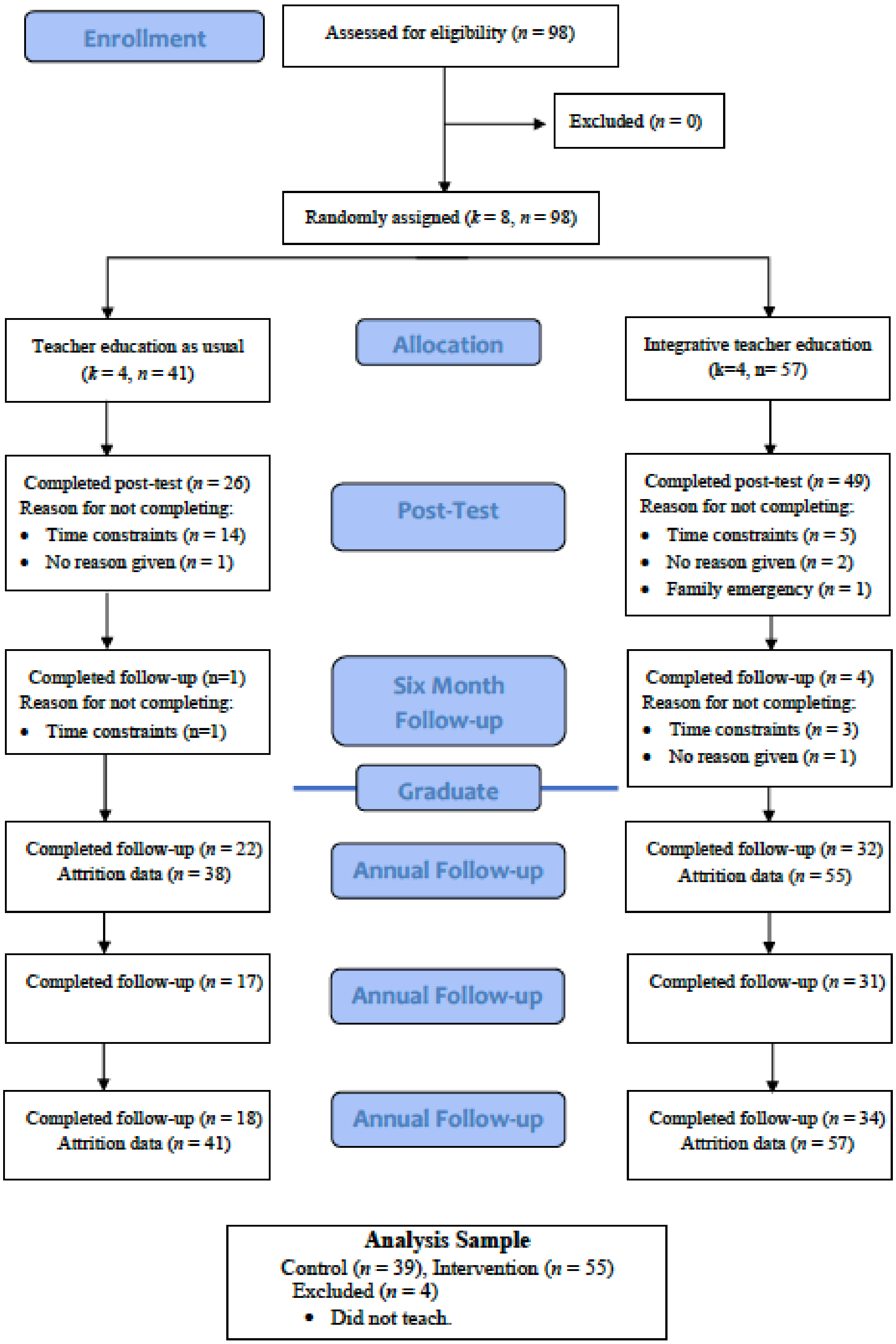


Table S1

Summary and Balance Statistics Between Intervention and Control Groups

Demographic Variables	Control		Intervention		
	M/*n* (%)	*SD*	*M*/*n* (%)	*SD*	*p*
Age (years)	21.90	0.59	22.84	5.11	.674
Gender					
Female	41 (100%)		54 (94.74%)		.722
Male	0 (0%)		3 (5.26%)		
Race					
Black / African American	2 (4.88%)		1 (1.75%)		.905
Asian / Pacific Islander	2 (4.88%)		2 (3.51%)		
Hispanic	3 (7.32%)		2 (3.51%)		
White / Caucasian	33 (80.49%)		51 (89.47%)		
Mixed Race	1 (2.44%)		1 (1.75%)		
Psychological Measures					
Teaching right career	4.29	0.81	4.29	0.63	.667
Happy teaching	8.80	1.10	8.88	1.56	.905
Want mindfulness	8.88	1.77	9.46	1.21	.062
Positive affect	33.24	6.50	35.63	5.43	.667
Negative affect	21.49	4.92	21.09	6.12	.905
Implicit positive affect	2.06	0.48	2.14	0.47	.835
Implicit negative affect	1.77	0.34	1.84	0.32	.722
Mindfulness	122.63	15.00	124.04	15.99	.905
Depression	0.94	0.66	0.94	0.47	.667
Anxiety	0.53	0.43	0.57	0.54	.905
Emotional Exhaustion	18.6	9.19	18.97	10.06	.917
Personal Accomplishment	38.24	6.36	38.24	5.62	.917
Depersonalization	4.20	3.47	4.20	4.05	.835
Perceived stress	21.22	5.63	21.47	5.77	.917
Self-efficacy	30.32	3.41	30.53	3.67	.905
Extraversion	8.17	3.30	8.88	2.79	.722
Agreeableness	10.59	2.14	10.79	2.17	.905
Conscientiousness	11.59	2.33	11.96	2.16	.835
Emotional stability	8.56	2.61	8.54	2.94	.976
Openness to experience	10.22	2.08	11.02	2.13	.667
Psychological well-being	188.15	22.07	194.96	19.96	.667
Emotional style	88.44	10.02	88.44	10.75	.723
Instructional supports	2.88	1.03	2.62	0.97	.723
Emotional supports	4.77	0.98	4.65	1.11	.905
Classroom organization	5.11	1.43	4.91	1.24	.835
Race bias (adult faces)	0.31	0.37	0.36	0.37	.835
Race bias (child faces)	0.23	0.31	0.32	0.29	.674
Emotion regulation	3.99	0.99	4.12	0.91	.835

Note. *P*-values are false discovery rate corrected and from Welch's *t*-tests (continuous variables) or χ^2 tests (dichotomous and categorical variables). "Teaching right career," "happy teaching," and "want mindfulness" were single items rated on 1 (*strongly disagree*) to 5 (*strongly agree*), 1 (*very unhappy*) to 10 (*very happy*), and 1 (*not at all interested*) to 10 (*extremely interested*) scales, respectively. General and implicit positive and negative affect were assessed with

Positive and Negative Affect Schedule (Watson et al., 1988) and the Implicit Positive and Negative Affect Test, respectively (Quirin et al., 2009). Mindfulness was assessed with the Five Facet Mindfulness Questionnaire (Baer et al., 2008). Depression and anxiety were assessed with the Symptoms Checklist 90-R (Derogatis, 1992). Burnout (i.e., emotional exhaustion through depersonalization) was assessed with the Maslach Burnout Inventory–Educator Survey (Maslach et al., 1996). Personality facets (i.e., extraversion through openness to experience) were assessed with the 10-item Big Five Inventory (Rammstedt & John, 2007). Healthy emotionality was assessed with the Emotional Styles Questionnaire (Kesebir et al., 2019). Classroom behaviors (i.e., Instructional supports through classroom organization) were rated by certified Classroom Assessment Scoring System observers (La Paro et al., 2004). Automatic race bias was assessed with the adult and child versions of the Black/White implicit association test, respectively (Greenwald et al., 2003). Emotion regulation was assessed with Emotional Go/No go task (Hare et al., 2008). Dprime is an index of task accuracy after accounting for response bias.

Multiverse Analyses Models 3–5 Methods and Results

Model 3: Firth's Bias Reduced Likelihood Regression

The canonical logistic model considers binary choice outcome Y with observed $y_i \in (0,1)$ $and\ is\ written\ as\ the\ P(Y = 1|x_i) = (1 + exp(-x_i\beta))^{-1}$. Firth (1993; p. 32) showed that for a class of exponential models penalizing the likelihood function by the square root of the determinant of the Fisher information matrix reduced the first order asymptotic bias in the maximum likelihood (ML) estimates of β. Firth's bias-reduced likelihood regression adjusts for bias in logistic regression with rare outcome events, such as attrition in these data (Firth, 1993) by one half of a ML logistic regression because $(1 + exp(-x_i\beta))^{-1}$ gets maximized at ½. It does not account for clustering, however, and therefore would only produce unbiased standard errors in the event that the clustering was ignorable. This model can be written as:

$$Y_i = 1/\ e^{-(\beta^0 + \beta^1 * \text{GROUP} + \beta_2 * Y1.Schooltype)}$$

where Y_i is the likelihood of participant *i* attrition at Year 3, $\beta^0$the attrition rate for the control condition, β^1, the effect of interest, is the effect of assignment to the intervention, and β^2 the effect of Year 1 school type. For details on the penalty in Firth's regression, see Firth (1993).

The odds of intervention group participant attrition at Year 3 were reduced by 83.9% compared to teacher education as usual controls (*OR* = 0.16, CI [0.03, 0.61], *p* = .006), controlling for Year 1 school type. Differences in school type did not significantly predict Year 3 attrition (*p*s > .400).

Model 4: Likelihood Regression with Cluster Robust Standard Errors

Cluster robust standard errors (i.e., sandwich estimators) account for heteroskedasticity across observations within clusters (e.g., the randomization unit is at the cluster not the individual-level; McNeish & Stapleton, 2016). More recently, methodologists have suggested bootstrapped and wild bootstrapped cluster robust standard errors in hierarchal data with small numbers of clusters (Deen & de Rooij, 2020; MacKinnon & Webb, 2018). Including the fixed effect of enrollment wave in theory would allow us to answer the question of whether, after removing enrollment timing effects, adjusting for clustering within cohorts, and controlling for school type at Year 1, there was a group difference in attrition. This model can be written as:

$$Y_i = 1/\left(1 + e^{-(\beta^0 + \beta^1 * \mathrm{GROUP} + \beta^2 * Y1.Schooltype + \beta^3 * Enrollmentwave)}\right)$$

where, as above, Y_i is the likelihood of participant *i* attrition at year 3, β^0 is the attrition rate for the control condition, β^1 is the effect of assignment to the intervention controlling for the fixed effect of enrollment wave and Year 1 school type, β^2 is the effect of Year 1 school type controlling for enrollment wave group assignment, and β^3 is the effect of enrollment timing controlling for Year 1 school type and group assignment.

The model produced warnings that 782 of the bootstrap samples returned at least one missing value and fitted probabilities of zero or one occurred, leading to uninterpretable model estimates that we do not report. Estimation of these methods is known to breakdown when either the outcome is close to perfectly discriminated by the explanatory variables or there is little variability in the outcome (Deen & de Rooij, 2020). In these data, both are potential concerns (Figure 2).

Model 5: Fisher's Exact Test

Due to concerns about statistical inferences from asymptotic *p*-values in relatively small sample sizes, we also estimated a Fisher's exact test comparing attrition rates between the groups. Fisher's exact test uses the true distribution rather than assumptions based on a large sample asymptotic distribution (Bind & Rubin, 2020). The model can be written as:

$$p = ((a + b)!\,(c + d)!\,(a + c)!\,(b + d)!) / a!b!c!d!n!$$

where p is the p-value of the one-tailed hypothesis that the control group is more likely to attrite, a is the number of participants who attrite in the intervention group, c is the number of participants who attrite in the intervention group, b is the number of participants who attrite in the control group, d is the number of participants who attrite in the control group, and n is the total sample size (i.e., a + b + c + d).

Assignment to the intervention was associated with a statistically significant 87.2% reduction in the odds of attrition at Year 3 in the intervention group (OR = 0.13, CI [0.013, 0.68], p = .007).

Sensitivity Analyses Removing Affected Control Cohort

Models 3 and 5 produced substantively equivalent results to ITT analyses (ORs = 0.12–0.15, ps = .007–.008). Model 4 again resulted in uninterpretable estimates.

Table S2

Statistical Software and Packages

Software / Package	Reference
R	R Core Team. (2021). *R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria*. ISBN 3-900051-07-0.
G*Power3.1	Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160.
lme4	Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using **lme4**. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01
sandwich	Zeileis A, Köll S, Graham N (2020). "Various Versatile Variances: An Object-Oriented Implementation of Clustered Covariances in R." *Journal of Statistical Software*, *95*(1), 1–36. doi: 10.18637/jss.v095.i01. Zeileis A (2004). "Econometric Computing with HC and HAC Covariance Matrix Estimators." *Journal of Statistical Software*, *11*(10), 1–17. doi: 10.18637/jss.v011.i10. Zeileis A (2006). "Object-Oriented Computation of Sandwich Estimators." *Journal of Statistical Software*, *16*(9), 1–16. doi: 10.18637/jss.v016.i09.
logistsf	Heinze, G., Ploner, M., Dunkler, D., & Southworth, H. (2013). Firth's bias reduced logistic regression. *R Package Version*, *1*, 33.
brms	Bürkner, P. C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*, 1–28.
bayestestR	Makowski, D., Lüdecke, D., Ben-Shachar, M. S., Wilson, M. D., Bürkner, P. C., & Mahr, T. (2020). Package 'bayestestR'. *last viewed August*, *20*, 2020.
Tidyverse	Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D. A., François, R., ... & Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, *4*(43), 1686.
ClusterBoostrap	Deen M, de Rooij M (2020). "ClusterBootstrap: An R package for the analysis of hierarchical data using generalized linear models with the cluster bootstrap." *Behavior Research Methods*, *52*(2), 572–590. https://doi.org/10.3758/s13428-019-01252-y.

Intervention

The intervention was partially integrated into the teacher education program. Thirty minutes of the mandatory weekly cohort seminar time was dedicated to the intervention for cohorts assigned to treatment. All cohort students received 30 min of the intervention regardless of their status as research study participants. Research participants also engaged in 60 min of additional intervention before or after cohort seminar, depending on cohort schedule availability, for a total of 90 min per week of intervention. In addition, two 4-hr intensive “retreat” days that involved little didactic instruction focusing almost entirely on formal mindfulness and connection practices were also part of the intervention (21.5 hr total). During the following semester (i.e., the final of the teacher education program), 15-min weekly booster practices were done during each cohort seminar. Once per month intervention instructors were present in person to answer practice-related questions. The other booster sessions followed a pre-established sequence of recorded mindfulness and connection practices.

The following description of the intervention is adapted from Hirshberg et al. (2020), in which the authors present pre-, post-, and 6-month follow-up effects (i.e., not long-term follow-up) on an outcome unrelated to the current results and not assessed during the long-term follow-ups.

The intervention has roots in Mindfulness-Based Stress Reduction (Kabat-Zinn, 2013) and Tibetan Buddhist approaches to mind-training. A novel secularized theory of change derived from Buddhist philosophy (Thrangu & Thrangu, 2004) was added to common presentations of mindfulness training. Based on the notion in Buddhist traditions that a conceptual understanding of the process of training the mind (i.e., the view) is an important element in learning mediation (Rinpoche, 1993), the view in this training was intended to provide appropriate mindsets for approaching mindfulness, loving-kindness, and intention/motivation practices in the context of learning to teach. For example, the view component of the third class was that desired qualities of mind like calmness and equanimity are already present but habitual approaches to experience (e.g., aversion to unwanted experiences) prevent qualities such as contentment from being noticed. The intent of this view is to shift purpose away from changing experience toward an openness to experiencing whatever is arising.

Mindfulness instruction emphasized (a) building clear awareness of the contents of the present moment (i.e., thoughts, sensations, and emotions) and an attitude of calmly resting with whatever contents arise, even if they are unpleasant; (b) strengthening the capacity to maintain an on-going, background monitoring of experience (i.e., meta-awareness) so that if the mind becomes distracted, agitated, or reactive, awareness of these processes quickly arises; and (c) using increased awareness and meta-awareness as a workspace in which response rather than habit or reaction drive behavior.

Connection practices included loving-kindness practices and compassion practices that seek to extend kindness and a desire to help relieve the difficulties of an ever-larger sphere of people. For example, the *Just like me* practice leads participants through a reflection on how everyone is just like me in sharing the basic desire to be happy and to avoid difficulty. This practice can be focused on those we feel close to or those we struggle with. Intention practices were intended to help participants clarify the intention and purpose that led them to enter the teacher education program and strengthen the prosocial elements of that intention (Hirshberg et al., 2020).

Below are the overarching tenets behind the construction of the intervention and example lesson. For intervention content, please cite Hirshberg et al. (2015).

Purpose

- To develop competencies that support well-being, effective classroom management, and persistence in teaching.

Key skills:

- **Self-awareness**
  - Awareness of bodily sensations
  - Awareness of emotions
  - Awareness of thoughts
- **Self-regulation**
  - Learning to respond rather than react
  - Attention
    - Stability
    - Flexibility
- **Acceptance**
  - Able to rest into experience as it is in this moment
- **Equanimity**
  - Not needing to change experience in any way, at least for a moment. Able to maintain a sense of ease and calmness as experience rises and falls.
- **Mindfulness**
  - *Generally*
    - To remember; to maintain a knowing awareness.
  - *During practice*
    - Remembering to bring the mind back to object of the practice.
- **Kindness**
  - Getting in touch with and developing our basic sense of goodwill toward others (and our own condition)

Key points of the view of practice

1. Curiosity – be willing to look without knowing what you will find.
2. The qualities of happiness and well-being reflect the basic nature of the mind, so by looking and seeing with equanimity, we are slowly allowing these qualities to come out.
3. We can find ease and well-being even in the midst of turmoil.
4. To find ease and well-being, we must experience that we experience thoughts, emotions, sensations etc., but we more than these.
5. The suffering of suffering.
6. The power of intention is mindfulness.
7. Awareness has room for everything.
8. All experience is impermanent.
9. Attachment and aversion.
10. Interconnectedness

Example lesson

Week 1 (Introduction, Coming into the body)

Theme: Introduce mindfulness and how it is related to health and well-being. Participants will practice mindfulness-based skills using the body as an anchor.

Attitude- <u>Curiosity</u>
****

10 min: 6-point body scan

- Emphasize in instructions just letting be into whatever sensations are arising, and gently inviting the mind back when it has wandered. Whatever you experience is fine just as it is.

10 min: Overview of course and view of practice part I:

- Welcome.
- Introduce mindfulness as a way of being - stepping out of autopilot. Mindfulness is paying attention in the present moment on purpose w/o judgment (or w/ awareness of judgment). It's a practice, something we will try out on a regular basis.
- Mindfulness is also translated as "to remember." As we learn this practice, we will over and over again be remembering to keep attention on the object of the practice. In life, we can remember in every moment to bring attention to whatever it is we are doing – reading, listening, speaking, etc.
- Note that each class will introduce and reinforce a key practice, and a key attitude. Attitudes are approaches to practice and life that can help us to remember, to be mindful.
- Today's attitude is Curiosity. Curiosity is the willingness to look. In all of the practices we learn, curiosity is always the first step. Just be curious and willing to try the practices, and to look at what arises in experiences. Curiosity also has the quality of not knowing. That is, when we are curious we are looking to see what is there, not looking to confirm what we think we already know to be. This quality of not-knowing, of simply looking and seeing what arises is what we will bring to practice today.
- Brief instructor introductions.
    - How and why you came to practice and what it has done for you. Emphasize role in teaching.

10 min. Meet participants:

- Expectations? Hopes? What do you know about mindfulness? Hesitations or fears?

5 min. Share Ojai council rules - agreements in how to be together during this time.

- Speak from own experience. Listen deeply (no side conversations, cell phone use, etc.). Confidentiality, emphasize that this class is for them...just experience it.

25 min. Holding breath in belly (Vase) breathing & Body scan

- Emphasize the "coming into the body and out of the head" aspect of vase breathing. Note that should not be forced or strained. Hold at own pace.
- **Body scan -** emphasize curiosity of physical sensations. Normalcy of distracted mind. Mindfulness as the moment of recognizing the mind has wandered and inviting it back (remembering).

10 min. Check-in

5 min. Introduce pause practice

5 min. Group share on pause, practicing pause before speaking.

- Notice whether communicating in this way is different

10 min. Overview of practice and the practice during the week.

- Difference between formal and informal.
- Filling out practice logs.
- How to access practice tracks, etc.

Practice this week:

- Vase breath and formal body scan everyday (~ 20 min)
- At least one 6-point, informal body scan each day (~ 2 min)
- Pause at least once a day

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