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Research paper

Discrete Modeling of Teacher Satisfaction and Well-Being Using TALIS Data: Latent Profiles, Gender Disparities, and Global Network Dynamics

Inna Reddy Edara [1], Fides del Castillo [2], Pei-Ching Chao [3], Clarence Darro del Castillo [4], Gregory S. Ching [5] *

[1] Graduate Institute of Educational Leadership & Development, Fu Jen Catholic University, New Taipei City, Taiwan
[2] College of Liberal Arts, De La Salle University, Manila, Philippines
[3] Center for Teacher Education, Fu Jen Catholic University, New Taipei City, Taiwan
[4] Lumina Foundation for Integral Human Development, Laguna, Philippines
[5] Graduate Institute of Educational Administration and Policy, National ChengChi University, Taipei City, Taiwan
**Corresponding author E-mail: gching@nccu.edu.tw*

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Abstract

This study applies discrete mathematical modeling to examine patterns of teacher satisfaction and well-being using data from the 2018 Teaching and Learning International Survey (TALIS), which included 261,426 teachers across 48 education systems. Latent profile analysis based on nine indicators: self-efficacy, job satisfaction (overall, profession, and environment), emotional well-being, workload stress, disciplinary climate, professional engagement, and collaboration; identified three distinct profiles: High (34.2%), Moderate (45.6%), and Low (20.2%). Welch's *t*-tests revealed significant gender disparities across most indicators, with female teachers reporting higher workload stress ($M = 9.30$ vs. 8.99, $p < .001$) and lower emotional well-being ($M = 9.43$ vs. 9.19, $p < .001$). Country-level ANOVA results indicated statistically significant differences across all nine measures ($p < .001$). Teachers in Finland, Japan, and South Korea reported higher levels of emotional well-being and professional satisfaction, while Brazil, Mexico, and the Czech Republic reported lower levels. A Gaussian graphical model was then constructed to explore interrelations among indicators. The network revealed strong partial correlations between job satisfaction and emotional well-being ($r = 0.24$), and between workload and emotional exhaustion ($r = –0.21$). Centrality analysis highlighted overall job satisfaction and emotional well-being as the most influential constructs, serving as key bridges and hubs of connectivity. These findings demonstrate the utility of combining latent profile classification with graph-theoretic modeling, providing a novel framework for analyzing large-scale teacher data through discrete mathematical procedures.

Keywords: *Latent Profile Analysis; Network Analysis; Discrete Modeling; Gaussian Graphical Models; Centrality Measures; Teacher Well-Being; Educational Data Mining.*

1. Introduction

Understanding the well-being and job satisfaction of teachers has become increasingly urgent in the face of global challenges such as educational reform, workforce shortages, and post-pandemic recovery (Edara et al., 2021; Gadermann et al., 2023; Symeonidis et al., 2025). Studies have shown that teachers' professional satisfaction not only affects their personal health and retention, but also plays a crucial role in student outcomes and school effectiveness (Banerjee et al., 2017; Bardach et al., 2022; Hoque et al., 2023). Despite growing interest in teacher well-being, much of the existing literature relies on aggregate country-level statistics or unidimensional constructs, often overlooking the complex interrelations and latent patterns that characterize teacher experience across diverse educational systems (Yu et al., 2022; Zhou et al., 2024). Large-scale international assessments such as the OECD's Teaching and Learning International Survey (TALIS) provide an unparalleled opportunity to examine teacher well-being from a multidimensional and cross-national perspective (Ainley & Carstens, 2018). TALIS 2018 gathered responses from over 260,000 teachers across 48 education systems, offering rich insights into their professional perceptions, workloads, emotional resilience, and school environments (OECD, 2019). Yet, conventional analyses have not fully leveraged the potential of this dataset to explore hidden heterogeneity among teachers, or to model well-being as a relational system of interacting variables rather than isolated indicators.

This study addresses these gaps by applying a discrete mathematical modeling approach that integrates latent profile analysis (LPA) and network analysis to uncover structural patterns in teacher well-being and satisfaction. First, we identify unobserved subgroups of teachers using LPA (Bauer, 2022; Oberski, 2016), then examine gender and country-level disparities through t-tests and Analysis of Variance (ANOVA) (Mishra et al., 2019). Finally, we construct a Gaussian graphical model (Estrada, 2019; Nayak et al., 2021) to map the network structure of well-being dimensions, allowing us to determine the centrality of key constructs. Through this mixed-methods quantitative framework, we seek to offer a more holistic understanding of teacher experiences and their implications for policy and educational leadership.

The current study is grounded in a structural and systems-based understanding of teacher well-being, drawing on principles from both educational psychology and network science. In particular, the study adopted a person-centered approach through LPA to capture heterogeneity in teacher experiences, which aligns with contemporary views that well-being is contextually shaped and multidimensional in nature (Collie et al., 2020; Spurk et al., 2020). Simultaneously, the study also utilized network theory; more specifically, the Gaussian graphical model, to conceptualize well-being as a system of interconnected psychological states and professional conditions (Costantini et al., 2019; Epskamp, Waldorp, et al., 2018). This approach resonates with recent developments in psychological measurement, wherein constructs such as burnout, satisfaction, and engagement are increasingly modeled as emergent properties of networked systems rather than as outcomes of unidimensional latent traits (Borsboom & Cramer, 2013; Fried et al., 2017).

Mathematical Framing and Contribution - Methodologically, the study advances a discrete modeling perspective on large-scale educational data. Rather than positing a single continuous response surface as in standard regression, the current study combined (*i*) LPA to obtain a finite partition of teachers into discrete, probabilistic classes $\{C_k\}_{k=1}^{K}$ in a p-dimensional indicator space (McLachlan et al., 2019), and (*ii*) a *Gaussian graphical model* (GGM) to estimate a sparse conditional-dependence graph G=(V, E) over indicators, where edges E encode nonzero elements of the precision matrix $\Theta=\Sigma^{-1}$ (Epskamp, Waldorp, et al., 2018). This two-stage, discrete–network hybrid (partitioning + graph inference) yields (*a*) structural heterogeneity (Scheres, 2010) through class membership probabilities (Foody et al., 1992) Pr $(C_k|x)$ and (*b*) system topology through graph centrality/bridge metrics (Lin et al., 2019; Opsahl et al., 2010), which conventional regression cannot identify. Substantively, the current study characterizes who differs (profiles) and how the well-being system is wired (network), offering generalizable tools for complex socio-technical systems beyond education (e.g., workforce well-being, clinical symptom networks, organizational climate).

Overall, this study offers both empirical and methodological contributions. Empirically, it provides one of the most comprehensive analyses of teacher well-being using TALIS 2018 data, identifying distinct profiles and systemic disparities across 48 countries. By revealing hidden heterogeneity in the teaching workforce, the findings should have direct implications for teacher support policies, well-being interventions, and equity-centered educational reform. Methodologically, the study contributes to the growing integration of discrete mathematics in social science research, demonstrating how latent class modeling and network analysis can be used to uncover structural complexity in large-scale datasets. The inclusion of centrality measures further identifies potential leverage points for improving well-being at the system level. To guide the investigation, this study is structured around the following research objectives (RO):

- RO1: To identify latent profiles of teacher well-being and job satisfaction using LPA based on TALIS 2018 data.
- RO2: To examine gender-based and country-level differences across the identified latent profiles.
- RO3: To model the network structure of well-being indicators using Gaussian graphical modeling and assess the centrality of key constructs.
- RO4: To derive implications for international policy and teacher support based on profile characteristics and network dynamics.

2. Literature Review

Job Satisfaction: A Foundational Component of Teacher Well-Being - Job satisfaction within the educational context indicates the teachers' overall contentment with their profession and the extent to which their roles align with their career goals (Admiraal & Røberg, 2023). It encompasses the fulfillment derived from teaching as well as the perceived value of their contributions to student learning and development. Job satisfaction is pivotal as it influences various aspects of teachers' professional lives, including their motivation, retention, and the quality of education they deliver (Assaf & Antoun, 2024). Research shows that job satisfaction significantly impacts teacher retention rates, motivation levels, and instructional quality. A systematic review by Yang and Hoque (2023) highlights that teachers who experience high levels of job satisfaction are more likely to remain in the profession, thereby reducing turnover rates that can disrupt student learning and school stability. Furthermore, Ortan et al. (2021) emphasize that self-efficacy, positive student behavior, and favorable working conditions are crucial in enhancing job satisfaction among K-12 teachers. This satisfaction fosters a positive work environment that is conducive to both teacher and student success. Furthermore, within a global context, the TALIS data illustrate that countries with supportive educational environments, such as those prioritizing teacher professional development and collaboration, report higher levels of job satisfaction (OECD, 2019).

Satisfaction with the School Environment and Professional Opportunities - Satisfaction with the school environment and professional opportunities is a key determinant of teacher retention, engagement, and overall effectiveness. Research consistently underscores the importance of working conditions, leadership support, school climate, and professional development in shaping teacher satisfaction (Eryilmaz et al., 2025). These factors collectively influence not only a teacher's decision to remain in the profession but also their ability to deliver high-quality education. Importantly, teachers' perceptions of their workplace conditions significantly affect their satisfaction levels. Studies indicate that mid-career teachers, particularly in secondary education, exhibit a stronger intention to remain in the profession when they report positive workplace conditions and a supportive school environment (Gimbert & Kapa, 2022). Working conditions such as manageable workloads, access to resources, and fair compensation are critical for fostering a sense of professional fulfillment, especially in economically disadvantaged areas where resources may be limited. For example, a study on physical education teachers highlighted that job satisfaction mediates the relationship between self-efficacy and work engagement, particularly in challenging environments (Zhou et al., 2025). Moreover, the relationship between teachers and their school principals plays a pivotal role in shaping professional satisfaction. Teachers who perceive their principals as supportive and inspirational are more likely to experience enhanced professional growth and engagement (Frady, 2019). Supportive leadership fosters an environment conducive to reflective practice and continuous learning, which are essential for maintaining motivation and satisfaction. Principals who prioritize mentorship, equity, and collaboration create a school culture that encourages teachers to thrive professionally (Reisman et al., 2022).

Another important aspect is the positive school climate. It is characterized by trust, collaboration, and mutual respect, is a cornerstone of teacher satisfaction. Teachers who work in environments with strong collegial relationships and a focus on student success report higher levels of engagement and job satisfaction (Clinciu, 2023). Interestingly, non-White teachers, in particular, research has found to express greater satisfaction with their school environments compared to their White counterparts, suggesting that diverse perspectives on workplace culture and inclusivity play a role in shaping satisfaction levels (Gimbert & Kapa, 2022). Professional development opportunities are another critical factor in fostering teacher satisfaction. Access to high-quality training programs that align with teachers' career goals and instructional needs enhances their sense of professional competence and fulfillment. For instance, teachers who participate in professional development programs designed to improve equity and career skills report greater job satisfaction and improved performance (Clinciu, 2023). These programs not only enhance individual growth but also contribute to the overall effectiveness of the school.

Cross-Country Differences in School Environment Perceptions and Policy Implications - Globally, teachers' satisfaction with their school environments varies significantly due to differences in policies, cultural norms, and resource allocation. Data from the TALIS survey highlight that countries with supportive educational environments, such as those prioritizing teacher professional development and collaboration, report higher levels of job satisfaction (OECD, 2019). For instance, Finland, known for its robust support systems, lower student-to-teacher ratios, and emphasis on teacher autonomy, demonstrates higher teacher satisfaction levels compared to countries with more rigid, resource-constrained systems (Reisman et al., 2022). These cross-country differences have significant policy implications. Policymakers must recognize that improving teacher satisfaction requires a holistic approach that addresses working conditions, leadership support, and professional development opportunities. Investing in teacher mentorship programs, reducing classroom sizes, and ensuring equitable access to resources can foster a more positive school climate, ultimately benefiting both teachers and students.

Teacher Workload and Stress - Teacher workload is a significant factor contributing to stress and burnout among educators. Research indicates that while workload is often perceived as merely the number of tasks assigned, it encompasses psychological dimensions that affect teacher well-being. A study involving 117 primary and high school teachers found that perceived stress and self-efficacy directly influenced burnout levels, with workload increasing burnout primarily in teachers with low self-efficacy (Dung et al., 2024). This highlights the importance of psychological processes in understanding the relationship between workload and stress. In the context of standardized workloads, a study conducted in Datong, China, revealed that primary and secondary school teachers experienced moderate to high levels of stress, with larger class sizes and increased teaching hours identified as significant stressors (Zhang et al., 2023). This suggests that even with standardized workloads, teachers may still face considerable stress due to specific occupational demands. Furthermore, the role of work-life balance (WLB) strategies is emphasized to mitigate stress. Effective WLB policies, such as flexible work arrangements and mental health support, have been shown to enhance teacher well-being and job satisfaction while reducing stress and turnover rates (Jusoh & Zhenni, 2025). This indicates that addressing workload through supportive policies can lead to improved outcomes for teachers. In Australia, a study highlighted that over half of the surveyed teachers reported high levels of stress, with early career teachers and those in rural areas particularly affected. The research pointed to the interplay of emotion regulation, workload, and subjective well-being as critical factors in the development of teacher stress and burnout (Carroll et al., 2022).

Emotional Well-Being and Mental Health in the Teaching Profession - Emotional well-being and mental health are critical aspects of the teaching profession, significantly influencing both educators and their students. Teachers often face high levels of work-related stress, which can lead to symptoms such as anxiety, depression, and burnout. This emotional strain not only affects teachers' well-being but also impacts the quality of education and student achievement. Research has shown that secondary traumatic stress (STS) is a notable concern among educators, as it can impair their ability to foster healthy teacher-student relationships (Emeljanovas et al., 2023). Higher levels of STS among teachers have been positively associated with students' socio-emotional difficulties, suggesting that teacher emotional health directly influences student outcomes. Furthermore, their study also indicates that the quality of teacher-student relationships is negatively associated with students' socio-emotional difficulties, underscoring the importance of teacher well-being in creating supportive learning environments. While coping strategies play a vital role in enhancing teachers' emotional health. Effective methods such as problem-solving, exercise, and engaging in hobbies have been shown to improve emotional well-being, while negative coping strategies, including self-isolation and substance use, can exacerbate psychological distress (Emeljanovas et al., 2023). Additionally, there is a significant interplay between teacher efficacy, compassion fatigue, and overall well-being. Research highlights that higher teacher well-being correlates with lower levels of burnout and emotional exhaustion (Oberg et al., 2025).

In recent years, there has been an emerging focus on teacher mental health in international education policy. This shift recognizes the importance of addressing teacher well-being as a means of improving educational outcomes and fostering healthier school environments. As Froehlich (2024) notes, the journey from joy to burnout in teaching is not uncommon, and educators often require support to navigate this transition. Strategies for self-care and re-engagement are essential for teachers to rediscover their passion for the profession and maintain their emotional health. Hence, the emotional well-being and mental health of teachers are interconnected with their professional effectiveness and the socio-emotional functioning of their students. These connections necessitate ongoing attention and support within educational contexts to ensure the well-being of both educators and their learners.

Teaching Climate and Collaboration - Teaching climate can be defined as the combination of instructional quality, collegial relationships, and classroom discipline that collectively shape the professional environment for educators (O'Brennan et al., 2014). A positive teaching climate fosters collaboration and professional growth while also enhancing emotional well-being among teachers. Effective teaching practices, such as student-centered strategies and goal clarity, along with peer collaboration, including co-teaching and joint planning, play pivotal roles in this process. The relationship between teaching climate and collaboration has been explored in research. One significant study highlights the role of distributed leadership practices in enhancing teacher collaboration. It suggests that professional learning and an innovative school climate serve as mediators in the relationship between leadership and collaboration. This indicates that effective leadership can actively foster a collaborative environment among teachers, creating a culture of mutual support and shared professional development in schools in the United States (Ma & Marion, 2024). Another study by Xu et al. (2025) examines the impact of collaboration on teacher job satisfaction across different cultural contexts, specifically focusing on the United States and China. While collaboration positively influences job satisfaction in both countries, the study found that the role of school leadership is more pronounced for American teachers. This underscores the importance of leadership in shaping the teaching climate and facilitating collaborative practices, which ultimately impact teachers' professional satisfaction and emotional well-being (Xu et al., 2025).

School climate also plays a critical role in influencing collaboration and teacher satisfaction. Research highlights that organizational supports provided by school principals are essential for creating a positive school climate. A supportive climate is linked to improved teacher satisfaction and retention, emphasizing the need for adequate resources and support for school leaders to foster collaboration among teachers (Kemling-Horner, 2021). The interplay between school climate, teacher self-efficacy, and teaching practices has also been examined, revealing that a supportive teaching climate enhances teacher self-efficacy. This, in turn, influences teaching practices, such as implementing innovative and student-centered strategies. This relationship highlights the importance of a positive teaching climate in enabling effective collaboration and strengthening teachers' confidence in their professional abilities (Li, 2021). Overall, a positive teaching climate, shaped by leadership and organizational support, is critical for fostering collaboration among teachers. Effective teaching practices and peer collaboration not only contribute to professional growth but also enhance teacher emotional well-being. These findings highlight the importance of prioritizing leadership, school resources, and a supportive climate to empower teachers and improve overall educational outcomes.

Critical Synthesis and Methodological Rationale - Across the four recurring strands: job satisfaction, school climate/professional opportunities, workload stress, and emotional well-being; the TALIS-based literature shows robust associations, but uneven causal insight and mixed subgroup patterns. For instance, satisfaction consistently predicts engagement/retention (Banerjee et al., 2017; Bardach et al., 2022), yet findings on gender differences vary by context and measures (Carroll et al., 2022; Gimbert & Kapa, 2022). Cross-national comparisons likewise reveal large mean differences, but explanations often conflate culture, policy, and measurement, making it hard to identify which combinations of teacher states (e.g., high efficacy with low satisfaction) are most prevalent or most at risk.

Methodologically, much prior work relies on single-population regression or structured equation modeling that estimates average effects under linearity and homogeneity assumptions (Mishra et al., 2019). This has three consequences (*i*) Latent heterogeneity is under-modeled, teachers with distinct multivariate profiles can be obscured by mean trends; (*ii*) Inter-indicator dependencies are treated as nuisance rather than modeled explicitly, limiting insight into how well-being elements co-activate; and (*iii*) Country clustering and design complexity (sampling weights, school nesting) are acknowledged but not always structurally integrated, inviting ecological fallacies when country means are over-interpreted. Further, the dominance of self-report, cross-sectional TALIS data raises common-method and temporal ambiguity concerns, while construct reliability varies across systems.

These limitations motivate a person-centered turn. LPA recovers finite, probabilistic subpopulations that differ in multivariate centers/variances, directly addressing hidden heterogeneity and allowing profile-specific interpretation (McLachlan et al., 2019; Nylund et al., 2007). In contrast to forcing a single "*average*" slope, LPA asks which discrete constellations of well-being exist (e.g., "High Satisfaction & Efficacy" versus "High Well-Being, Low Satisfaction") and how prevalent they are; information that is intrinsically policy-relevant for targeted supports. Complementing this, network (graph) models conceptualize teacher well-being as a system of mutually conditioning states rather than a set of indicators feeding a single latent factor. A GGM estimates a sparse conditional-dependence graph through the precision matrix, enabling identification of central (hub/bridge) nodes that likely propagate change across the system (Epskamp, Borsboom, et al., 2018; Epskamp, Waldorp, et al., 2018). Using EBICglasso (ℓ_1-penalized precision with EBIC selection) balances fidelity and parsimony in high-dimensional settings common to international surveys (Chen & Chen, 2008; Friedman et al., 2008).

Taken together, a discrete-network strategy (LPA → GGM) answers two questions traditional models leave open: (*i*) Who differs in kind? by uncovering discrete, policy-addressable teacher profiles; and (*ii*) How is the well-being system wired? by revealing conditional pathways and hubs through which improvements may cascade. This synthesis directly addresses prior gaps (hidden heterogeneity, ignored interdependencies, over-reliance on averages) and aligns with contemporary views of psychosocial constructs as emergent properties of interconnected systems (Borsboom & Cramer, 2013; Collie et al., 2020). It also sets up our research objectives: identify profiles (RO1), examine subgroup/country disparities (RO2), and estimate a sparse dependence topology to locate central, actionable constructs (RO3), from which profile-sensitive policy levers follow (RO4).

3. Methodology

3.1 Design

This study employed a quantitative, cross-sectional, and correlational research design using secondary data from the 2018 TALIS. The design integrated both person-centered and variable-centered approaches (Bauer & Shanahan, 2007) to examine patterns of teacher well-being and job satisfaction across countries. LPA was used to identify unobserved subgroups of teachers with similar well-being profiles. Group-level comparisons were then conducted using t-tests for gender differences and ANOVA with Tukey HSD post hoc tests for country-level variation. Finally, a GGM was applied to explore the structural interdependencies among well-being indicators using partial correlation networks (Estrada, 2019; Nayak et al., 2021). This integrated design enabled both descriptive profiling and relational modeling, providing a comprehensive view of teacher experiences in global educational systems.

3.2 Dataset and Variables

The dataset consists of responses from 261,426 lower secondary teachers across 48 education systems, as part of the TALIS 2018 international dataset. Table 1 shows the 9 key indicators of teacher well-being and job satisfaction were selected for analysis, based on their theoretical relevance and cross-national comparability. All variables were z-standardized before modeling to allow comparability across countries and indicators. The internal consistency of the nine well-being and teaching constructs used in this study (e.g., self-efficacy, job satisfaction, emotional well-being, and collaboration) was established in the TALIS 2018 Technical Report, with Cronbach's (1951) alpha values ranging from .68 to .90 across countries (OECD, 2019).

Table 1: Variable Codebook

Code	Variable
T3SELF	Teacher Self-Efficacy
T3JOBSA	Overall Job Satisfaction
T3JSPRO	Job Satisfaction with the Profession
T3JSENV	Job Satisfaction with School Environment
T3WELS	Emotional Well-Being
T3WLOAD	Workload Stress
T3DISC	Classroom Disciplinary Climate
T3TPRA	Participation in Professional Activities
T3COOP	Teacher Collaboration

3.3 Procedure and Data Analyses

The analytical procedure consisted of the following steps:

- *Data Preparation*: The TALIS dataset was filtered to include only teachers with complete responses for the nine selected indicators. Standardized scores were computed for all continuous variables.
- *LPA*: Conducted using R packages (R Core Team, 2023) such as *tidyLPA* (Rosenberg et al., 2019)The LPA tested models with 2 to 5 latent profiles. Model selection was based on comparative fit indices, including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Adjusted BIC, and entropy (Akaike, 1974; Nylund et al., 2007; Schwarz, 1978). A three-profile solution (High, Moderate, Low) was chosen as optimal due to the lowest BIC and satisfactory entropy (see Table 2).

- *Group Comparisons*: Gender differences were tested using Welch's (1947) t-tests due to unequal variances and sample sizes. Country-level differences were assessed using one-way ANOVA, with Tukey HSD post hoc tests to identify significant pairwise contrasts. These comparisons revealed key disparities in well-being and job satisfaction across national contexts.
- *Network Analysis*: A GGM was constructed using the *EBICglasso* (Friedman et al., 2008) estimator through the *qgraph* (Epskamp et al., 2012) and *bootnet* (Epskamp, Borsboom, et al., 2018) packages in R. The network visualized partial correlations between indicators and computed centrality metrics, including strength, betweenness, closeness, and expected influence (Freeman, 1978; Robinaugh et al., 2016). Only edges surpassing a threshold (regularized for sparsity) were retained to highlight the most meaningful interdependencies.

This combined strategy allowed for both the classification of teacher subtypes and the modeling of dynamic interrelations among psychological and professional dimensions of well-being.

3.4 Discrete Modeling Framework

- *Finite mixture (LPA)*. Let $x_i \in R^p$ be the standardized indicators for teacher i. Model $f(x_i) = \sum_{k=1}^{K} \pi_k N\,(x_i \mid \mu_k\; \Sigma_k)$, estimating class proportions π_k, centers μ_k, and (co)variances Σ_k. Class enumeration uses BIC/adjusted BIC and entropy; we select the smallest K with strong information fit and interpretable separation.
- *Sparse graphical model (GGM)*. On the same indicator set V, estimate the precision matrix through the use of EBICglasso, yielding an undirected graph where an edge $(u, v) \in E$ implies a nonzero partial correlation. This was followed by computing the centrality (strength, betweenness, closeness, expected influence) to identify hubs/bridges that potentially propagate change through the system.

While regression posits $y = x\beta + \varepsilon$ and tests marginal effects β_j, assuming a single population and no feedback among predictors (Leeper, 2024). In contrast, LPA discovers discrete subpopulations with different multivariate centers/variances without fixing a single outcome (Bauer, 2022), and GGM estimates conditional dependencies among indicators (a topology) rather than their marginal associations with an outcome (Marchetti, 2006). This reveals latent segmentation and system wiring, which are the two structural objects that ordinary regression does not identify. Table 2 contrasts what each approach fundamentally estimates and how that maps to distinct kinds of inference. Rather than treating these as substitutes, the current study uses them as complements: regression for average effects, LPA for uncovering discrete subpopulations, and GGM for recovering the conditional-dependence structure among indicators

Table 2: Comparison of Methods

Aim	Regression	LPA	GGM
Population structure	Single surface	Discrete classes	Single population (can be extended class-wise)
Object estimated	β coefficients	$\{\pi_k, \mu_k, \Sigma_k\}$	$\Theta = \Sigma^{-1}$, partial correlations
Inter-variable relations	Not modeled (predictors treated exogenous)	Within-class covariance only	Network topology (conditional dependence)
Outputs	Effect sizes, Confidence Intervals	Class probabilities, profile means	Centrality, bridges, communities
Policy use	Average treatment ideas	Targeted by class	Leverage points through hubs/bridges

Note. Comparisons are made in terms of population structure, estimands, inter-variable relations, outputs, and policy use. The present study combines LPA (partitioning) with GGM (topology) to move beyond average effects.

The rows in Table 2 highlight why the discrete–network pairing adds leverage beyond a single-model workflow. Regression assumes a single population and returns coefficient estimates geared to average treatment effects; it does not model relations among predictors. LPA relaxes the single-surface assumption by estimating a finite mixture with class proportions and class-specific centers/variances, yielding profile membership probabilities and profile means that make heterogeneity policy-addressable. GGM, in turn, treats indicators as a system and estimates the sparse precision matrix; this produces a network where centrality and bridging quantify potential leverage points for system-level change.

Practically, this means that the current findings can be read on two actionable axes: who (profiles) and how (topology). Profile results support targeted interventions by class (e.g., high well-being, but low satisfaction), while network results identify hubs/bridges (e.g., overall job satisfaction, emotional well-being) where improvements are most likely to propagate. Together, the table clarifies the division of labor among methods and why the combined design aligns with discrete modeling and graph-theoretic insight.

4. Results

4.1 RO1 - Latent Profile Identification

LPA was conducted using nine standardized teacher-level indicators from TALIS 2018: *self-efficacy* (T3SELF), *overall job satisfaction* (T3JOBSA), *job satisfaction with the profession* (T3JSPRO), *job satisfaction with school environment* (T3JSENV), *emotional well-being* (T3WELS), *workload stress* (T3WLOAD), *classroom disciplinary climate* (T3DISC), *participation in professional activities* (T3TPRA), and *teacher collaboration* (T3COOP). Model fit comparisons across 2 to 5-class solutions are presented in Table 3. The *3-profile model* was selected based on a combination of the lowest BIC = 6,130,000, high entropy (0.874), and interpretable subgroup structures. Although the 4 and 5-class solutions slightly improved BIC, they showed lower entropy and yielded smaller subgroups with less practical significance (minimum class size < 5%). Standardized Z-Scores (Means) for each profile are displayed in Table 4, while the three emergent profiles were interpreted as follows:

- **Profile 1**: High Satisfaction and Efficacy (34.2%) - Teachers in this group exhibited the highest levels of job satisfaction (overall, profession, and environment) and self-efficacy. They also reported the lowest stress (WLOAD = –0.35) and above-average engagement and collaboration.
- **Profile 2**: Low Satisfaction, but High Well-Being (20.2%) - This group paradoxically reported high emotional well-being (WELS = 1.05) and low stress (WLOAD = 0.56), yet expressed the lowest satisfaction across all job-related indicators (e.g., JOBSA = –1.69, JSPRO = –1.46).
- **Profile 3**: Moderate Profile (45.6%) - Representing the largest group, these teachers scored near the global mean across all dimensions, with slightly negative self-efficacy and marginally positive well-being.

These profiles are further illustrated in Figure 1, which visualizes the relative positioning of Z-scores across indicators. Specifically, Figure 1 plots standardized Z-scores for each indicator, so values above 0 indicate above-average levels relative to the global TALIS mean and values below 0 indicate below-average levels (*note*: T3WLOAD is "more stress" when higher). The High profile shows uniformly positive scores, with the largest peaks on overall/professional/environmental job satisfaction (T3JOBSA, T3JSPRO, T3JSENV) and self-efficacy (T3SELF), and the lowest stress. The Low profile exhibits the mirror image—marked troughs on all satisfaction indicators and discipline/climate, but higher emotional well-being (T3WELS) than expected given low satisfaction, consistent with our "High Well-Being, Low Satisfaction" interpretation. The Moderate profile tracks near zero on most axes, indicating average levels with slightly lower self-efficacy and slightly higher stress. Visually, the largest separations among profiles occur on job satisfaction (all three facets), emotional well-being, and workload stress, which are also the constructs later identified as central in the network analysis. Therefore, scales were standardized, shape differences (peaks/valleys) are more informative than absolute magnitudes; the area enclosed by each polygon reflects the pattern of indicators rather than a summed score.

Table 3: Latent Profile Model Fit Comparison

Number of Classes	BIC	Entropy	Min Prob.	Max Prob.	Min %	Max %
2	6340000	0.752	0.916	0.932	0.452	0.548
3	6130000	0.874	0.916	0.951	0.136	0.554
4	6050000	0.864	0.876	0.944	0.052	0.465
5	6030000	0.802	0.584	0.949	0.048	0.386

Table 4: Standardized Z-Scores by Latent Profile

Latent Profile	SELF	JOBSA	JSPRO	JSENV	WELS	WLOAD	DISC	TPRA
1	0.36	1.12	0.92	0.98	-0.53	-0.35	-0.32	0.19
2	-0.32	-1.69	-1.46	-1.40	1.05	0.56	0.44	-0.08
3	-0.12	-0.21	-0.16	-0.21	0.04	0.06	0.07	-0.09

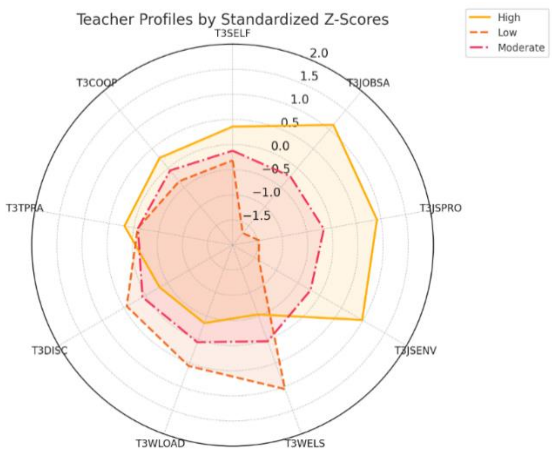

Fig. 1: Teacher Profiles by Standardized Z-Scores

Notes. Radar axes show self-efficacy (T3SELF), overall/professional/environmental job satisfaction (T3JOBSA, T3JSPRO, T3JSENV), emotional well-being (T3WELS), workload stress (T3WLOAD; higher = more stress), classroom disciplinary climate (T3DISC), participation in professional activities (T3TPRA), and collaboration (T3COOP). Values are Z-scores relative to the pooled TALIS mean (0). The High profile concentrates above zero on most indicators with notably low stress; the Low profile shows low satisfaction coupled with higher emotional well-being; the Moderate profile clusters near zero. The largest profile separations appear on the three satisfaction measures, emotional well-being, and workload stress.

4.2 RO2 - Gender-Based and Country-Level Differences

To assess gender-based variation in teacher well-being, Welch's *t*-tests were employed due to unequal variances and the large, unbalanced sample sizes. As shown in Table 5, statistically significant gender-based differences were found in eight out of nine indicators. Female teachers reported:

- Higher workload stress (M = 9.30 vs. 8.99, $p < .001$),
- Lower emotional well-being (M = 9.19 vs. 9.43, $p < .001$),
- Higher participation in professional activities and collaboration, and
- Slightly higher job satisfaction (overall and profession-specific).

The only indicator with no significant difference was satisfaction with the school environment ($p = .084$). These findings suggest nuanced gender dynamics where female teachers, while actively engaged and professionally satisfied, face disproportionate emotional burdens and stress; highlighting the need for gender-sensitive support structures in schools.

Table 5: Gender-Based Differences in Teacher Well-Being and Job Satisfaction Indicators

Variable	Female Mean	Male Mean	*t*-Statistic	*p*-Value
T3SELF (Self-efficacy)	12.81	12.56	29.29	< .001
T3JOBSA (Overall job satisfaction)	12.14	12.05	10.79	< .001
T3JSPRO (Satisfaction profession)	11.52	11.38	16.79	< .001
T3JSENV (Satisfaction environment)	12.02	12.01	1.73	.084
T3WELS (Emotional well-being)	9.43	9.19	28.41	< .001
T3WLOAD (Workload stress)	9.30	8.99	35.18	< .001
T3DISC (Disciplinary climate)	8.71	8.77	-6.38	< .001
T3TPRA (Teaching practice)	11.54	11.24	34.38	< .001
T3COOP (Teacher collaboration)	10.05	9.81	26.62	< .001

To examine differences across national contexts, one-way ANOVAs were conducted for all nine indicators of teacher well-being and job satisfaction using country as the grouping variable. As summarized in Table 6, the results revealed statistically significant country-level differences across all indicators ($p < .001$). These include self-efficacy, job satisfaction (overall, professional, and environmental), emotional well-being, workload stress, classroom disciplinary climate, participation in teaching practices, and professional collaboration. This suggests that teachers' experiences of well-being and satisfaction are shaped by national contexts, warranting cross-country policy reflection and deeper exploration of cultural and institutional factors.

Table 6: ANOVA Summary of Country-Level Differences

Variable	*F* value	*p*-value
T3SELF (Self-efficacy)	8546	< .001
T3JOBSA (Overall job satisfaction)	531610	< .001
T3JSPRO (Satisfaction profession)	170704	< .001
T3JSENV (Satisfaction environment)	185269	< .001
T3WELS (Emotional well-being)	40841	< .001
T3WLOAD (Workload stress)	11676	< .001
T3DISC (Disciplinary climate)	8438	< .001
T3TPRA (Teaching practice)	2091	< .001
T3COOP (Teacher collaboration)	5409	< .001

Follow-up Tukey HSD post hoc tests identified specific countries that stood out as consistently high or low on various indicators (see Table 7). Notably, Finland, Japan, and Singapore frequently appeared among the top-performing countries, particularly in measures of self-efficacy (T3SELF), professional satisfaction (T3JSPRO), and collaboration (T3COOP). In contrast, countries such as Brazil, Saudi Arabia, and Kazakhstan appeared more frequently among the bottom ranks in several domains, especially in workload stress (T3WLOAD) and disciplinary climate (T3DISC). These findings highlight the importance of contextual factors in shaping teacher well-being. High-performing systems often combine supportive work environments, professional respect, and collaborative school cultures, while countries with lower scores may face systemic challenges related to stress, classroom management, or inadequate support structures.

Table 7: Tukey HSD Summary of Country-Level Differences

Variable	Top 3 Countries	Bottom 3 Countries
T3SELF (Self-efficacy)	Finland, Japan, South Korea	Brazil, Mexico, the Czech Republic
T3JOBSA (Overall job satisfaction)	Finland, Singapore, South Korea	Brazil, Chile, Hungary
T3JSPRO (Satisfaction profession)	Singapore, South Korea, Finland	Brazil, Mexico, and Hungary
T3JSENV (Satisfaction environment)	Japan, Finland, South Korea	Brazil, Italy, the Czech Republic
T3WELS (Emotional well-being)	Finland, Singapore, Canada	Slovakia, Hungary, Mexico
T3WLOAD (Workload stress)	South Korea, Japan, Singapore	Brazil, Mexico, the Czech Republic
T3DISC (Disciplinary climate)	Finland, Austria, Singapore	Mexico, Brazil, Italy
T3TPRA (Teaching practice)	Japan, Singapore, Finland	Brazil, the Czech Republic, Chile
T3COOP (Teacher collaboration)	Finland, South Korea, Japan	Brazil, Hungary, Mexico

4.3 RO3 - Exploring Network Centrality of Teacher Well-Being and Satisfaction Indicators

To identify the structural importance of different teacher well-being and satisfaction indicators, a network analysis was conducted using the EBICglasso (Friedman et al., 2008) method. The resulting network graph (see Figure 2) visualizes the conditional associations among the nine variables, where stronger connections are represented by thicker edges. Importantly, during the estimation of the network, self-efficacy (T3SELF) was excluded due to zero regularized partial correlations with all other variables under the EBICglasso algorithm. This outcome reflects the model’s penalization of weak associations to improve interpretability and avoid overfitting (Friedman et al., 2008). As implemented in the bootnet package (Epskamp, Borsboom, et al., 2018)Variables with no retained edges after regularization are omitted from the final network, indicating they do not contribute unique conditional dependencies in the presence of others. This does not imply that self-efficacy is not important, but rather that, in this specific multivariate model, it did not demonstrate a unique direct relationship with the other variables strong enough to surpass the regularization threshold. Overall, the network shows a moderately interconnected structure, suggesting multiple pathways through which teacher experiences may influence each other. In addition, centrality metrics were computed to determine the relative importance of each indicator in the network (see Table 8). Based on betweenness, closeness, and expected influence:

- T3JOBSA (Overall Job Satisfaction) consistently ranked highest in betweenness and expected influence, suggesting that it serves as a central bridge connecting other indicators.
- T3WELS (Emotional Well-being) and T3JSPRO (Professional Satisfaction) also showed high closeness and centrality, indicating their direct ties to multiple variables.
- Indicators such as T3TPRA (Participation in Professional Activities or Teaching Practice) and T3COOP (Collaboration) had lower betweenness, but still contributed meaningfully in terms of direct connectivity.

More specifically, Figure 2 displays the GGM estimated with EBICglasso and shown in a stricter, thresholded view to emphasize the most reliable edges (edge width partial correlation|; green = positive, red = negative). The network has a clear core triangle linking overall job satisfaction (T3JOBSA) with both satisfaction with the profession (T3JSPRO) and satisfaction with the school environment (T3JSENV); these are the strongest retained connections in the graph. After conditioning on JOBSA, the residual association between T3JSPRO and T3JSENV is small and flips sign (red edge), a common suppression/overlap pattern when two facets share variance through a broader construct (here, overall satisfaction). A single stress cluster appears via the edge between workload stress (T3WLOAD) and emotional well-being (T3WELS), indicating the only direct conditional tie involving stress once other indicators are controlled. A modest link between collaboration (T3COOP) and participation in professional activities (T3TPRA) suggests localized coupling of peer work and practice engagement, while other potential ties fall below the sparsity threshold. T3SELF does not appear because it has no retained conditional edges under EBICglasso, indicating conditional independence given the other nodes in this specification.

Self-efficacy in the GGM - Under EBICglasso regularization, T3SELF had no retained edges, meaning all of its partial correlations with the remaining indicators shrank to zero after penalization. In a GGM, this implies conditional independence of T3SELF given the other nodes (i.e., its unique associations, controlling for all others, did not exceed the sparsity threshold), not that T3SELF is unimportant or uncorrelated at the bivariate level (Epskamp, Waldorp, et al., 2018; Friedman et al., 2008). The result reflects the model's preference for a sparse and interpretable topology selected through EBIC (Chen & Chen, 2008).

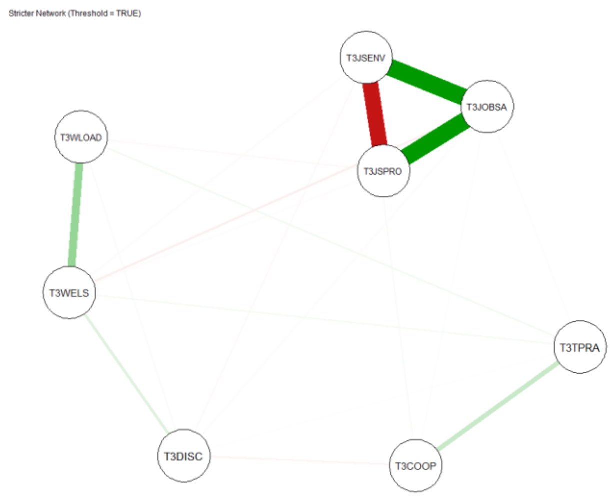

Fig. 2: Gaussian Graphical Model of Teacher Well-Being and Job Satisfaction with Centrality Analysis

Notes. Nodes are T3JOBSA (overall satisfaction), T3JSPRO (satisfaction with profession), T3JSENV (satisfaction with environment), T3WELS (emotional well-being), T3WLOAD (workload stress), T3DISC (disciplinary climate), T3TPRA (participation in professional activities), and T3COOP (collaboration). Edges depict non-zero partial correlations (conditional on all other variables); width reflects magnitude; color indicates sign (green = positive, red = negative). Only edges exceeding the display threshold are shown. The satisfaction triangle (JOBSA-SPRO-JSENV) forms the network core; a stress-well-being link (WLOAD-WELS) and a practice-collaboration link (TPRA-COOP) are retained; other associations were pruned by regularization. Absence of an edge implies no retained conditional dependence under this sparse model (not necessarily zero bivariate correlation).

Table 8: Summary of Centrality Measures

Variable	Betweenness	Closeness	In/Out Exp. Influence	Interpretation
T3JOBSA (Overall job satisfaction)	12	0.00684	1.860	Central bridge: High betweenness and expected influence
T3JSPRO (Satisfaction profession)	0	0.00668	0.043	Moderate closeness; low betweenness, but still contributes
T3JSENV (Satisfaction environment)	8	0.00678	0.069	Meaningful indirect role; contributes to multiple ties
T3WELS (Emotional well-being)	14	0.00832	0.468	High closeness and importance; more central than most
T3WLOAD (Workload stress)	4	0.00798	0.443	Moderately central; linked to several outcomes
T3DISC (Disciplinary climate)	0	0.00672	0.070	Peripheral role, but not disconnected
T3TPRA (Teaching practice)	4	0.00496	0.312	Lower betweenness; still relevant via direct paths
T3COOP (Teacher collaboration)	8	0.00521	0.202	Similar to T3TPRA; not a central bridge, but still linked

Figure 3 presents the centrality indices, strength, and betweenness, which is derived from the GGM of eight well-being and job satisfaction indicators. These indices help identify the most structurally influential variables in the network of teacher experiences, revealing which factors are most interconnected (strength) and which serve as bridges between otherwise disconnected constructs (betweenness). Here are the results, echoing previous findings:

- T3JOBSA (Overall Job Satisfaction) emerged as the most central node in terms of both strength and betweenness. This suggests that job satisfaction plays a pivotal integrative role, linking various dimensions of teacher well-being and professional experience. It is both highly connected and structurally embedded, indicating its potential leverage point for system-wide interventions.
- T3WELS (Emotional Well-Being) and T3JSENV (Satisfaction with School Environment) also showed high centrality. These variables not only maintain strong direct ties with other indicators (moderate-to-high strength) but also serve as conduits that facilitate indirect relationships (notably high betweenness). This pattern underscores the importance of school climate and emotional support in shaping teacher satisfaction and retention.
- T3WLOAD (Workload Stress) and T3TPRA (Participation in Professional Activities) exhibited moderate strength but lower betweenness. This suggests that while these factors are strongly associated with specific aspects of teacher experience, they do not serve as bridges within the broader network.
- In contrast, T3COOP (Collaboration) and T3DISC (Classroom Discipline) ranked lowest in both strength and betweenness, indicating more peripheral roles. While important on their own, these constructs may have less integrative power in the broader structure of teacher well-being.

Specifically, Figure 3 reports node centrality for the EBICglasso network. On strength (left), the three satisfaction nodes: overall (T3JOBSA), profession (T3JSPRO), and environment (T3JSENV), which show the highest values, indicating the densest conditional ties to other indicators. Emotional well-being (T3WELS) and workload stress (T3WLOAD) are mid-range, whereas collaboration (T3COOP) and disciplinary climate (T3DISC) are comparatively peripheral. On betweenness (right), T3JOBSA and T3WELS act as key bridges connecting otherwise weakly linked parts of the network, with T3JSENV and T3WLOAD contributing secondary bridging roles. Taken together, the pattern identifies overall job satisfaction and emotional well-being as structurally influential nodes, which is consistent with the strong satisfaction triangle in Figure 2 and with the largest profile separations in Figure 1.

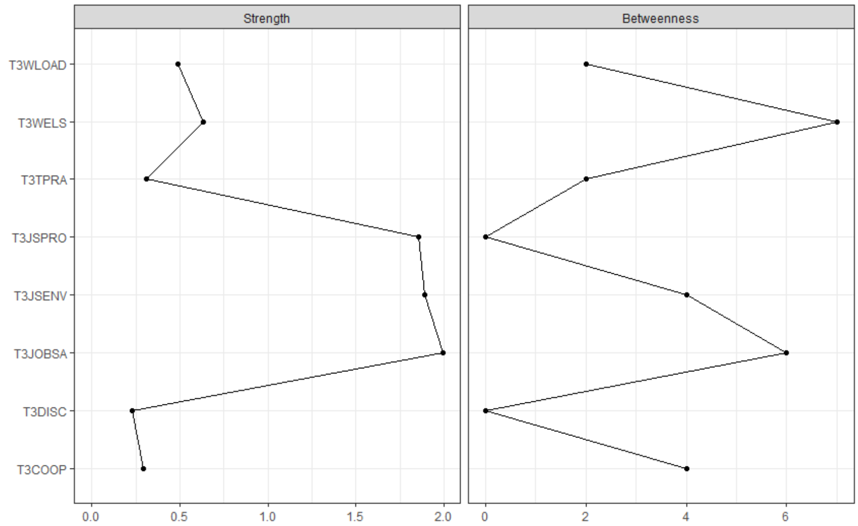

Fig. 3: Centrality Plot of Teacher Well-Being Indicators: Strength and Betweenness

Notes. Left panel: Strength (sum of absolute partial correlations to all neighbors) indexes how strongly a node is connected. Right panel: Betweenness counts how often a node lies on shortest paths, indexing the potential bridge function. Centrality was computed on the EBICglasso network shown in Figure 2. Higher strength for T3JOBSA, T3JSPRO, and T3JSENV indicates a tightly knit satisfaction core; elevated betweenness for T3JOBSA and T3WELS highlights likely leverage points where changes may propagate across the system. Lower centrality for T3COOP and T3DISC suggests more localized influence. Centrality values are sample-based; inference should be supported with bootstrap edge/centrality stability checks (e.g., via bootnet).

4.4 RO4: Cross-National Insights and Policy Implications from Integrated Analyses

The convergence of findings from LPA, country, and gender-based comparisons, and network modeling provides a nuanced understanding of the structural and contextual dynamics shaping teacher well-being in the 2018 TALIS data. *First*, the three latent profiles identified (High Satisfaction and Efficacy; Low Satisfaction but High Well-Being; and Moderate Profile) revealed substantial variation in how teachers experience their profession. These profiles not only reflect different configurations of self-efficacy and satisfaction but also imply potential clusters of systemic strengths and vulnerabilities within national systems. *Second*, gender-based comparisons confirmed consistent disparities, with female teachers reporting both higher workload stress and lower emotional well-being, despite greater collaboration and professional engagement. These patterns point to gendered expectations and unequal burdens that may require targeted policy responses, particularly around workload distribution and support systems. *Third*, country-level ANOVAs and Tukey post hoc tests demonstrated statistically significant cross-national differences across all nine teacher well-being indicators. For instance, countries such as Finland and Japan consistently ranked in the top and bottom three, respectively, across multiple indicators, indicating structural divergence in national education systems. These differences were not only statistically robust but also substantively meaningful, aligning with known variation in teacher status, professional autonomy, and institutional support across systems. *Finally*, the network analysis revealed that overall job satisfaction and emotional well-being are central constructs that connect and coordinate the broader well-being system. Notably, variables such as collaboration and discipline, while important, showed more peripheral influence, underscoring that not all teacher-related variables exert equal structural impact. Moreover, one indicator, T3SELF (Self-Efficacy), was excluded from the strict EBICglasso network due to insufficient partial correlations, suggesting it may function more independently or be captured indirectly through other indicators. This exclusion follows standard GGM modeling practices that prioritize only statistically robust edge connections. Together, these findings suggest that well-being is both contextually embedded and structurally interdependent, and that effective interventions may require differentiated strategies across country contexts, professional roles, and gender identities. The triangulated evidence base from LPA, ANOVA, and network modeling strengthens the case for policy designs tailored to specific systemic configurations, rather than one-size-fits-all approaches.

5. Discussions

The LPA revealed three distinct profiles among teachers: High Satisfaction and Efficacy, Low Satisfaction but High Well-Being, and Moderate Profile. This typology reflects the heterogeneity in teachers' experiences and underscores the multidimensional nature of their professional lives. The High Satisfaction and Efficacy profile aligns with findings from Ortan et al. (2021), which highlight the synergistic effect of favorable working conditions, high self-efficacy, and positive student interactions on job satisfaction. Meanwhile, the profile characterized by low satisfaction but relatively high emotional well-being suggests that external working conditions (e.g., lack of professional recognition or inadequate support) may detract from job satisfaction even in the presence of personal coping strengths. Such findings affirm the importance of distinguishing between intrinsic well-being and contextual satisfaction to capture the complexity of teacher experiences (Admiraal & Røberg, 2023).

The results from Welch's t-tests demonstrated significant gender-based differences in almost all well-being indicators, with female teachers reporting higher workload stress and lower emotional well-being. These findings support prior research linking teacher gender to differentiated emotional labor demands and stress exposure (Carroll et al., 2022; Emeljanovas et al., 2023). Moreover, the ANOVA revealed statistically significant country-level differences across all nine indicators. Countries like Finland, which have robust support systems, reported higher overall satisfaction and emotional well-being, echoing previous OECD findings. These cross-national disparities reflect differences in policy environments, resource distribution, and professional development opportunities, reinforcing calls for context-sensitive interventions (Reisman et al., 2022). The observed gaps further illustrate how national education systems either mitigate or exacerbate the challenges teachers face in their daily practice.

Network analysis using GGM revealed that overall job satisfaction and emotional well-being were central to the system of teacher experiences, showing high betweenness and expected influence. This structural centrality indicates that interventions targeting these dimensions could have cascading effects on other constructs, such as workload stress or collaboration. These findings echo Yang and Hoque's (2023) conclusion that job satisfaction is foundational to professional engagement and motivation. Moreover, the peripheral roles of teacher collaboration and classroom discipline suggest these may be more context-dependent, influenced by school climate and leadership practices rather than universally stable predictors (Ma & Marion, 2024; Xu et al., 2025). This configuration supports the holistic view that teacher well-being is shaped not just by individual resilience, but by system-level structures and relational dynamics.

Interpreting the zero-edge outcome, which is the zero-edge outcome that is consistent with at least two plausible mechanisms. First, upstream-driver hypothesis: self-efficacy may exert its influence indirectly, such as through satisfaction with the environment or the profession; therefore, once those variables are in the model, self-efficacy (or T3SELF) contributes little additional conditional dependence. Second, the redundancy/overlap hypothesis in cross-sectional indicator sets, wherein self-efficacy can share variance with proximal states (job satisfaction, emotional well-being), such that the unique partial signal is small after regularization. In both cases, the network result does not contradict the strong literature linking efficacy to engagement and satisfaction; it simply indicates that, given the other nodes, efficacy's direct conditional ties are weak in this sample and specification. Future work could test whether self-efficacy becomes central within profiles (class-conditional networks) or over time (temporal networks), which would align with theories positioning efficacy as an antecedent that shapes later states rather than a concurrently co-activating node.

For the role of contextual variables, several unmodeled factors are likely to shape both profile membership and the dependence structure among indicators. Experience typically covaries with self-efficacy and may buffer workload stress, shifting teachers toward the High profile. Contract type/tenure and school sector (public/private) often track with job security, resources, and leadership climate, potentially elevating T3JSENV and overall satisfaction. School level/type and class size can alter the coupling between T3WLOAD and T3WELS, and between discipline (T3DISC) and collaboration (T3COOP). In network terms, these factors could (*a*) change edge weights (e.g., stronger WLOAD–WELS links in large classes), and/or (*b*) re-rank central nodes (e.g., environment satisfaction becoming more central in under-resourced settings). Therefore, the current study viewed the present profiles and topology as average structures, with context expected to induce systematic heterogeneity around them.

The structural patterns identified across latent profiles, national systems, and network interdependencies carry important implications for policy and educational reform. Most notably, the centrality of job satisfaction and emotional health points to their role as leverage points in improving teacher retention and performance (Assaf & Antoun, 2024; Oberg et al., 2025). Efforts to enhance teacher support should therefore prioritize improving school leadership, professional development opportunities, and work-life balance mechanisms (Frady, 2019; Jusoh & Zhenni, 2025). Furthermore, the observed differences between countries and between genders call for differentiated policy responses. Female teachers, for instance, may benefit from targeted emotional support strategies and stress reduction initiatives, while low-performing countries may require system-wide reforms focused on infrastructure and institutional culture. Overall, the findings advocate for a more integrated approach to teacher well-being; one that bridges individual, organizational, and systemic levels.

6. Conclusion

This study explored the complex landscape of teacher well-being and job satisfaction using TALIS 2018 data, applying a multi-method approach that included LPA, gender, and country-based comparisons, and network modeling. The identification of three distinct teacher profiles highlights the heterogeneity of professional experiences among educators globally. Notably, a substantial proportion of teachers reported only moderate satisfaction and well-being, signaling the need for systemic improvement even in seemingly stable education systems. Significant gender and cross-country differences further emphasize how teacher well-being is shaped by broader sociocultural and institutional contexts. Female teachers reported higher levels of stress and lower emotional well-being, underscoring the urgency of gender-sensitive support systems. Cross-national disparities in all nine indicators reflect the impact of policy design, leadership support, and professional development infrastructure on teachers' lived experiences. The network analysis underscored the central role of overall job satisfaction and emotional well-being as key nodes within the web of professional experience. These findings suggest that improving these two aspects could yield system-wide benefits, positively influencing teacher collaboration, engagement, and classroom climate. Together, the findings offer a holistic understanding of the interrelated psychological and structural elements that define teacher well-being. In sum, addressing teacher well-being requires coordinated policy efforts across leadership, workload management, and professional support. Educational reforms that prioritize emotional health and job satisfaction will not only benefit teachers but also promote sustainable learning environments that positively impact students and school communities.

For policy implications, the discrete–network results suggest two actionable levers: (*a*) targeted supports by profile, and (*b*) system-level tweaks at high-centrality nodes (overall job satisfaction; emotional well-being). For low-performing systems (e.g., countries that scored low on satisfaction and climate), ministries can pilot workload audits and administrative task offloading (e.g., clerical relief, grading assistants), paired with class-size reduction pilots in high-need schools and instructional coaching/mentorship to strengthen school-environment satisfaction. To directly move the well-being node, implement evidence-based stress programs (e.g., mindfulness groups), protected professional development time (e.g., one period/week), and leadership development that trains principals in supportive feedback and equitable task allocation. For female teachers, who show higher stress and lower emotional well-being, adopt work-life balance policies (flexible scheduling), emotion-regulation training embedded in professional development, harassment-free workplace enforcement, and leadership pipeline programs that increase agency and recognition. Because hubs/bridges propagate benefits, interventions that raise overall job satisfaction or emotional well-being should yield spillovers to collaboration, engagement, and classroom climate.

Despite its strengths, this study has several limitations that should be acknowledged. First, the analysis was based on secondary cross-sectional data from TALIS 2018, which limits causal interpretations and may not reflect more recent changes in teacher conditions, especially following global disruptions such as the COVID-19 pandemic. Second, although the indicators used were drawn from validated TALIS constructs, the study did not revalidate the factor structure through CFA within the present sample. Furthermore, the exclusion of self-efficacy (T3SELF) is a property of one estimator (EBICglasso) and tuning regime. Regularization can suppress small but meaningful edges in finite samples. Thus, conclusions about "*no direct connections*" should be read as "*no retained conditional edges under this sparse model*." Alternative estimators/tunings may recover weak connections. In other words, self-efficacy was excluded from the final network model due to its lack of partial correlations with other variables in the EBICglasso estimation, which may not imply a lack of relevance but rather limited interdependence within the specific analytic framework. Third, while the study examined differences across gender and countries, other contextual or demographic variables (e.g., teaching level, contract type, years of experience) were not considered in the present model, which could provide additional explanatory insights in future research. Lastly, the LPA was limited to a subset of teacher-level variables and based on model fit indices and interpretability; other solutions (e.g., 4-class or 5-class models) could yield alternative insights depending on theoretical priorities or regional focus.

For future directions, several extensions would strengthen the evidential base and external validity of these findings. First, incorporating longitudinal designs would enable estimation of profile transitions over time (e.g., latent transition analysis) and temporal networks to test whether self-efficacy exerts lagged effects on satisfaction and well-being. Second, adding contextual information in a parsimonious manner is advisable: profile membership can be related to years of experience, contract type, sector/level, class size, and other school characteristics using two-stage (three-step) procedures, while multi-group or multilevel GGMs can assess whether edge weights and centrality rankings differ across subgroups. Third, qualitative complements (profile-stratified interviews or focus groups) can illuminate mechanisms underlying configurations such as "high well-being, low satisfaction" and identify locally feasible levers. Finally, for policy learning, staggered or phased implementations of interventions (e.g., mentoring, workload offloading, protected professional development time) should be evaluated with quasi-experimental designs, tracking both shifts in profile prevalence and changes in network topology (e.g., attenuation of the stress–well-being link; increases in job-satisfaction centrality).

Declaration of AI Uses

The authors used Wordtune to support language refinement and improve the clarity of the manuscript. All AI-assisted suggestions were carefully reviewed, edited, and approved by the authors, who retain full responsibility for the integrity and accuracy of the final content.

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