Research Article

Teachers’ Resilience and Burnout in the United Arab Emirates: Teaching Through the COVID-19 Pandemic

Christopher Bryan¹ and Antje von Suchodoletz²

¹Department of Psychology, American University of Sharjah, United Arab Emirates
²Department of Psychology, New York University Abu Dhabi, Abu Dhabi, United Arab Emirates

ORCID
Christopher Bryan: https://orcid.org/0000-0001-7515-4862
Antje von Suchodoletz: https://orcid.org/0000-0002-4261-9317

Abstract

Many factors contributed to resilience and burnout among teachers during the COVID-19 pandemic, as educators were forced to respond quickly to unexpected and unmanageable job demands and stressors. This research investigates the factors perceived by expatriate teachers in the United Arab Emirates (UAE) that influenced resilience and burnout one year from the start of the pandemic. The study observed \( n = 529 \) expatriate teachers spread across three distinct waves of data collection as schools transitioned from online to in-person education delivery in the UAE. A series of structural equation model analyses examined the relationships between latent variables of supportive and challenge factors with outcomes of resilience and burnout. Results highlight that supportive organizational environments were directly associated with higher resilience and indirectly with lower burnout scores across all three samples. Together, the results suggest that characteristics of the organizational environment should be viewed as key influencing factors in the development of teachers’ resilience. Thus, resilience interventions should go beyond individualistic approaches and include organizational factors. Additionally, education policies should prioritize creating work environments where emotional resources are available; leadership is perceived as supportive, fair, and accepting; and teachers are proud to be employed.

الملخص

ساهمت العديد من العوامل في المرونة والإرهاق بين المعلمين خلال جائحة كوفيد-19، حيث أثير المعلمين على الاستجابة بسرعة لتحديات العمل ومنظمات العمل غير المتوقعة وغير القابلة للإدارة. يبحث هذا البحث في العوامل التي رأى المعلمون الوافدون في الإمارات العربية المتحدة والتي أثرت على المرونة والإرهاق بعد عام واحد من بداية الوباء. لاحظت الدراسة أن عدد المعلمين الوافدين = 529 ينتمون إلى ثلاث موجات متتالية من جمع البيانات مع انتقال المدارس من قمّة التعليم عبر الإنترنت إلى قمّة التعليم الشخصي في الإمارات العربية المتحدة. درست سلسلة من تحليلات النماذج الهيكلية اللاسلكية بين المتغيرات العاملة للظاهرة وحول النتائج مع تناول المرونة والإرهاق. نتائج التحليل الضمني على أن البنية التنظيمية الإدائية كانت مسئولة بشكل مباشر برورة أعلى وشكل غير مباشر مع التأثير في درجات الإرهاق في جميع العوامل الثلاث. تشير النتائج المهمة إلى أن يجب النظر إلى تحصيل البنية التنظيمية على أنها عامل مؤثر رئيسي في تطور مرونة المعلمين. وبالتالي يجب أن يتجاوز تدخلات المرونة الهيكلية الفردية وكامل العوامل التنظيمية. بالإضافة إلى ذلك يجب أن تعكس السياسات التعليمية الأولوية قلص بيئة عمل تتوفر فيها المواد العاطفية، ينظر إلى القيادة في أنها داعمة وعائدة ولمبهرة، والمعلمين تحتويون توظيفهم.

Page 23
1. Introduction

The COVID-19 pandemic prompted debates in many countries about the preparedness of schools and teachers for online instruction. Teachers needed to learn new skills for remote education – such as online course design, communication, time management, and platform familiarity (Hilger et al., 2021). Recent data suggest that educational disruptions during the COVID-19 pandemic were so severe that many teachers believe that educational practices have been forever altered, and that more online teaching and learning will be integrated at all grade levels even when the pandemic ends (School Education Gateway, 2020). Given these perceptions, it’s important to understand how teachers, as the primary facilitators of education, adjusted to remote learning. An exploration of specific challenges faced, especially threats to teachers’ mental health, as well as protective and supportive factors, will help prepare teachers and educational organizations to develop resilience to similar stressors in the future.

Beltman (2015) proposes that teacher resilience is best understood as a dynamic process through which individual and contextual factors interact during one’s adaptation to adversity, and this in turn affects positive outcomes. This malleable process of resilience acknowledges that the continuous impact of risk (challenges) and asset (supportive factors) can either impair or promote resilience (Masten & Reed, 2002). Past research on teacher resilience, however, has focused predominantly on idiosyncratic factors unrelated to environmental conditions of teachers’ work and lives (Gu & Day, 2013). The COVID-19 pandemic shifted attention on how teachers persevere and “stay afloat” amid external adversity.

To combat the spread of the virus, schools were closed in many countries and teachers were expected to display creativity, stress management, and tolerance for ambiguity while also delivering education online and connecting with students virtually (Anderson et al., 2021). This sudden increase in job expectations may have added new challenge factors affecting teachers’ resilience, which, in turn, may have decreased teachers’ abilities to regulate their emotions in an increasingly demanding environment as the pandemic continued (Sokal et al., 2021).

Emotionally demanding or stressful situations are common in the teaching profession, but long-term exposure to stressful situations can lead to teacher burnout (Gillet et al., 2015).
Further, burnout is highly prevalent in teachers and has been characterized as a chronic state of resource depletion (Schaufelli et al., 2009). Since the onset of the COVID-19 pandemic, a fast-growing body of research has shown an unprecedented rise in perceived stress and burnout in teachers worldwide (MacIntyre et al., 2020; Sokal et al., 2020). Teachers who live and work abroad (expatriate teachers) were particularly vulnerable in the wake of the pandemic. Dealing with increased work demands and facing higher job insecurity while away from family added to teacher stress (Erfurth & Ridge, 2020). Specifically, in the United Arab Emirates (UAE), most expatriate teachers are employed in private school settings, where COVID-19 had budgetary implications (Masudi, 2020). To justify tuition fees, teachers were under pressure by school administrators to maintain the highest standards of online and hybrid learning (mix of online and in-person education) (Dawson & Heylin, 2022).

The present study focuses on the UAE, a Gulf Cooperation Council (GCC) country where expatriate teachers make up most of the educator workforce (Ridge et al., 2015). The UAE has not been immune to the disruptions caused by the COVID-19 pandemic. Nationwide restrictions began in March 2020, with curfews imposed together with the closure of businesses, places of worship, day care centers, and schools.

Initially, the Ministry of Education (MOE) announced a four-week closure of all public and private schools and higher education institutions across the UAE starting on March 8, 2020. However, it wasn't until September 2020 that some schools reopened, with periodic closures being implemented several times as infection rates climbed. This left teachers juggling between fully remote instruction and a hybrid mix of online and in-person teaching, as per MOE guidelines. These educational disruptions created delays in learning, particularly with younger students, where gaps between post-COVID abilities and pre-COVID age-level norms have been highlighted (Hammerstein et al., 2021).

Teachers have been called upon to close these gaps, and it’s unclear how educators have responded to this added pressure (Sokal et al., 2021). Although the educational impact of COVID-19 may be slowing, the effect of the pandemic on the coping abilities of expatriate teachers in the UAE remains unstudied. The present research addresses this shortcoming and examines both challenge and supportive environmental factors contributing to expatriate teachers’ resilience and burnout as they returned to full-time in-person education in the UAE.
2. Literature Review

2.1. Expatriate teachers in the United Arab Emirates

There are few places in the world with more diverse schools than the UAE (OECD, 2019). Teachers working in the UAE school system must be prepared to adapt their teaching to the cultural, religious, and historical understanding of students from a wide range of backgrounds and languages. Furthermore, a shortage in the supply of Emirati teachers has led schools in the UAE to engage in massive recruitment efforts to hire teachers from around the world (McKinnon et al., 2013; Yang et al., 2018). As a result, the UAE has surpassed Australia, Canada, and Singapore as the most popular destination for expatriate educators (Maceda, 2015).

The choice factors that influence expatriates to become a teacher in the UAE are both intrinsic (making a social contribution and shaping the future of children and youth) and extrinsic (social status and salary) (Sharif et al., 2016). While the recruitment of expatriate teachers with the necessary skills and expertise is crucial to filling the demand–supply gap in the UAE, it’s equally important to address issues of retention and quality (Barza, 2017; Carson, 2013; Sharif et al., 2016). Despite high-quality teacher education and training in their home countries, many expatriate teachers struggle with adapting their teaching skills to meet the needs of students from different cultures (Barza, 2017). Therefore, understanding expatriate teachers and their associated job demands during a period of increased adversity may offer insights into teacher attrition in the region.

During the COVID-19 pandemic, expatriate teachers in the UAE were at a higher risk for burnout for several reasons. First, expatriate teachers are contracted and must leave the country when their employment contract expires (Yang et al., 2018). The economic impact of the COVID-19 pandemic was felt globally (Nicola et al., 2020), and uncertainty about contract renewal, combined with potential income loss, posed substantial stress for expatriate teachers. Second, expatriate teachers are often away from their families and social networks in their home country and are at heightened risk for social isolation. Social distancing mandates combined with school closures and a lack of in-person contact with colleagues may have contributed to expatriate teachers’ feelings of loneliness during the pandemic. Supportive social and interpersonal relationships play an important protective role for occupational well-being; if social and organizational support is lacking, expatriate teachers may be more vulnerable to burnout or attrition (Yang et al., 2018).
Finally, the COVID-19 pandemic highlighted the challenges associated with the “digital divide” in education systems. Funding disparities across rural and urban areas, for example, have created inequitable access to technology, with schools in urban areas often being better equipped (Kormos, 2018). The shift to online learning and its success depends on the availability of technological resources, high-quality implementation, and consistency of technology integration. Thus, it’s possible that expatriate teachers in lower-resourced schools or rural areas experienced more challenges in providing remote instruction to their students. Surveying expatriate teachers in the UAE during the COVID-19 pandemic can offer valuable insights for organizations and help them to retain teachers.

2.2. Teacher stress and burnout during the COVID-19 pandemic

Teacher stress is broadly defined as “the experience by a teacher of unpleasant, negative emotions, such as anger, anxiety, tension, frustration, or depression, resulting from some aspect of their work” (Kyriacou, 2001, p. 28). Whether an individual views a stressor as a threat or challenge plays a role in predicting changes in overall burnout trajectories (McCarthy et al., 2016). Furthermore, the availability of immediate resources that place an individual in a psychologically advantageous position may facilitate the reappraisal of certain stressors as a challenge rather than a threat (Hobfoll, 2001).

During the COVID-19 pandemic, news headlines about high levels of teacher stress and burnout were substantiated by research that relates burnout to changes in teachers’ workload, the use of technology for remote teaching, and concerns about their own work–life balance (Sokal et al., 2020). For expatriate teachers, stress may have been heightened during the pandemic because of the additional challenge of adapting new modes of instruction to meet the needs of students from cultures different than their own (Barza, 2017; Ng et al., 2021).

Work-related burnout can be viewed as a psychological reaction to a chronically demanding work environment, characterized by physical, emotional, and mental exhaustion and fatigue (Kristensen et al., 2005). The World Health Organization (2019) classifies burnout as an officially recognized syndrome due to unmanaged, chronic workplace stress. Work-related burnout has been especially prevalent in so called “helping professions,” which includes teachers (Montgomery & Rupp, 2005). The Job Demands-Resources (JD-R) theory (Demerouti et al., 2001) is one of the most common and widely published theoretical frameworks to explain employee workplace stress and
associations with their mental health (such as burnout) and performance. The central premise of the theory is defining workplace conditions as either “job demands” or “job resources” that in turn impact employees’ motivation and engagement (Demerouti et al., 2001; Khan et al., 2014). Research during the COVID-19 pandemic linked job resources and demands with leadership and teacher burnout, but additional research is needed to confirm these trends (Sokal et al., 2021).

2.3. Teacher resilience

Studies have highlighted that the construct of resilience is often marred by myths, misunderstandings, and colloquialisms (Bryan et al., 2019; Gu & Day, 2013). Resilience in teachers is often thought to embody a preferable characteristic or personality trait of successful adaptation to adversity, which is both an incomplete and inadequate conceptualization of resilience in the teaching context (Drew & Sosnowski, 2019).

Instead, resilience in teachers should be considered a dynamic process to maintain high functioning during stressors or bounce-back following difficulties; this is accomplished with both individual and environmental factors (Bryan et al., 2019; Mansfield et al., 2016). Although resilience can be viewed as a cognitive–affective construct, it has been shown to be influenced by a wide range of environmental factors such as social, cultural, organizational, political, economic, occupational, and/or technological resources (Fletcher & Sarkar, 2013). Therefore, facilitative resources related to resilience are thought to develop over time because of ongoing context-specific experiences (Fredrickson & Branigan, 2005). As such, resilience shouldn’t be viewed as a fixed trait or as being solely dependent on individual resources. Rather, resilience is shaped by an individual’s ongoing interactions with their environment (Masten & Reed, 2002).

As working conditions continue to evolve due to ongoing disruptions of the COVID-19 pandemic, the capacity for resilience may change. Fletcher and Sarkar (2016) outlined a challenge–support matrix for developing resilience to explain the interplay between the individual and the immediate environment in which they operate. Based on this matrix, a facilitative environment, one with high levels of support during stressors, fosters resilience.

However, in workplaces where challenges are high but environmental support low, an individual might experience compromises to their well-being that could result in a higher risk of burnout (as opposed to too much support but not enough challenge, which will produce an overly comfortable environment). Finally, a stagnant environment occurs...
when challenge and support are both low. Without any challenge, neither resilience nor burnout is affected.

In the case of teacher resilience during the pandemic, we expect that the organizational environment will play a key role in resilience maintenance, disruption, or development. The outcome will depend on the interaction of key risk and protective factors that may either add support or challenge as teachers transition between remote and in-person instruction. Data collected during the COVID-19 pandemic will inform evidence-based approaches of how organizational systems may support teachers not only to buffer the immediate effects of challenging conditions, but also to develop and maintain resilience in the future.

2.4. The present study

The closure of schools around the world in Spring 2020 in response to the COVID-19 pandemic was unprecedented, and left school systems and governments questioning how to respond so that education could continue uninterrupted (Erfuth & Ridge, 2020). The transition from in-person education to distance learning also threatened teachers’ well-being and became a potential chronic stressor given the duration and intensity of the pandemic. As schools return to in-person instruction, it’s important to understand the primary challenges and supportive factors experienced by teachers during the pandemic.

The present study (see Figure 1 for conceptual framework) aims to investigate challenge factors (demands and risks that may either increase or decrease resilience) and support factors (resources and protective factors that may increase resilience) that lead to burnout in expatriate teachers. This work builds on the assumptions of the JD-R framework to better understand how expatriate teachers’ protective factors at work (job resources) and risk factors (job demands) might affect resilience and burnout outcomes. We would expect that as work demands increased due to disrupted education under COVID-19 restrictions, negative outcomes like stress also increased. Further, we hypothesize that when teachers returned to in-person education after restrictions were lifted, a decrease in negative stress outcomes would be observed.

More specifically, the following research questions are addressed:

RQ1: Did perceived challenges decrease as schools transitioned back to in-person instruction, producing lower burnout and higher resilience over time?
RQ2: Did higher perceived environmental support relate to reduced burnout and higher resilience at each time point as the pandemic regressed?

RQ3: Did higher perceived challenges relate to an increase or decrease in resilience at each time point?

This research aims to contribute knowledge to the complex topic of workplace resilience, beyond idiosyncratic factors. By examining elements of resilience – environmental support and challenge factors – we can better understand what elements are key in facilitating and sustaining teachers’ resilience during a period of major adversity. Results from this study may lead to a better understanding of resilience globally in education (Beltman et al., 2011), and may inform policy and practice for creating facilitative teaching environments that better support expatriate teachers as they return to full-time in-person education.
3. Methodology

3.1. Samples

The target study population was expatriate teachers across the UAE. A convenient sampling methodology was applied, where expatriate teachers were asked to participate in an online survey over multiple time points. While we aimed to follow up with as many teachers as possible across the study’s three time points, not every teacher completed the three surveys. To account for attrition, we recruited new participants at each time point.

This approach kept the sample size relatively stable but resulted in different samples of teachers participating at each time point. In total, 722 link clicks to the online survey were recorded (W1 = 267; W2 = 255; and W3 = 200). Of these responses, 193 provided only demographics variables (<20% of data collected) and were removed. The final sample consisted of 529 expatriate teachers in three samples (Sample W1 = 202; Sample W2 = 173, and Sample W3 = 154). Participants were fluent in English (a requirement of expatriate teachers in the UAE). Expatriate teachers originated from 38 countries. The full breakdown of demographic variables within each time point and sample is presented in Table 1.

A series of ANOVAs were run to compare the samples. Several important similarities were shared across the samples, including gender (74–83% female), experience teaching in the UAE (on average, 9 years), school location (62%-75% urban), and marital status (63–72% married). As expected, the samples were diverse with regards to vaccination status (82% in June 2021 and 98% in May 2022) and in-person education delivery (12% in June 2021; 70% in November 2021; and 84% in May 2022). Although the teachers’ nationalities varied across samples, the top two nationalities (India and the United Kingdom) were the same at each wave.

3.2. Procedure

The study was approved by the researchers’ university institutional review board and conducted in accordance with human subject guidelines. Further approvals were obtained from required local authorities. Once approvals were received initial recruitment was conducted through expatriate teacher networks in the UAE. A second sampling method used paid placements on social media platforms (Facebook and Twitter) and Google advertisements. The paid ads and network email distributions
Table 1

Demographic information.

<table>
<thead>
<tr>
<th></th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
<th>ANOVA F (P-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>June ’21 (n = 202)</td>
<td>Nov ’21 (n = 173)</td>
<td>May ’22 (n = 154)</td>
<td></td>
</tr>
<tr>
<td><strong>Demographic variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender: female</td>
<td>0.75</td>
<td>0.83</td>
<td>0.74</td>
<td>0.51 (0.60)</td>
</tr>
<tr>
<td>Marital status: married</td>
<td>0.72</td>
<td>0.63</td>
<td>0.69</td>
<td>1.12 (0.35)</td>
</tr>
<tr>
<td>Living with family</td>
<td>0.67</td>
<td>0.6</td>
<td>0.71</td>
<td>0.59 (0.44)</td>
</tr>
<tr>
<td>Years in the UAE</td>
<td>9.18</td>
<td>9.39</td>
<td>9.45</td>
<td>0.88 (0.32)</td>
</tr>
<tr>
<td>Received vaccination**</td>
<td>0.87</td>
<td>0.98</td>
<td>0.98</td>
<td>12.86 (0.00)</td>
</tr>
<tr>
<td><strong>Teaching-related variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Years of experience in UAE*</td>
<td>7.71</td>
<td>6.27</td>
<td>6.25</td>
<td>4.83 (0.04)</td>
</tr>
<tr>
<td>Teaching assistant availability**</td>
<td>0.19</td>
<td>0.29</td>
<td>0.36</td>
<td>11.23 (0.00)</td>
</tr>
<tr>
<td>Urban school (versus rural)</td>
<td>0.73</td>
<td>0.71</td>
<td>0.62</td>
<td>1.71 (0.19)</td>
</tr>
<tr>
<td>Courses taken in 2019–2020**</td>
<td>4.19</td>
<td>5.14</td>
<td>7.8</td>
<td>22.31 (0.00)</td>
</tr>
<tr>
<td>Courses taken in 2020–2021**</td>
<td>4.91</td>
<td>5.39</td>
<td>8.6</td>
<td>2769 (0.00)</td>
</tr>
<tr>
<td><strong>Education delivery type</strong></td>
<td></td>
<td></td>
<td></td>
<td>85.12 (0.00)</td>
</tr>
<tr>
<td>Hybrid instruction</td>
<td>43%</td>
<td>29%</td>
<td>23%</td>
<td></td>
</tr>
<tr>
<td>Full in-person instruction</td>
<td>12%</td>
<td>71%</td>
<td>74%</td>
<td></td>
</tr>
<tr>
<td>Full remote (online) instruction</td>
<td>45%</td>
<td>1%</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td><strong>Scale Variables</strong></td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td></td>
</tr>
<tr>
<td>Outcome variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resilience</td>
<td>3.69 (0.72)</td>
<td>3.76 (0.61)</td>
<td>3.84 (0.62)</td>
<td>3.76 (0.05)</td>
</tr>
<tr>
<td>Burnout Scale*</td>
<td>3.42 (1.32)</td>
<td>3.78 (1.21)</td>
<td>3.63 (1.23)</td>
<td>7.13 (0.01)</td>
</tr>
<tr>
<td>Predictors</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Challenge factors (Challenge latent factor)

<table>
<thead>
<tr>
<th></th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
<th>ANOVA F (P-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C19 fear</td>
<td>44.9 (20.39)</td>
<td>46.15 (17.33)</td>
<td>50.35 (18.34)</td>
<td>1.32 (0.29)</td>
</tr>
<tr>
<td>C19 distress**</td>
<td>1.85 (0.59)</td>
<td>1.88 (0.54)</td>
<td>2.22 (0.69)</td>
<td>18.97 (0.00)</td>
</tr>
<tr>
<td>Perceived social isolation</td>
<td>2.11 (1.09)</td>
<td>2.25 (1.01)</td>
<td>2.10 (1.12)</td>
<td>0.49 (0.51)</td>
</tr>
<tr>
<td>Pressure climate*</td>
<td>4.13 (1.69)</td>
<td>4.86 (1.53)</td>
<td>4.51 (1.51)</td>
<td>7.10 (0.01)</td>
</tr>
<tr>
<td>Daily Life Stress Scale**</td>
<td>1.82 (0.46)</td>
<td>2.02 (0.48)</td>
<td>2.07 (0.65)</td>
<td>30.82 (0.00)</td>
</tr>
<tr>
<td>Cognitive demands*</td>
<td>3.37 (0.96)</td>
<td>3.69 (0.83)</td>
<td>3.65 (0.87)</td>
<td>5.80 (0.02)</td>
</tr>
<tr>
<td>Emotional demands*</td>
<td>2.93 (0.98)</td>
<td>3.47 (0.86)</td>
<td>3.17 (0.87)</td>
<td>7.56 (0.01)</td>
</tr>
</tbody>
</table>

Support factors (Support latent factor)

<table>
<thead>
<tr>
<th></th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
<th>ANOVA F (P-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organizational pride**</td>
<td>3.55 (0.63)</td>
<td>3.37 (0.63)</td>
<td>3.28 (0.73)</td>
<td>10.98 (0.00)</td>
</tr>
<tr>
<td>Cognitive resources*</td>
<td>3.34 (0.84)</td>
<td>3.72 (0.63)</td>
<td>3.33 (0.79)</td>
<td>6.34 (0.02)</td>
</tr>
<tr>
<td>Emotional resources*</td>
<td>2.88 (0.91)</td>
<td>3.4 (0.79)</td>
<td>3.27 (0.88)</td>
<td>4.76 (0.04)</td>
</tr>
<tr>
<td>Teacher self-efficacy</td>
<td>7.58 (1.23)</td>
<td>7.63 (1.00)</td>
<td>7.41 (1.14)</td>
<td>0.03 (0.87)</td>
</tr>
<tr>
<td>Supportive climate</td>
<td>5.19 (1.46)</td>
<td>4.72 (1.47)</td>
<td>5.06 (1.43)</td>
<td>0.08 (0.78)</td>
</tr>
<tr>
<td>Intrinsic recognition</td>
<td>4.92 (1.45)</td>
<td>4.55 (1.39)</td>
<td>4.64 (1.54)</td>
<td>0.34 (0.56)</td>
</tr>
</tbody>
</table>
Table 1

(Continued)

<table>
<thead>
<tr>
<th></th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
<th>ANOVA F (P-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>June ’21 (n = 202)</td>
<td>Nov ’21 (n = 173)</td>
<td>May ’22 (n = 154)</td>
<td></td>
</tr>
<tr>
<td>Cohesive climate</td>
<td>4.92 (1.22)</td>
<td>4.95 (1.10)</td>
<td>5.10 (0.98)</td>
<td>2.94 (0.09)</td>
</tr>
<tr>
<td>Impartiality climate</td>
<td>4.49 (1.42)</td>
<td>4.19 (1.35)</td>
<td>4.50 (1.60)</td>
<td>0.06 (0.80)</td>
</tr>
</tbody>
</table>

Note. Sample breakdown per country was 34.5% from India, 18.0% from the United Kingdom, 6.6% from the Republic of Ireland, 5.9% from the Philippines, 5.0% from South Africa, 4.4% from Egypt, 3.8% from the United States, 3.4% from Pakistan, 2.5% from Germany, 2.2% from Syria, 2.1% from Jordan, and 11.6% from 27 other countries. *P < 0.05 significance test from one-way ANOVA; **P < 0.01 significance test from one-way ANOVA.

included a link to an online survey (using Qualtrics), which requested informed consent prior to completing the questionnaire. Participants were offered the chance to win a 500 AED voucher upon full completion of the survey. All participants were sent follow-up reminders through the Qualtrics platform via emails for the second and third measurements. The online survey remained open for a period of four weeks at each data collection wave. This procedure for recruitment was carried out for each wave of data collection, which resulted in new participants at each wave. Even though all participants were contacted again for follow-up surveys, only \( n = 30 \) participants answered the survey at all three time points, and \( n = 55 \) participants answered at both wave 2 and wave 3 time points.

The data collection time points corresponded to the following teaching phases of the COVID-19 pandemic:

1. Remote education (June 2021): Most expatriate teachers in the UAE were teaching either remotely or using a mix (hybrid) of online and in-person instruction.

2. Initial return (November 2021): After more than one year of disrupted education, the MOE announced plans for a partial return to in-person teaching.

3. Full transition (May 2022): Most teachers had fully transitioned back to in-person classroom instruction.

Given that most teachers in the sample didn’t participate across all periods, we compared different cohorts of teachers from the same population at each time point. Therefore, our main analytical model didn’t include all three time points but instead focused on each point separately.
3.3. Measures

The first part of the survey collected demographic information, work experience, location of employment in the UAE, and education delivery. The second part asked about teachers’ organizational and individual challenges and supportive factors, as well as COVID-19-related experiences. The same survey questions were used at all time points.

3.4. Outcome factors

3.4.1. Burnout

Emotional exhaustion was measured using the emotional exhaustion subscale of the Maslach Burnout Inventory, Educators Survey (Skaalvik & Skaalvik, 2011). The response scale ranged from (1) Completely disagree to (6) Completely agree. Item examples included: “Working with people is a strain.” The short six-item scale has been shown to have good psychometric properties within a teacher sample (α = 0.88) (Skaalvik & Skaalvik, 2010). The scale reflected acceptable internal validity in the present study (α = 0.89–0.92).

3.4.2. Resilience

The 10-item Connor–Davidson Resilience Scale (CD-RISC-10) (Campbell-Sills & Stein, 2007) was used to measure resilience. The response scale ranged from (0) Never to (4) Almost always. Item examples included: “I can deal with whatever comes my way.” Previous research showed good internal consistency of the scale (α = 0.85) (Campbell-Sills & Stein, 2007). The scale reflected acceptable internal validity in the present study (α = 0.86–0.88).

3.5. Challenge factors

3.5.1. Cognitive and emotional job demands

Job demands were measured with 11 items from the Demand-Induced Strain Compensation (DISC 2.0) questionnaire (De Jonge et al., 2007). Item examples included: “Employee X will have to do a lot of emotionally draining work.” (De Jonge et al., 2007). The response scale ranged from (1) Never or very rarely true to (5) Very often or always true.
The questionnaire has been validated and applied in different working environments, including schools (α = 0.75–0.80) (Näring et al., 2012) and reflected acceptable internal validity in the present study (α = 0.77–0.87).

3.5.2. Pressure climate

The Organizational Climate Scale (OCS) was used to determine perception of teachers’ pressure climate at work. OCS was first developed by Koys and DeCotiis (1991) and was modified by Montes et al. (2004) as a 15-item scale and has been adapted for application with teachers (Balkar, 2015). A three-item pressure climate subscale was used with a response scale ranging from (1) Totally disagree to (7) Totally agree. Item examples included: “I have too much work and too little time to do it in.” The subscale has good internal reliability (α = 0.73) (Balkar, 2015) and reflected acceptable internal validity in the present study (α = 0.78–0.81).

3.5.3. Perceived social support and social isolation

Perceived social isolation was measured with three items from the UCLA Loneliness Scale (Russell, 1996). The response scale ranged from (1) None to (5) A lot. Item examples included: “How many people are so close to you that you can count on them if you have great personal problems?” The scale has strong internal consistency (α = 0.89–0.94) and test–retest reliability over a one-year period (r = 0.73). The scale reflected acceptable internal validity in the present study (α = 0.93–0.94).

3.5.4. Daily life stress

Daily stress was measured using items from the Daily Life Stress Scale UAE (DLSS-UAE) (Thomas et al., 2016). This scale was based on the daily hassles and uplifts scale by Delongis et al. (1988) but applied to regular stressors within the UAE context using a total of 34 items. The response scale ranged from (0) Not at all to (3) Severely. Item examples included: “Inconsiderate and/or irresponsible drivers.” This scale has good internal reliability (α = 0.90) (Thomas et al., 2016). The scale reflected acceptable internal validity in the present study (α = 0.86–0.92).
3.6. Support factors

3.6.1. Cognitive and emotional job resources

Job resources were measured with 11 items from the DISC 2.0 32-item questionnaire (De Jonge et al., 2007, see above). The response scale ranged from (1) Never or very rarely true to (5) Very often or always true. Item examples included: “Employee X will get emotional support from others (clients, colleagues, or supervisors) when a threatening situation at work occurs.” The scale reflected acceptable internal validity in the present study ($\alpha = 0.79–0.82$).

3.6.2. Self-efficacy

Teacher self-efficacy beliefs were measured using the Teachers’ Sense of Efficacy 12-item Short Form scale (Tschannen-Moran & Hoy, 2001). The response scale ranged from (0) Nothing to (9) A great deal. Item examples included: “How well can you implement alternative strategies in your classroom?” Good psychometric reliability has been demonstrated in teacher samples ($\alpha = 0.90$) (Tschannen-Moran & Hoy, 2001). The scale reflected acceptable internal validity in the present study ($\alpha = 0.90–0.93$).

3.6.3. School climate and support

Four subscales of the OCS (Balkar, 2015, see above) were used to determine perceptions of (1) organizational supportive climate (four items), (2) cohesive climate (four items), (3) recognition climate (two items) and (4) impartial climate (two items). Item examples included: “My principal backs me up and lets me learn from my mistakes” (support); “People pitch in to help each other out” (cohesive); “My principal is quick to recognize good performance” (recognition); and “If my principal terminates someone, the person probably deserved it” (impartial). Work Climate factors of supportive climate and intrinsic recognition were mostly related to perceptions of principal leadership. Good internal reliability has been shown across each subscale: support ($\alpha = 0.91$), fairness ($\alpha = 0.82$), cohesion ($\alpha = 0.88$), and recognition ($\alpha = 0.81$) (Balkar, 2015). The scales reflected acceptable internal validity in the present study: support ($\alpha = 0.80$), fairness ($\alpha = 0.84$), cohesion ($\alpha = 0.90$), and recognition ($\alpha = 0.82$).
3.6.4. Organizational pride

Organizational pride was measured by using the three-item Attitudinal Organizational Pride Scale developed by Gouthier and Rhein (2011). The response scale ranged from (1) Definitely false to (4) Definitely true. Item examples included: “I feel proud to contribute to my company’s success.” Scale has strong internal consistency ($\alpha = 0.71$) (Mas-Machuca et al., 2016). The scale reflected acceptable internal validity in the present study ($\alpha = 0.75–0.80$).

3.7. COVID-19-related factors

3.7.1. COVID-19 fear

Attitudes about COVID-19 were measured using a scale adapted for use in the UAE by Nisa et al. (2021). Teachers rated four items on a scale of 0–100 to indicate the perceived likelihood of the scenario (0 = exceptionally unlikely to 100 = all but certain). Higher values reflected greater perceived COVID-19 fear. Teachers were asked this question, “How likely is it that the following will happen to you in the next few months?” and then presented with four items: (1) “Someone in your family will get infected with coronavirus;” (2) “Your family situation will get worse due to economic consequences of coronavirus;” (3) “The coronavirus situation will improve in the UAE;” and (4) “You will get infected with coronavirus.” The present research reflected acceptable internal validity ($\alpha = 0.74–0.77$).

3.7.2. COVID-19 distress

Participants were asked a single item question: “Overall, how much distress have you experienced due to the COVID-19 pandemic?” Participants could answer on a scale ranging from (1) No distress to (10) Extreme distress.

3.7.3. Additional variables

Additional information asked and used as control variables in the model included: school location (binary, 1: urban, or 0: rural), age (continuous), gender (binary, 1: male or 0: female), teaching assistant availability (binary, 1: yes or 0: no), teaching experience (in years), and UAE experience (in years).
3.8. Analytical strategy

3.8.1. Factor computation

The mean estimated factor scores were determined for all supportive and challenge factors (cognitive demands, cognitive resources (CR), emotional demands, emotional resources (ER), organizational pride, self-efficacy, supportive climate, cohesive climate, pressure climate, impartial climate, recognition climate, social isolation, daily life stress, and COVID-19 distress) using the “psych” package in Rstudio (version 1.4.1106). This included the “psych::factor.scores( )” function and used the “fa” method (“fa” incorporates five alternative algorithms: minres factor analysis, principal axis factor analysis, weighted least squares factor analysis, generalized least squares factor analysis, and maximum likelihood factor analysis). Due to sample size restrictions, mean factor models were chosen over latent factor models for secondary constructs (constructs that were factors of the support and challenge latent variables).

Next, latent variables were created for the primary constructs (resilience, burnout, supportive factors, challenge factors) using confirmatory factor analyses (CFA). When necessary, modifications were introduced to reach the best fitting model. Because constructs were measured at three time points, CFAs were explored within each wave sample and then tested for measurement invariance of the latent constructs of resilience and burnout across gender, time, and education delivery type.

3.9. Tests of measurement invariance

Three levels of measurement invariance were attempted: configural, metric, and scalar (results in Appendix Table B1 and B2). Change in comparative fit index across the configural, metric, and scalar models (>±0.01 considered the cut-off) was used to determine measurement invariance (Sass et al., 2014). Measurement invariance was achieved across time for both burnout (Metric ∆χ2 = 17.76, P = 0.22; Scalar ∆χ2 = 4.43, P = 0.99) and resilience (Metric ∆χ2 = 19.39, P = 0.25; Scalar ∆χ2 = 10.61, P = 0.83), and education delivery type for both burnout (Metric ∆χ2 = 23.52, P = 0.05; Scalar ∆χ2 = 18.40, P = 0.19) and resilience (Metric ∆χ2 = 11.22, P = 0.80; Scalar ∆χ2 = 14.12, P = 0.59). Measurement invariance was achieved for gender with the burnout scale (Metric ∆χ2 = 7.77, P = 0.35; Scalar ∆χ2 = 11.50, P = 0.12), however, it was not achieved for resilience (Metric ∆χ2 = 19.33, P = 0.01; Scalar ∆χ2 = 27.00, P = 0.00). Thus, meaningful comparisons
across gender could not be tested for resilience and gender was introduced as a control in our final model for resilience.

3.9.1. SEM approach

The first two research questions were explored using a series of three structural equation models (SEM) for each time point sample using latent variables. These analyses were completed cross-sectionally to explore relationships between challenge and support factors with both resilience and burnout at each time point. Each model contained the same variables of interest (resilience, burnout, challenge factors, and support factors) and control variable, UAE experience, teaching experience, and teaching assistant availability. For all cross-sectional models, tests of direct and indirect effects were run. To formally test the full mediation effect, an inferential test of the entire specific indirect effect in question was conducted. For each predictor-to-outcome effect, lavaan (Rosseel, 2012) was directed to first compute the direct effect and then the indirect effect (along with standard errors and significance tests). Standard errors were computed using the delta method (producing what is known as the Sobel test for indirect effects).

To answer the third research question, two separate SEM models using mean factor scores for all variable were performed: one with predictive and lagged effects across wave 1 and wave 2 ($n = 30$), and a second with predictive and lagged effects across wave 2 and wave 3 ($n = 55$). This was done to understand the lagged effects of challenge and support over time on resilience and burnout as the pandemic continued. All data preparation and analyses were performed using Rstudio.

4. Results

4.1. Preliminary analyses

Table 1 reports one-way ANOVA tests regarding differences across each variable in each cross-sectional sample. Some significant differences were found and are described below.
4.2. Outcome factors preliminary analysis

The levels of reported resilience in teachers who responded to the survey in June 2021 compared to those who responded in May 2022 showed no statistical differences ($F = 3.76, P > 0.05$). Burnout scores between samples were lowest in June 2021 ($S1 = 3.42$) and highest in the sample who completed the survey in November 2021 ($S2 = 3.78$). The final sample collected in May 2022 showed higher levels of burnout ($S3 = 3.63$) than the sample collected in June 2021 but lower levels than the sample collected in November 2021. ANOVA results showed statistically significant sample differences ($F = 7.13, P < 0.05$).

4.3. Challenge factors preliminary analysis

Distress due to COVID-19 showed statistically significant differences across the samples ($F = 18.97, P < 0.01$). Participants in June 2021 showed lower levels of distress compared to participants in November 2021. The highest levels were observed in participants in May 2022 ($S1 = 1.85, S2 = 1.88, S3 = 2.22$). Daily life stress showed similar significant differences across samples ($F = 30.82, P < 0.01; S1 = 1.82, S2 = 2.02, S3 = 2.07$). Finally, the mean sample scores of participants’ work climate pressure ($F = 7.10, P < 0.05; S1 = 4.13, S2 = 4.86, S3 = 4.51$), emotional demands ($F = 7.56 , P < 0.05; S1 = 2.93, S2 = 3.47, S3 = 3.17$), and cognitive demands ($F = 5.80 , P < 0.05; S1 = 3.37, S2 = 3.69, S3 = 3.65$) all reflected a significant difference, with highest levels observed in participants in November 2021.

4.4. Support factors preliminary analysis

Compared to participants in June 2021, teachers who completed the survey in November 2021 reported higher levels of work-related CR and ER, compared to participants in June 2021 and in May 2022. Differences were statistically significant (CR: $F = 6.34, P < 0.05; S1 = 3.33, S2 = 3.72, S3 = 3.22$; ER: $F = 4.74, P < 0.05; S1 = 2.88, S2 = 3.40, S3 = 3.27$). Supportive climate ($F = 0.08, P > 0.05; S1 = 5.19, S2 = 4.72, S3 = 5.06$) and intrinsic recognition climate ($F = 0.34, P > 0.05; S1 = 4.92, S2 = 4.55, S3 = 4.64$) did not show statistically significant differences across sample. Organizational pride showed a significant difference across samples ($F = 10.98, P < 0.01$). Participants’ levels of pride progressively reflected lower scores from June 2021 to May 2022 ($S1 = 3.55, S2 =$
3.37, S3 = 3.28). Finally, no statistically significant differences were observed between
participants at each time point for cohesive climate \( (F = 2.94, P > 0.05) \), impartiality
climate \( (F = 0.06, P > 0.05) \), and teacher self-efficacy \( (F = 0.03, P > 0.05) \).

4.5. Cross-sectional SEM models at each time point

4.5.1. Model fit

Results for the three models for each time point are shown in Table 2a. Overall, the
model fit was excellent for sample 1, collected in June 2021 (CFI: 0.99, RMSEA: 0.03,
SRMR: 0.05) and sample 2, collected in November 2021 (CFI: 0.96, RMSEA: 0.07, SRMR:
0.06). The model fit for the third sample (May 2022), however, was poor (CFI:0.89,
RMSEA: 0.11, SRMR: 0.11).

In the initial SEM model (see Figure A1), we examined the challenge and support
factors’ latent structure related to unique factor weights. The initial exploratory model
highlighted certain factors in the latent variable that reflected weaker factor weights.
To improve model fit, these aspects were removed. Iterative models were run and
the weakest related latent variable factors were removed until appropriate model fit
was achieved. Regarding the latent variable of challenge factors, the non-work-related
challenge factors of COVID-19 fear and distress, social isolation, and daily life stress
were removed for better model fit. Regarding the latent variable of supportive factors,
teacher self-efficacy, CR, and cohesive work climates were removed to achieve better
model fit. Iterative models were run concurrently for each of the samples to ensure
similar results were seen across each group until the best global model represented
the best fit across each sample. The final fitted cross-sectional model results can be
seen in Figure 2.

4.5.2. Association between resilience and burnout

The direct association between resilience and burnout was inconsistent across the three
samples. In Sample 1 (June 2021), higher levels of perceived resilience were related to
lower levels in perceived burnout \( (S1: \beta = -0.18, P < 0.01) \). In Sample 2 (November 2021)
and Sample 3 (May 2022), this relationship was in the same direction but not significant
\( (S2: \beta = -0.13, P = 0.05; S3: \beta = -0.07, P > 0.05) \).
RQ1: Challenge factors associated with resilience and burnout. Higher levels of perceived challenge factors were related to higher levels of perceived burnout across the three samples (standardized regression co-efficient range $\beta = 0.78–0.86$, $P < 0.01$). The total effect of all challenge factors on burnout was significant ($\beta = 0.77–0.84$, $P < 0.01$). However, regarding resilience, no significant associations with challenge factors were found ($\beta = –0.05$ to $–0.13$, $P > 0.05$).

RQ2: Supportive factors associated with resilience and burnout. Supportive factors did not directly relate to perceived levels in burnout ($\beta = –0.02$ to $–0.09$, $P > 0.05$). No total effect of supportive factors on burnout was found ($\beta = –0.09$ to $–0.05$, $P > 0.05$). However, supportive factors were related to burnout indirectly through resilience in the first sample (S1, June 2021; $\beta = –0.05$, $P < 0.05$). Further, supportive factors were significantly and positively related with resilience across all three samples (standardized regression co-efficient $\beta = 0.28–0.34$, $P < 0.01$).
Table 2

SEM model path regressions.

<table>
<thead>
<tr>
<th></th>
<th>Sample 1: June 2021</th>
<th></th>
<th>Sample 2: November 2021</th>
<th></th>
<th>Sample 3: May 2022</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate Std.</td>
<td>Std. Err.</td>
<td>P- value</td>
<td>Estimate Std.</td>
<td>Std. Err.</td>
<td>P- value</td>
</tr>
<tr>
<td>Challenger factors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chall.l = ~ CLIPR_fs</td>
<td>0.85</td>
<td>0.07</td>
<td>0.00</td>
<td>0.80</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Chall.l = ~ COGD_fs</td>
<td>0.52</td>
<td>0.07</td>
<td>0.00</td>
<td>0.55</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Chall.l = ~ EMTD_fs</td>
<td>0.64</td>
<td>0.07</td>
<td>0.00</td>
<td>0.64</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Supportive factors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supp.l = ~ CLISU_fs</td>
<td>0.89</td>
<td>0.06</td>
<td>0.00</td>
<td>0.94</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Supp.l = ~ CLIREC_fs</td>
<td>0.90</td>
<td>0.06</td>
<td>0.00</td>
<td>0.82</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Supp.l = ~ CLIIM_fs</td>
<td>0.73</td>
<td>0.05</td>
<td>0.00</td>
<td>0.72</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td>Supp.l = ~ OPR_fs</td>
<td>0.45</td>
<td>0.07</td>
<td>0.00</td>
<td>0.61</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Supp.l = ~ EMTR_fs</td>
<td>0.41</td>
<td>0.09</td>
<td>0.00</td>
<td>0.59</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Regressions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RES_fs ~ Chall.l</td>
<td>0.02</td>
<td>0.10</td>
<td>0.86</td>
<td>0.13</td>
<td>0.09</td>
<td>0.21</td>
</tr>
<tr>
<td>RES_fs ~ Supp.l</td>
<td>0.28</td>
<td>0.10</td>
<td>0.00</td>
<td>0.34</td>
<td>0.08</td>
<td>0.00</td>
</tr>
<tr>
<td>BURN_fs ~ Chall.l</td>
<td>0.78</td>
<td>0.08</td>
<td>0.00</td>
<td>0.86</td>
<td>0.08</td>
<td>0.00</td>
</tr>
<tr>
<td>BURN_fs ~ Supp.l</td>
<td>-0.09</td>
<td>0.07</td>
<td>0.23</td>
<td>-0.02</td>
<td>0.08</td>
<td>0.80</td>
</tr>
<tr>
<td>BURN_fs ~ RES_fs</td>
<td>-0.18</td>
<td>0.05</td>
<td>0.00</td>
<td>-0.13</td>
<td>0.07</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Model fit statistics: Wave1: χ²: 40; df: 36; CFI: 0.99; RMSEA: 0.03; SRMR: 0.05. Wave 2: χ²: 63; df: 39; CFI: 0.96; RMSEA: 0.07; SRMR: 0.06. Wave 3: χ²: 104; df: 43; CFI: 0.89; RMSEA: 0.11; SRMR: 0.11. Note. Gender, experience teaching in the UAE, and teaching assistant availability were all control for within the model. Abbreviations. CLIPR: pressure climate; CLISU: supportive climate; CLIREC = recognition climate; CLIIM: impartial climate; COGD: cognitive demands; EMTD: emotional demands; EMTR: emotional resources; OPR: organizational pride; Chall.l: challenge latent variable; Supp.l: support latent variable; BURN: burnout; RES: resilience; _fs: mean factor model.

4.6. Time-lagged SEM models in subsample

RQ3. Lagged effects of challenge factors over time. The time lagged model was broken into two separate analyses to answer the research question regarding lagged effects over time. The first model explored the n = 30 participants who completed the survey at time points 1 and 2 (see Appendix Figure A2). The second model explored the n = 55 participants who responded at time points 2 and 3 (see Appendix Figure A3). Similar patterns of relationships were observed as reflected by the cross-sectional analyses at each wave (see Table 3). Burnout was related to challenge factors at each time point (β = 0.68–0.94, P < 0.05) and resilience was related to supportive factors at each time point (β = 0.36–0.67, P < 0.05). However, contrary to the cross-sectional models reported above, there was no effect of resilience on burnout at each time point (β = –0.05 to –0.33, P > 0.05).
Table 3

Direct, indirect, and total effects on burnout.

<table>
<thead>
<tr>
<th>Supporting factors</th>
<th>Direct (β)</th>
<th>P-value</th>
<th>Indirect (β)</th>
<th>P-value</th>
<th>Total (β)</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1: June 2021</td>
<td>–0.09</td>
<td>0.23</td>
<td>–0.05</td>
<td>0.04</td>
<td>–0.09</td>
<td>0.22</td>
</tr>
<tr>
<td>Sample 2: Nov 2021</td>
<td>–0.02</td>
<td>0.80</td>
<td>–0.04</td>
<td>0.11</td>
<td>–0.04</td>
<td>0.63</td>
</tr>
<tr>
<td>Sample 3: May 2022</td>
<td>–0.09</td>
<td>0.32</td>
<td>–0.02</td>
<td>0.44</td>
<td>–0.09</td>
<td>0.34</td>
</tr>
</tbody>
</table>

Regarding the third research question, there was no significant lagged relationship between supportive factors ($β = –0.70$ to $–0.27, P > 0.05$) or challenge factors ($β = –0.04$ to $0.13, P > 0.05$) with resilience over time. The lagged effects of challenge factors on burnout showed a significant relationship, but only from wave 1 to wave 2 ($β = 0.47, P < 0.05$). Significant lagged relationships were found in both models, showing that higher resilience levels at previous time points predicted lower levels of burnout at subsequent time points (W1–W2: $β = –0.29, P < 0.05$; W2–W3: $–0.23, P < 0.05$).

5. Discussion

The COVID-19 pandemic introduced additional stressors for teachers. The purpose of this study was to analyze factors related to expatriate teachers’ burnout and resilience across three specific time points as teachers transitioned back to in-person education. Three samples of data collected during the pandemic highlight that a combination of work-related challenge factors was associated with teachers’ burnout at each time point. As schools returned to more traditional learning formats (full in-person education) two years after the start of the pandemic, expatriate teachers found themselves with increased demands trying to “catch-up” after an extended period of disrupted education.

In our results, the highest levels of challenge factors were found in the November 2021 sample (S2) and associated with the highest levels of burnout. This is consistent with previous studies. Dorn et al. (2020) pointed out that students were falling behind expected grade-level standards in the U.S. from the beginning of the pandemic, and that this in turn would present future challenges for educators and add to their already high levels of occupational demands.
Perhaps, after more than a year of remote education, teachers and students had grown accustomed to a “new normal.” Metrailer and Clark (2022) outlined that the behavioral changes and emotional stressors associated with the pandemic may have become habitual in nature and seen as normal daily occurrences rather than chronic stressors; this may have been reflected in our first sample as teachers adapted to remote education. However, in November 2021, conditions of higher perceived challenge factors alongside lower perceived support may have led to an unrelenting environment (see challenge–support matrix; Fletcher & Sarkar, 2016) that resulted in higher burnout scores. Results are in line with the Job Demands-Resources (JD-R) theory (Demerouti et al., 2001), where an increase of challenge factors led to a higher likelihood of teacher burnout.

These findings add to the results of similar research related to the effects of the COVID-19 pandemic, such as a study by Gillani et al. (2022) that found an increase in job demands and pressures that ultimately resulted in higher burnout and teacher attrition.

**Table 4**

*Time lagged SEM model regressions at each wave.*

<table>
<thead>
<tr>
<th>Relationship pathways</th>
<th>Wave 1 regressions (n = 30)</th>
<th>Wave 2 regressions (n = 30)</th>
<th>Wave 2 regressions (n = 55)</th>
<th>Wave 3 regressions (n = 55)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resilience ~ Support</td>
<td>0.45</td>
<td>0.23</td>
<td>0.04*</td>
<td>0.67</td>
</tr>
<tr>
<td>Resilience ~ Challenge</td>
<td>−0.65</td>
<td>0.21</td>
<td>0.00*</td>
<td>−0.04</td>
</tr>
<tr>
<td>Burnout ~ Support</td>
<td>0.03</td>
<td>0.19</td>
<td>0.84</td>
<td>−0.15</td>
</tr>
<tr>
<td>Burnout ~ Challenge</td>
<td>0.94</td>
<td>0.19</td>
<td>0.00*</td>
<td>0.64</td>
</tr>
<tr>
<td>Burnout ~ Resilience</td>
<td>0.09</td>
<td>0.17</td>
<td>0.50</td>
<td>0.33</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lagged relationship</th>
<th>Wave 1–2 lagged regressions (n = 30)</th>
<th>Wave 2–3 lagged regressions (n = 55)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Est. Std. (β)</td>
<td>Std. Err.</td>
<td>P-value</td>
</tr>
<tr>
<td>Resilience ~ Support</td>
<td>−0.70</td>
<td>0.53</td>
</tr>
<tr>
<td>Resilience ~ Challenge</td>
<td>−0.04</td>
<td>0.34</td>
</tr>
<tr>
<td>Burnout ~ Support</td>
<td>−0.24</td>
<td>0.38</td>
</tr>
<tr>
<td>Burnout ~ Challenge</td>
<td>0.47</td>
<td>0.26</td>
</tr>
<tr>
<td>Burnout ~ Resilience</td>
<td>−0.29</td>
<td>0.19</td>
</tr>
<tr>
<td>Support ~ Support</td>
<td>0.91</td>
<td>0.10</td>
</tr>
<tr>
<td>Challenge ~ Challenge</td>
<td>0.97</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Model fit statistics: Wave 1–2 model: χ²: 12.03; df: 6; CFI: 0.94; RMSEA: 0.24; SRMR: 0.05. Wave 2–3 model: χ²: 6.65; df: 7; CFI: 1.00; RMSEA: 0.00; SRMR: 0.04. Note: *P < 0.05.
teachers and policymakers regarding education globally. While adversities experienced during the COVID-19 pandemic cannot translate perfectly to future adverse situations, this research highlights the significant role the educational organization can have on developing teacher’s resilience. Future research can build upon these experiences and further investigate how supportive environmental factors can be successfully implemented into resilience intervention strategies moving forward.

Results from each sample did offer a consistent story: a combination of organizational factors might foster changes in resilience. The findings suggest that the expatriate teacher population in the UAE was generally quite resilient (with average scores of 3.76 out of a possible 4 across the whole sample). The challenge—support matrix posited by Fletcher and Sarkar (2016) suggests that it’s a combination of both challenge and support factors that will promote facilitative environments that support resilience development.

No associations between resilience and supportive factors were observed in the time lagged subsample. This suggests that previously perceived supportive factors (such as leadership support) may not have any impact on future resilience. To promote teachers’ resilience, supportive organizational environments must be concurrently present. Further to developing resilience, Rutter (2012) has theorized that challenging experiences might stimulate a subsequent “steeling” or strengthening effect in the face of adversity that might make future challenges more manageable over time. This may have been observed in the decrease of challenge factors and increase in resilience from the June 2021 sample (S1) to the May 2022 sample (S3), as all expatriate teachers in the region continued to adjust back to in-person education. However, these changes were small, and we cannot interpret results in a meaningful longitudinal manner as results are ultimately from three different samples, albeit from the same general population of expatriate teachers.

Overall, the results suggest that organizational environments played a substantial role in teachers’ resilience during the COVID-19 pandemic in the UAE. Despite the importance placed on teachers’ resilience for performance, resilience and wellbeing do not often feature on organizational agendas (Mansfield et al., 2016). In our study, it was evident that perceived levels of leadership support (organizational supportive climate, recognition climate, and impartial climate scales) was lower during the initial return to education in November 2021 (S2) as compared with samples in June 2021 (S1). If levels of challenge cannot be reduced, the presence of additional organizational supportive factors may offer a pathway for resilience development and indirectly reduce negative effects on burnout as reflected in our results. Therefore, organizations should
try to adapt and acknowledge the growing expectations of teachers to help alleviate work-related pressure as it arises – for instance, by acknowledging the difficulties upon returning to in-person education.

Although resilience-building interventions are often aimed solely at developing idiosyncratic resilience factors, there is often a tendency for neglecting the crucial role of the work environment (Fletcher & Sarkar, 2016). Research on resilience by Beltman et al. (2011) found that teachers’ resilience can be amplified by high-quality relationships within the school setting, social support, years of experience, self-efficacy, and further idiosyncratic characteristics.

Our results reflected the strongest resilience relationship with contextual factors, such as organizational climate, support of leadership, cohesiveness with peers, and workplace pride. The findings demonstrate how educational organizations can make a significant impact on teachers’ resilience by addressing these organizational factors. Moreover, deficient organizational support may also have some detrimental effects on teachers’ burnout. Failure of educational organizations to promote supportive environments may create an unrelenting environment, reducing resilience and affecting burnout indirectly. These findings suggest that organizations should intervene quickly during challenging times to develop perceptions of support that may act as a supportive asset for sustaining employee well-being and promoting resilience (Lilja et al., 2022).

Many practices can be implemented to promote supportive factors and positive organizational work culture. Organizational and leadership approaches should strive to build a safe work environment and encourage employees to feel treated fairly and to express opinions. The relationship between organization and staff can be strengthened through enhancement of teachers’ pride for their school. Our results reflect how teachers’ levels of organizational pride decreased at later time points compared with the initial time point. Similarly, Metrailer and Clark (2022) found a negative association between COVID-19-related stress with teachers’ perceptions of their school climate (as teachers’ stress increased, their perceptions of school climate tended to decrease). Other research has shown how the development of organizational pride can reduce potential burnout and turnover intentions (Kraemer & Gouthier, 2014) and may be a rich area for future research related to teacher resilience.
6. Limitations

As with most studies, this research has important limitations. First, this study used multiple samples across three time points of data collection. This approach was taken due to high levels of participant dropout between each wave. The high attrition rate limited the interpretation of change over time. Further research needs to be done on individual teacher trajectories of resilience related to individual and environmental factors. Future studies should also examine growth curve analyses to determine if facilitative environments categorized by high challenge and high support foster the development of resilience over time.

Second, the sole use of self-report survey measures to understand teachers’ perceived stress may have biased the results due to shared-method variance. In addition, teachers who were already experiencing higher job demands may have perceived the survey as an additional demand. This may have influenced the time spent responding to the survey as well as the subsequent participation at future waves of data collection. In addition, limitations due to the quantitative nature of the study to analyze abstract concepts such as resilience and burnout should be considered. As such, interpretations and generalizations of results must be done with caution, and we recommend future researchers and policymakers review additional qualitative sources of data in the same domain.

Third, the sample size limited the degrees of freedom that were available for analysis. This led to a reduction in model complexity in favor of model fit and the removal of any ill-fitting factors. For example, reduced model fit in the confirmatory factor model for both the challenge latent factor and supportive latent factor forced the loss of factors such as COVID-19 distress, which otherwise may have offered further insights into burnout and resilience.

7. Conclusion

This research focused on expatriate teachers’ resilience during the COVID-19 pandemic in the UAE and the relationship with burnout and associated factors (defined as either challenge or supportive factors). Using structural equation modelling methodology, three similar samples from a population of expatriate teachers were compared across three waves of data collection. Results suggest that the return to full in-person education reflected a challenging time when job demands and pressures were related to teacher
burnout. Further, results suggest that organizational supportive factors were related to higher levels of resilience. These results highlight the need for resilience interventions to focus on environmental influences at the organizational level beyond that of idiosyncratic approaches. Organizational-level approaches to developing teachers’ resilience may help improve the quality of teacher performance and well-being, and strengthen retention of expatriate teachers in the region.

Acknowledgements

None

Funding Information

This research was funded by the Sheikh Saud bin Saqr Al Qasimi Foundation for Policy Research.

Competing Interests

None.

Author Biography

Christopher Bryan’s research focusses on stress psychology with a focus of measuring resilience across education, sports and the workplace. His research is focused on defining and measuring resilience over time. His previous research projects include occupational resilience fluctuations in the workplace and defining resilience in the domains of work and sport. He is also interested in the physiological process of stress regulation and strength-based approached to resilience development. Currently, Christopher is an Assistant Professor of Psychology in American University of Sharjah.

Antje von Suchodoletz’s research is broadly focused on optimizing children’s development. In her research, she emphasizes the interactional and contextual nature of learning and development. Her current work focuses on helping schools develop their readiness to implement effective teaching strategies and to improve young children’s learning-related skills (including self-regulation and social competence). She is also interested in physiological and biological foundations of self-regulation and how classroom
processes and teacher-child-relationships relate to these processes. Antje is currently an Associate Professor of Psychology in NYU in Abu Dhabi.

References


