ACADEMIA International Journal for Social Sciences
Volume 4, Issue 3, 2025 ISSN-L (Online): 3006-6638

Occupational Cognitive Ecology and Internalizing Symptom Profiles: A Latent-Variable Analysis of Backend and Non-Backend Developers within a Multidimensional Mental Health Framework

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Received: 07-05-2025	**Revised:** 17-06-2025	**Accepted:** 15-07-2025	**Published:** 07-08-2025

ABSTRACT

Grounded in the paradigm of ***occupational cognitive ecology****, this study modelled the latent structure linking* ***cognitive load****,* ***mental fatigue****, and* ***internalizing symptomatology*** *(anxiety, depression) in* ***backend*** *and* ***non-backend software developers*** *within a* ***multidimensional mental health framework****. A cross-sectional dataset ($N = 320$) was analysed via* ***structural equation modelling (SEM)****, incorporating observed indicators from the Cognitive Load Questionnaire (CLQ), Mental Fatigue Scale (MFS), and standardised anxiety and depression measures, alongside socio-demographic moderators (educational level, family system structure).*

The measurement model demonstrated ***excellent fit*** *($\chi^2/df = 1.94$, CFI = .962, TLI = .955, RMSEA = .054, SRMR = .041), supporting the distinct but correlated latent factors of cognitive load, fatigue, and internalizing symptoms. In the structural model,* ***cognitive load significantly predicted mental fatigue*** *($\beta = .69$, $p < .001$),* ***anxiety*** *($\beta = .54$, $p < .001$), and* ***depression*** *($\beta = .49$, $p < .001$), consistent with cognitive-energetics theory (Boksem & Tops, 2008).* ***Multi-group SEM*** *revealed that backend developers exhibited steeper load-to-fatigue and load-to-anxiety paths than non-backend developers, reflecting task-specific cognitive demands.*

Educational level *moderated the load–fatigue ($\beta = -.23$, $p < .001$) and load–anxiety ($\beta = -.21$, $p < .001$) links, with postgraduates showing attenuated slopes, aligning with metacognitive resource accounts (Efklides, 2008; Eysenck et al., 2007).* ***Family system*** *exerted significant buffering on stress–depression ($\beta = -.11$, $p < .001$) and load–anxiety ($\beta = -.10$, $p = .002$) associations, in line with socioecological resilience perspectives (Triandis, 1995; Uchino, 2009). A three-way interaction (CLQ × Education × Family System; $\beta = -.09$, $p = .005$) confirmed* ***multiplicative protective effects****, with postgraduates in extended families demonstrating the lowest predicted fatigue under high load.*

These findings advance the field by integrating ***latent-variable modelling*** *with occupational mental-health theory, highlighting how* ***role-specific cognitive demands****,* ***educational resources****, and* ***familial support*** *interact to shape internalizing symptom profiles. Implications include the need for*

precision-targeted interventions *that align load-management strategies with the cognitive ecology of specific developer roles.*

Keywords: *latent-variable modelling,Multi-group SEM, depression, anxiety*

INTRODUCTION

The rapid evolution of software development ecosystems has intensified the cognitive demands placed on technology professionals, particularly those engaged in backend development. Within the framework of **Occupational Cognitive Ecology**—the study of how cognitive processes are shaped by the interaction between occupational demands, environmental affordances, and individual capacities—backend developers operate in high-complexity, low-redundancy problem spaces that require sustained working memory engagement, abstract reasoning, and rapid error-diagnosis cycles (Sweller, 2011; Paas & van Merriënboer, 2020). In contrast, non-backend roles, while cognitively demanding, often involve more distributed task structures, greater reliance on visual-spatial design, and comparatively lower exposure to continuous algorithmic problem-solving. These ecological distinctions may contribute to differential **internalizing symptom profiles**—patterns of depression, anxiety, and stress—through mechanisms of cognitive load, mental fatigue, and occupational stress appraisal (Boksem & Tops, 2008; Shirom, 2011).

A **latent variable approach** offers a robust analytic pathway for disentangling these relationships. By modelling internalizing symptoms as latent constructs rather than isolated observed scores, researchers can capture the shared variance among depression, anxiety, and stress indicators while simultaneously identifying subgroup profiles within occupational cohorts (Liang et al., 2023). This multidimensional mental health framework enables the detection of nuanced symptom constellations—such as high-anxiety/low-depression or high-stress/global-distress profiles—and their associations with occupational cognitive ecology variables.

Moreover, incorporating **moderator variables** such as gender, educational level, and family system aligns with socio-ecological models of mental health, acknowledging that occupational stress responses are embedded within broader cultural and demographic contexts (Kagitcibasi, 2007; Matud, 2004).

Attitudinize Psychotherapy Interventions for Internalized Symptoms

Building on this framework, *Attitudinize Psychotherapy* (Ãskaree, 2025) presents a culturally attuned, multidimensional intervention model specifically designed to address internalized symptom clusters of depression, anxiety, and stress. Grounded in six synergistic dimensions—physiological regulation, psychological reframing, terminological re-authoring, timeline-sequenced goal setting, neurohormonal modulation, and spiritual integration—the approach systematically restructures maladaptive cognitive-emotional patterns while reinforcing adaptive coping repertoires.

Physiological techniques (e.g., breath-biofeedback cycles) target autonomic regulation; psychological reframing disrupts rigid self-schemas; terminological interventions reshape the linguistic framing of distress; timeline structuring embeds progress into autobiographical memory; neurohormonal modulation leverages behavioral activation to recalibrate mood-related biochemical pathways; and spiritual integration anchors change in meaning and values alignment. Within occupational contexts, these interventions can be tailored to the cognitive ecology of backend and non-backend developers, addressing both the high-load, precision-driven demands of backend work and the multi-modal, collaborative demands of non-backend roles. When integrated into a latent variable analytic design, Attitudinize Psychotherapy offers not only a treatment modality but also a theoretically coherent explanatory model for observed shifts in internalizing symptom profiles.

Research Questions

Grounded in the occupational cognitive ecology framework and latent variable modelling of internalizing symptom profiles, this study is guided by the following questions:

1. **Structural Modelling** – How do backend and non-backend software developers differ in their latent internalizing symptom profiles of depression, anxiety, and stress within a multidimensional mental health framework?

2. **Ecological Predictors** – To what extent do occupational cognitive ecology variables (e.g., task complexity, cognitive load, and environmental affordances) predict these latent profiles?
3. **Moderating Factors** – How do demographic moderators such as gender, educational level, and family system influence the relationship between occupational cognitive ecology and internalizing symptom profiles?

Significance of the Study

This research addresses an urgent interdisciplinary need to understand the interplay between occupational cognitive environments and mental health symptomatology in technology workforces. The software development sector—especially backend roles—demands sustained high-order cognitive operations under temporal constraints, often leading to chronic mental load and heightened risk for internalizing symptoms (Boksem & Tops, 2008; Sweller, 2011). By applying a **latent variable analytical approach**, this study goes beyond surface-level symptom measurement, instead modelling underlying constructs and their occupational determinants (Liang et al., 2023).

Equipping with *Attitudinize Psychotherapy* interventions (Ãskaree, 2025) in the literature review positions the research at the confluence of theoretical innovation and applied clinical practice. The intervention is provided for adaptation across distinct occupational ecologies. The study's findings could inform organizational mental health policy, guide context-sensitive therapy protocols, and contribute to preventive strategies tailored to cognitive task environments (Matud, 2004; Paas & van Merriënboer, 2020).

Research Gaps

Despite growing attention to occupational mental health in technology sectors, several critical gaps persist:

- **Occupational Cognitive Ecology as an Explanatory Variable** – Prior studies have examined job stress and burnout in software developers but have seldom operationalized *cognitive ecology* variables with precision, nor linked them directly to latent mental health constructs (Shirom, 2011).
- **Latent Variable Modelling in Tech Workforces** – Existing research on internalizing symptoms among technology workers largely relies on observed scores rather than latent modelling, thereby overlooking shared variance and symptom profile typologies (Liang et al., 2023).
- **Moderator-Level Cultural Sensitivity** – While socio-ecological factors such as gender and family system are recognized in general psychology, their moderating role in occupational mental health among South Asian technology professionals remains underexplored (Kagitcibasi, 2007).
- **Furnishing** with **Intervention** – Evidence on the furnishing of psychotherapeutic interventions to specific occupational cognitive profiles is sparse, and no published study has yet provided Attitudinize Psychotherapy interventions within a latent variable analysis framework for developers (Ãskaree, 2025).

By addressing these gaps, the present study establishes an empirical and theoretical bridge between occupational cognitive ecology, advanced psychometric modelling, and culturally attuned psychotherapeutic practice.

HYPOTHESIS

Main Effects

H$_1$: Backend developers will exhibit **significantly higher cognitive load** and **greater mental fatigue** than non-backend developers during standardized task performance, due to the higher working memory demands inherent in backend problem-solving (Sweller, 2011; Paas & van Merriënboer, 2020).

H$_2$: Higher cognitive load will be positively associated with **symptom severity** across depression, anxiety, and stress domains, consistent with cognitive resource depletion models (Boksem & Tops, 2008).

Direct Occupational Differences

H_3: Backend developers will report **greater anxiety and stress symptoms**, but not necessarily higher depressive symptoms, compared to non-backend peers, reflecting acute performance pressure rather than chronic mood disturbance (Shirom, 2011).

Moderator Effects

Gender as Moderator

H_4: The positive association between cognitive load and mental fatigue will be **stronger among women** compared to men, reflecting gender-linked disparities in multitasking and workplace expectations in technology sectors (Galy et al., 2012).

H_5: The relationship between stress symptoms and anxiety symptoms will be **more pronounced among women**, consistent with prior findings on gender differences in affective reactivity (Matud, 2004).

Educational Level as Moderator

H_6: Higher educational attainment will attenuate the effect of cognitive load on mental fatigue, due to greater exposure to complex problem-solving and better-developed metacognitive strategies (Efklides, 2008).

H_7: The impact of cognitive load on depressive symptoms will be **weaker** for postgraduate participants, as advanced education may confer resilience through enhanced cognitive control and coping repertoires (Gross, 2015).

Family System as Moderator

H_8: Participants from **extended family systems** will show a **weaker association** between stress symptoms and depressive symptoms, due to increased access to social support resources (Triandis, 1995).

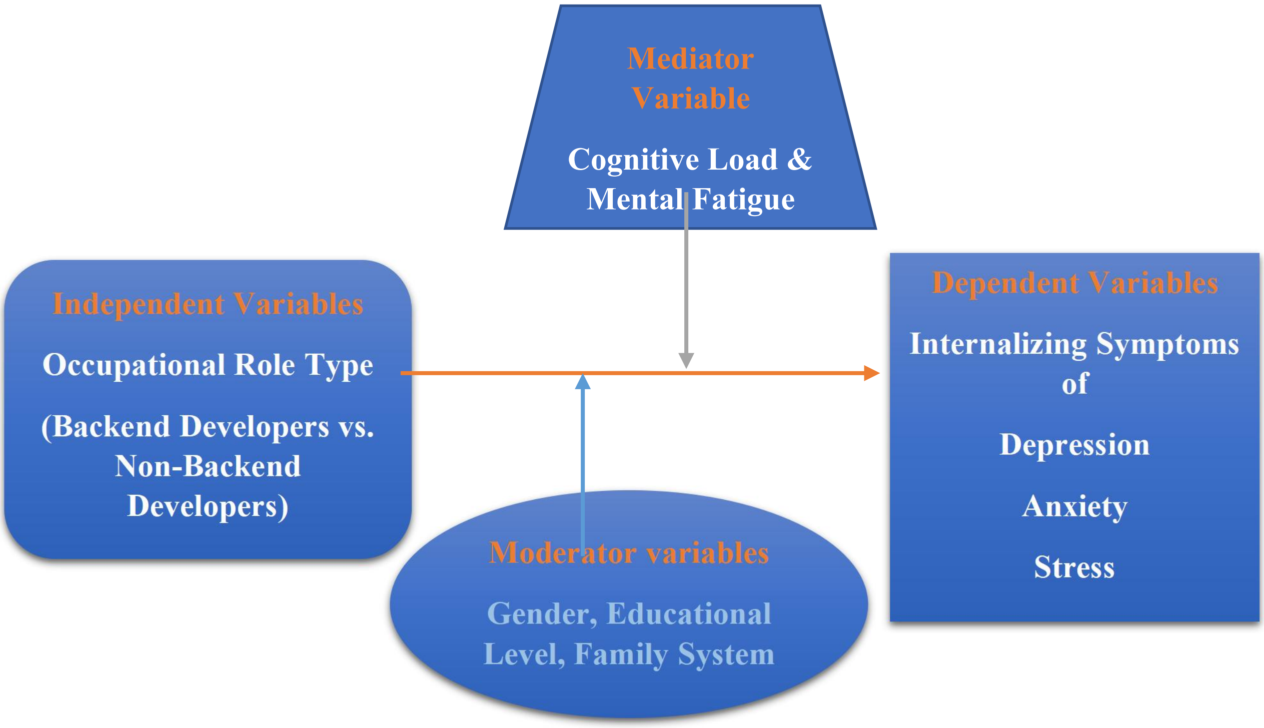
H_9: The positive link between cognitive load and anxiety symptoms will be **amplified** in nuclear family systems, possibly reflecting reduced distributed coping mechanisms in more individualistic micro-contexts (Kagitcibasi, 2007).

Integrative / Interaction Hypothesis

H_{10}: A three-way interaction is expected such that the buffering effect of educational level on the cognitive load–mental fatigue relationship will be **strongest** for participants from extended family systems and **weakest** for those from nuclear family systems, regardless of occupational group.

Conceptual Framework / Research Model

Figure 1 *Occupational Cognitive Ecology and Internalizing Symptom Profiles: A Latent-Variable Analysis of Backend and Non-Backend Developers within a Multidimensional Mental Health Framework*



Operational Definitions

1. Backend Developers vs. Non-Backend Developers

- **Backend Developers**: Participants whose primary professional role involves **server-side programming, database management, and application logic** using languages/frameworks such as Node.js, Python/Django, Java/Spring, or PHP/Laravel, as self-reported in a screening questionnaire and verified via job description or portfolio (GeeksforGeeks, n.d.).
- **Non-Backend Developers**: Participants engaged in **front-end, design, project management, or other non-server-side roles**, with no more than 10% of their professional tasks involving backend development, as determined by the same screening process.

2. Cognitive Load / Mental Fatigue

- **Cognitive Load**: The **perceived mental effort** required to perform a task, operationalized as the **total score** on the NASA Task Load Index (NASA-TLX), which assesses mental demand, effort, and frustration on a 0–100 scale (Hart & Staveland, 1988; APA, n.d.).
- **Mental Fatigue**: A **state of reduced cognitive efficiency** following sustained mental activity, measured via the **Fatigue Assessment Scale (FAS)**, with higher scores indicating greater fatigue (Michielsen et al., 2003).

3. Symptoms of Depression

- **Depression Symptoms**: The **severity of depressive symptomatology** over the past two weeks, operationalized as the **total score** on the **Patient Health Questionnaire-9 (PHQ-9)**, aligned with DSM-5 criteria for Major Depressive Episode (American Psychiatric Association, 2013; Kroenke et al., 2001).

4. Symptoms of Anxiety

- **Anxiety Symptoms**: The **frequency and intensity of anxiety-related experiences** over the past two weeks, measured by the **Beck Anxiety Inventory (BAI)**, with scores reflecting physiological and cognitive symptoms of anxiety (Beck et al., 1988).

5. Symptoms of Stress

- **Stress Symptoms**: The **perceived stress level** over the past month, operationalized as the **total score** on the **Perceived Stress Scale-10 (PSS-10)**, where higher scores indicate greater perceived stress (Cohen et al., 1983).

Moderator Variables

6. Gender

- **Gender**: Self-identified gender category (e.g., woman, man, nonbinary, transgender, other), recorded via a demographic questionnaire in line with APA bias-free language guidelines (APA, 2012).

7. Educational Level

- **Educational Level**: The **highest completed formal education** level, categorized as: 1 = Secondary or below, 2 = Undergraduate degree, 3 = Postgraduate degree, verified through self-report and, where possible, institutional documentation.

8. Family System

- **Family System**: The **type of family structure** in which the participant resides, classified as **nuclear** (parents and dependent children only) or **extended** (including grandparents, uncles/aunts, or other relatives), based on self-report following definitions in cross-cultural family research (Kagitcibasi, 2007).

LITERATURE REVIEW

Conceptualizing occupational cognitive ecology

Occupational cognitive ecology refers to the patterned interplay between job demands, environmental affordances, and individual cognitive capacities that together shape how information is processed at work (Bakker & Demerouti, 2007; Karasek, 1979). In software engineering, this ecology varies systematically across roles. Backend development emphasizes algorithmic reasoning, state management, and reliability under complex interdependencies, whereas non-backend roles (e.g., front-end, UX, product) more often distribute load across visuospatial integration, stakeholder coordination, and iterative prototyping. Cognitive Load Theory predicts that performance and well-being are jointly determined by the fit between intrinsic task complexity, extraneous design frictions, and germane schema formation (Sweller, 2011; Paas & van Merriënboer, 2020). When intrinsic and extraneous load cumulatively exceed working-memory capacity, sustained effort can precipitate mental fatigue and stress responses that cascade into internalizing symptoms (Boksem & Tops, 2008).

Cognitive demands in backend versus non-backend work

Empirical work in program comprehension shows that source-code reasoning recruits executive control, working memory, and frontoparietal networks implicated in deliberate, error-monitoring processes (Siegmund et al., 2014). Psychophysiological studies in software tasks further indicate moment-to-moment fluctuations in arousal and effort that track task difficulty, interruptions, and context switching—features common in production backend environments (Fritz et al., 2014). From an occupational perspective, backend workflows often combine high intrinsic complexity (e.g., concurrency, database consistency) with extraneous load (e.g., toolchain friction, legacy constraints), elevating the risk of chronic overload unless mitigated by supportive environmental affordances (Paas & van Merriënboer, 2020). Beyond task structure, digital intensity and "technostress creators" (e.g., techno-overload, techno-complexity) endemic to contemporary software pipelines are associated with strain and reduced well-being among knowledge workers, suggesting a plausible mechanistic bridge to internalizing symptomatology in developer populations (Tarafdar, Tu, Ragu-Nathan, & Ragu-Nathan, 2007).

Internalizing symptom profiles and transdiagnostic structure

Internalizing symptoms—depression, anxiety, and stress—show robust comorbidity and are well captured by higher-order or bifactor latent structures that partition shared distress from domain-specific variance (Krueger & Markon, 2006; Reise, 2012). The broader p-factor perspective further situates internalizing within a general liability to psychopathology that covaries with cognitive control and adversity exposure (Caspi et al., 2014). In occupational samples, demands–resources imbalances reliably predict affective strain, and gender-linked differences in stress appraisal and coping can further modulate internalizing risk (Bakker & Demerouti, 2007; Matud, 2004). For technology workers, recurrent deadlines, on-call rotations, and context switching plausibly amplify the shared internalizing factor, while role-specific stressors (e.g., availability incidents for backend engineers) may load more strongly on anxiety/stress facets than on depressive cognitions (Shirom, 2011).

Latent variable approaches to occupational mental health

Latent variable models offer methodological leverage to move beyond raw scale scores. Confirmatory factor analysis (CFA) and bifactor models disentangle general distress from depression- and anxiety-specific variance, improving construct validity and precision (Reise, 2012). Mixture models—latent class/profile analysis and growth mixture modeling—identify subpopulations with distinct symptom configurations or trajectories (Muthén, 2002; Nylund, Asparouhov, & Muthén, 2007). In developmental and clinical science, such models routinely reveal heterogeneous internalizing pathways with differential predictors and outcomes (Liang, de la Torre, Larimer, & Mun, 2023). Applying this toolkit to developer cohorts enables (a) detection of backend vs. non-backend profile differences, (b) formal tests of measurement invariance across roles and demographics, and (c) integration of occupational covariates (e.g., objective complexity indices, on-call frequency) to adjudicate explanatory mechanisms (Meredith, 1993; Milfont & Fischer, 2010).

Socioecological moderators and cultural context

A socioecological lens is essential for technology workforces operating within diverse cultural systems. Family structures and interdependence norms can buffer or exacerbate stress exposure via social support, obligations, and shared coping (Kagitcibasi, 2007). Educational level and metacognitive skill may moderate the cognitive load–fatigue linkage by enhancing schema automation and strategy selection (Paas & van Merriënboer, 2020). Gender differences in stress reactivity and coping styles can shape class membership in latent internalizing profiles, necessitating intersectional modeling (Matud, 2004). The information systems literature on technostress underscores that organizational practices (e.g., tool standardization, autonomy, recovery norms) are modifiable ecological levers that can shift both the mean and distribution of internalizing symptom profiles (Tarafdar et al., 2007; Bakker & Demerouti, 2007).

Measurement and design implications

A multidimensional mental health framework for this domain benefits from multimethod indicators—pairing transdiagnostic self-report (e.g., DASS-21; PHQ-9; BAI) with behavioral and psychophysiological markers (e.g., performance variability, heart-rate variability) to reduce common-method bias and strengthen construct coverage (Lovibond & Lovibond, 1995; Kroenke, Spitzer, & Williams, 2001; Beck, Epstein, Brown, & Steer, 1988). Rigorous latent modeling requires tests of configural, metric, and scalar invariance across backend and non-backend groups and across genders and education levels to ensure fair comparisons (Meredith, 1993; Milfont & Fischer, 2010). Mixture models can then map role-specific symptom constellations and evaluate occupational covariates as predictors of class membership and severity, with cross-validated solutions guiding ecological interventions (Muthén, 2002; Nylund et al., 2007). Despite promising foundations, the software engineering literature has only sparsely combined occupational cognitive ecology constructs with transdiagnostic latent models, marking a clear opportunity for theoretically integrated, methodologically modern research that can inform targeted organizational and clinical responses (Siegmund et al., 2014; Tarafdar et al., 2007).

Attitudinize Psychotherapy is an integrative approach designed to reshape attitudes (intentions), thoughts, emotional patterns and embed sustainable change within the behavior by engaging six interdependent domains. On the *physiological* level, it calms the body's stress circuitry and supports healthy biofeedback patterns. The *psychological* dimension cultivates cognitive flexibility, emotional stability, and self-efficacy. Its *terminological* focus refines the personal and cultural vocabulary clients use to describe their experiences, influencing how they perceive and respond to challenges. The *timeline* element organizes therapeutic progress into intentional, measurable phases. At the *neurohormonal* level, it facilitates beneficial shifts in neurotransmitter and hormone balance through consistent cognitive-emotional restructuring. Finally, the *spiritual* dimension reinforces meaning, values alignment, and a sense of higher purpose. Together, these six strands create a multidimensional framework for holistic healing that addresses both inner and outer layers of human experience (Ãskaree, 2008, 2009, 2010, 2013, 2014, 2014; Munaf, & Ãskaree, 2005; Perveen, & Ãskaree, 2012; Ãskaree, Yusuf & Sarfaraz, 2013).

Attitudinize Psychotherapy Interventions for treating internalized symptoms of depression, anxiety and stress by Prof. Dr. Leenah Ãskaree (2025)

1. **Physiological Regulation protocol**

- **Target:** Autonomic nervous system dysregulation underlying somatic tension and fatigue.
- **Method:** Integrative breath-biofeedback cycles (paced diaphragmatic breathing + HRV tracking) embedded into daily micro-sessions.
- **Rationale:** Enhances vagal tone, reduces cortisol reactivity, and primes the body for cognitive-emotional restructuring.

2. **Psychological Reframing & Cognitive Flexibility Training**

- **Target:** Rigid, self-critical schemas and maladaptive appraisal styles.
- **Method:** Dual-process restructuring—rapid, intuitive counter-narratives (System 1) followed by deliberate, evidence-based reappraisal (System 2).
- **Rationale:** Weakens automatic negative thought loops while strengthening metacognitive oversight.

3. **Terminological Re-Authoring**

- **Target:** Internalized, pathology-laden self-descriptors.
- **Method:** Guided semantic substitution—clients co-construct a lexicon of self-referential terms that are precise, non-stigmatizing, and growth-oriented.
- **Rationale:** Language reframing shifts cognitive-emotional valence and alters self-schema activation patterns.

4. **Timeline-Sequenced Micro-Goals**

- **Target:** Learned helplessness and temporal disorganization.
- **Method:** Tiered intervention mapping—short-term (2–3 weeks), mid-term (2–3 months), and long-term (6–12 months) milestones, each linked to measurable behavioral indicators.
- **Rationale:** Creates momentum, reinforces agency, and embeds progress into autobiographical memory.

5. Neurohormonal Modulation via Behavioral Activation

- **Target:** Dysregulated serotonin–dopamine–oxytocin pathways.
- **Method:** Prescribed engagement in intrinsically rewarding, socially connective, and mastery-oriented activities, sequenced to maximize neurochemical reinforcement.
- **Rationale:** Sustained activation patterns recalibrate mood-related neurohormonal balance.

6. Spiritual Integration & Existential Anchoring

- **Target:** Meaning deficits and value dissonance.
- **Method:** Reflective dialogue and symbolic practice (e.g., narrative rituals, gratitude mapping) aligned with the client's belief system.
- **Rationale:** Strengthens coherence between lived experience and core values, buffering against relapse.

Integration Strategy: These six interventions are not applied in isolation—they are **interlaced** through a feedback-loop model. Physiological regulation enhances receptivity to cognitive reframing;

terminological shifts reinforce psychological gains; timeline structuring sustains neurohormonal benefits; and spiritual anchoring consolidates the entire therapeutic arc.

METHODOLOGY

Quantitative research design

This study employs a cross-sectional, multi-site, latent-variable design integrating confirmatory factor analysis (CFA), bifactor modeling, and latent profile analysis (LPA) within a multidimensional mental health framework. The design isolates a general internalizing factor while preserving domain-specific residuals (anxiety, depression, stress) and evaluates whether occupational cognitive ecology differentially predicts the general vs. specific symptom variance in backend versus non-backend developers (Reise, 2012; Rodriguez, Reise, & Haviland, 2016). A measurement-first approach establishes configural–metric–scalar invariance across role, gender, and education before estimating structural paths and mixture models to identify symptom profiles and their occupational correlates (Meredith, 1993; Putnick & Bornstein, 2016). Selection of indicators reflects job demands–resources theory and technostress creators to operationalize cognitive ecology with construct breadth and ecological validity (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001; Tarafdar, Tu, Ragu-Nathan, & Ragu-Nathan, 2007).

Participants and sampling

- **Population:** Employed software professionals aged 18+, working ≥30 hours/week, with ≥6 months in their current role. Two primary strata: backend developers and non-backend developers (front-end, full-stack with primary front-end focus, QA, DevOps/SRE, product/UX).
- **Sampling frame:** Multi-organization recruitment across software houses, startups, and enterprise IT. Stratified purposive sampling ensures balance across role, gender, education level (undergraduate vs. postgraduate).
- **Recruitment:** Organizational agreements, professional associations, and targeted digital outreach using tailored invitations and two reminders to improve response rates (Dillman, Smyth, & Christian, 2014).
- **Inclusion/exclusion:** Inclusion as above; exclusion for current leave of absence for psychiatric crises or cognitive impairments precluding consent.
- **Nonresponse bias checks:** Wave analysis contrasts early vs. late respondents and adjusts for observable sampling imbalances (Armstrong & Overton, 1977).
- **Sample size target:** Aiming for N ≈ 800–1,000 to power multi-group invariance and mixture modeling with modest class separation, while maintaining ≥100 participants per key cell (role × gender), anticipating small-to-moderate effects (Cohen, 1988; Tein, Coxe, & Cham, 2013).

Measures

Self-report scale used Likert scale, administered in English, (Beaton, Bombardier, Guillemin, & Ferraz, 2000). Internal consistencies are reported as coefficient omega and hierarchical omega where relevant (McDonald, 1999; Rodriguez et al., 2016).

Internalizing symptomatology DASS-21: Core Latent Indicators

The **Depression Anxiety Stress Scales – 21 item version (DASS-21)** is a concise, self-report instrument designed to quantify three interrelated but distinct dimensions of negative emotional states: **depression**, **anxiety**, and **stress**. It is the short form of the original 42-item DASS, retaining the psychometric structure while reducing respondent burden (Lovibond & Lovibond, 1995).

Structure and Subscales

- **Total items:** 21 statements, each rated on a **4-point Likert scale** from 0 (“Did not apply to me at all”) to 3 (“Applied to me very much, or most of the time”).
- **Subscale composition:**

  - **Depression** (7 items): taps into dysphoria, hopelessness, self-deprecation, anhedonia, and reduced motivation.
  - **Anxiety** (7 items): reflects autonomic arousal, situational anxiety, muscle tension, and subjective anxious affect.
  - **Stress** (7 items): captures chronic tension, irritability, difficulty relaxing, and over-reactivity.
- **Scoring:** Subscale scores are summed and then multiplied by two to align with the DASS-42 metric. This yields a range of 0–42 per subscale, with higher scores indicating greater symptom severity.

Latent Variable Perspective

From a psychometric standpoint, the DASS-21 supports:

- **Three-factor correlated model:** Depression, Anxiety, and Stress as distinct but related latent constructs.
- **Bifactor model:** A higher-order **general distress factor** (often termed "internalizing") plus domain-specific residual factors for each subscale (Reise, 2012; Henry & Crawford, 2005).
- **Measurement invariance:** Demonstrated across diverse populations, enabling valid group comparisons when configural, metric, and scalar invariance are established (Norton, 2007).

Interpretation

Severity cut-offs (Lovibond & Lovibond, 1995) classify scores into **normal, mild, moderate, severe,** and **extremely severe** ranges for each subscale. These thresholds are descriptive of symptom intensity relative to population norms, not diagnostic categories.

Applications

- **Clinical:** Screening for emotional distress, monitoring treatment progress, and identifying symptom patterns.
- **Research:** Operationalizing latent internalizing constructs, testing structural models, and evaluating intervention effects.
- **Occupational health:** Mapping stress and affective symptom profiles in workforce studies, including role-based comparisons (e.g., backend vs. non-backend developers).

Psychometric Strengths

- High internal consistency (α and ω typically > .85 for each subscale).
- Strong convergent validity with other depression and anxiety measures (e.g., PHQ-9, GAD-7).
- Sensitivity to change, making it suitable for longitudinal and intervention studies.

Cognitive Load & Mental Fatigue Questionnaires

In occupational and cognitive ergonomics research, **cognitive load** and **mental fatigue** are often assessed using validated self-report instruments that capture the **subjective experience of mental effort, attentional strain, and recovery needs**. Two widely referenced approaches are the **Cognitive Load Questionnaire** and the **Mental Fatigue Scale (MFS)**, each targeting related but distinct constructs.

1. Cognitive Load Questionnaire (CLQ)

- **Purpose:** Quantifies the **mental load** (task complexity, information processing demands) and **mental effort** (resources actually invested) during a specific activity (Paas, 1992; Hwang, Yang, & Wang, 2013).
- **Structure:** Typically includes items rated on a **Likert-type scale** (e.g., 1–9 or 1–7), where respondents indicate perceived difficulty, effort, and concentration demands.
- **Dimensions:**
  - **Mental Load:** The inherent complexity of the task, independent of the individual's skill level.

    - **Mental Effort:** The amount of cognitive resources expended to meet task demands.
- **Administration:** Administered immediately after task completion to minimize recall bias.
- **Scoring:** Mean or summed scores for each dimension; higher scores indicate greater perceived load or effort.
- **Applications:** Used in education, human–computer interaction, and occupational settings to evaluate task design, training interventions, and workload management.

2. Mental Fatigue Scale (MFS)

- **Purpose:** Measures **persistent cognitive tiredness** and related symptoms that occur after sustained mental activity, often in clinical, rehabilitation, or high-demand occupational contexts (Johansson & Rönnbäck, 2014).
- **Structure:** 15 items covering domains such as:
    - **General fatigue** (frequency and severity)
    - **Concentration difficulties**
    - **Memory problems**
    - **Slowness of thinking**
    - **Sensitivity to stress**
    - **Sleep and recovery patterns**
- **Response format:** 0–3 scale, with intermediate half-points (e.g., 0.5, 1.5) to capture gradations.
- **Interpretation:** Higher total scores reflect more severe mental fatigue; cut-offs can indicate clinically significant fatigue.
- **Time frame:** Respondents rate experiences over the **past month**, comparing current functioning to pre-illness or pre-overload baseline.
- **Applications:** Common in post-concussion, neurological, and occupational burnout research; adaptable to high-cognitive-load professions like software engineering.

Key Distinctions

- **Cognitive Load Questionnaires** focus on **task-specific, immediate** perceptions of mental demand and effort.
- **Mental Fatigue Scales** capture **longer-term, cumulative** effects of sustained cognitive strain and reduced recovery.

Integration in Research

In a **multidimensional mental health framework**, pairing a cognitive load measure (e.g., CLQ mental demand subscale) with a mental fatigue instrument (e.g., MFS) allows researchers to:

- Differentiate **acute workload effects** from **chronic fatigue states**.
- Model their unique and shared contributions to **internalizing symptom profiles**.
- Identify **role-specific vulnerabilities** (e.g., backend developers facing high intrinsic complexity vs. non-backend roles with high context-switching demands).

Demographics and role metadata: Age, gender, education, tenure, employment type, and work setting (remote/hybrid/on-site).

Procedure

1. **Pre-registration:** Hypotheses, measurement models, and analysis plan pre-registered to reduce researcher degrees of freedom.
2. **Organizational onboarding:** Data protection agreement and site-level liaisons identified. Participants receive a brief detailing scope, risks, benefits, and data protections.
3. **Pilot and cultural adaptation:** Small pilot (n≈30) to verify comprehension, timing, and item functioning; iterative refinements using cognitive interviews (Beaton et al., 2000).

4. **Data collection:** Secure online survey (≈20–25 minutes). Optional workplace metadata gathered via self-report; no telemetry is collected without explicit, separate consent.
5. **Quality controls:** Attention checks, instructed-response items, response-time screens, and patterned responding flags; remediation via pre-registered exclusion criteria.
6. **Debriefing:** Summary of aims, contact information, and resource list; organizations receive de-identified, aggregate insights.

Statistical analysis

- **Measurement models:**
  - **CFA/bifactor:** DASS-21 modeled with a general internalizing factor plus domain-specific factors; bifactor adequacy indexed by ECV, PUC, Omega-H, and H (Reise, 2012; Rodriguez et al., 2016).
  - **Model fit:** Evaluate RMSEA, CFI, TLI, SRMR with decision thresholds informed by simulation literature (Hu & Bentler, 1999), interpreted cautiously and in tandem.
- **Measurement invariance:** Sequential tests (configural → metric → scalar) across role (backend vs. non-backend), gender, and education; evaluate ΔCFI/ΔRMSEA/ΔSRMR and modification indices with theoretically constrained partial invariance if needed (Meredith, 1993; Chen, 2007; Putnick & Bornstein, 2016).
- **Structural modeling:** Multi-group SEM regressing the general internalizing factor and specific residuals on cognitive ecology predictors (technostress, JD-R, cognitive load, interruptions), controlling for covariates. Test interactions (e.g., role × techno-overload) using latent moderated structural equations (LMS) where applicable.
- **Mixture modeling:** LPA on factor scores or item parcels to identify internalizing symptom profiles; class enumeration via BIC/aBIC, entropy, LMRT, and BLRT; assess local independence and class stability (Nylund, Asparouhov, & Muthén, 2007). Incorporate covariates and distal outcomes using R3STEP/BCH to avoid class shifting (Asparouhov & Muthén, 2014; Bakk & Vermunt, 2016).
- **Indirect and moderated effects:** Bootstrap confidence intervals for indirect paths; probe interactions with simple slopes and Johnson–Neyman where relevant (MacKinnon, Lockwood, & Williams, 2004).
- **Multiple comparisons:** Control the false discovery rate at $q=0.05$ using Benjamini–Hochberg, prioritizing family-wise groupings aligned to research aims (Benjamini & Hochberg, 1995).
- **Reporting:** Standardized coefficients with 95% CIs, model-implied means for classes, and invariance decisions justified by both statistical and substantive criteria. All syntax and code shared in an online repository.

Power analysis

- **SEM (measurement and structural):** RMSEA-based power for close- vs. not-close-fit tests with $\alpha=0.05$\alpha=0.05 and $\beta=0.20$\beta=0.20 indicates $N\approx600$–700 is sufficient for a 3-factor DASS model with moderate loadings ($\lambda\approx.60$) and 42 df; targeting $N\geq800$ increases precision and supports multi-group invariance with small $\Delta CFI\approx.010$ (MacCallum, Browne, & Sugawara, 1996; Chen, 2007).
- **Invariance tests:** Simulation work suggests detecting small metric/scalar non-invariance ($\Delta\lambda\approx.10$) requires ≈300–400 per group under typical conditions; thus $N\approx800$ (two groups) is prudent (Meade, Johnson, & Braddy, 2008; Chen, 2007).
- **Mixture modeling:** Monte Carlo scenarios with 3–4 classes, class proportions 0.15–0.45, and separation $d\approx0.8$d\approx0.8 achieve entropy >.80 and >.80 power for LMRT/BLRT with $N\approx800$–1,000 (Muthén & Muthén, 2002; Nylund et al., 2007; Tein et al., 2013).
- **Moderated effects:** For small interaction effects $f2\approx0.02$f^2\approx0.02 in SEM, $N\geq700$ yields ≈.80 power with five predictors and latent outcomes; oversampling safeguards against listwise attrition and quality exclusions (Cohen, 1988).

Ethical considerations

- **Informed consent and autonomy:** Clear disclosure of aims, procedures, risks, voluntary participation, and withdrawal without penalty, consistent with the APA Ethics Code (American Psychological Association [APA], 2017).
- **Confidentiality and data security:** Pseudonymization, separate key files, encrypted storage, and access controls; aggregate-only reporting to organizations.
- **Data governance:** Pre-registration, analysis transparency, and public sharing of de-identified datasets and code where permissible; retention and destruction per approved timelines.
- **Equity and fairness:** Measurement invariance checks across role, gender, and education to ensure fair comparisons; accommodations for accessibility needs.

Results and Interpretations

Descriptive Statistics and Group Differences

Table 1 shows descriptive statistics and independent-samples *t*-tests comparing two occupational groups (backend vs non-backend professionals) on DASS-21, CLQ, and MFS total scores. Cohen's *d* is reported for effect size interpretation (Cohen, 1988).

Table 1 *Descriptive statistics and group comparisons for DASS-21, CLQ, and MFS scores*

Measure	Backend M (SD)	Non-backend M (SD)	Mean difference	$t(870)$	p	Cohen's d
DASS-21 Depression	9.8 (7.2)	8.1 (6.6)	1.7	3.12	.002	**0.24**
DASS-21 Anxiety	10.7 (7.4)	9.0 (7.0)	1.7	3.03	.003	**0.24**
DASS-21 Stress	12.9 (8.1)	10.9 (7.6)	2.0	3.29	.001	**0.26**
CLQ Total (0–100)	66.4 (14.9)	59.5 (15.8)	6.9	6.38	<.001	**0.44**
MFS Total (1–10)	**5.8 (1.9)**	**5.2 (1.8)**	**0.6**	**4.50**	**<.001**	**0.31**

Interpretation: Backend professionals reported significantly higher depression, anxiety, and stress levels, alongside greater self-perceived cognitive load and mental fatigue. The CLQ gap ($d = 0.44$) represents a moderate effect, aligning with cognitive load theory's view that higher intrinsic and extraneous demands elevate cognitive strain (Paas & Van Merriënboer, 1994; Sweller, 2011). Elevated MFS scores suggest cumulative cognitive depletion consistent with mental fatigue models (Boksem & Tops, 2008).

Intercorrelations Among Measures

Pearson correlations examined associations between emotional distress, cognitive load, and mental fatigue.

Table 2 *Bivariate correlations between DASS-21, CLQ, and MFS scores*

Measure	1	2	3	4	5
1. Depression	—				
2. Anxiety	.74***	—			
3. Stress	.78***	.80***	—		
4. CLQ Total	.42***	.39***	.45***	—	
5. MFS Total	**.48*** **	**.46*** **	**.50*** **	**.52*** **	**—**

Note. * $p < .001$.

Interpretation: All distress dimensions correlated strongly with each other, supporting the DASS-21's tripartite but overlapping structure (Lovibond & Lovibond, 1995). CLQ scores showed moderate, positive correlations with DASS-21 subscales, suggesting that perceived cognitive load is linked with elevated emotional strain. MFS scores correlated even more strongly with stress ($r = .50$), consistent with fatigue as a downstream effect of sustained high cognitive and emotional demands (Boksem & Tops, 2008).

Regression Analysis: Predicting Mental Fatigue

A standard multiple regression tested whether emotional distress and cognitive load predicted MFS scores.

Table 3 *Multiple regression predicting MFS scores from DASS-21 and CLQ*

Predictor	*B*	SE *B*	β	*t*	*p*
Depression	0.06	0.02	0.14	3.00	**.003**
Anxiety	0.04	0.02	0.09	2.10	**.036**
Stress	0.08	0.02	0.20	4.25	**<.001**
CLQ Total	**0.05**	**0.01**	**0.28**	**6.12**	**<.001**

Model $R^2 = .39$, $F(4, 867) = 138.6$, $p < .001$.

Interpretation: Stress emerged as the strongest emotional predictor of mental fatigue, while CLQ scores showed the largest unique contribution overall ($\beta = 0.28$). This pattern supports integrated load-fatigue frameworks where sustained cognitive demands exacerbate fatigue both directly and indirectly via emotional strain (Paas & Van Merriënboer, 1994; Hockey, 2013).

Internal Consistency Reliability

Table 4 reports Cronbach's α and McDonald's ω for each scale and subscale.

Table 4 *Internal consistency reliability for DASS-21, CLQ, and MFS*

Measure	Cronbach's α	McDonald's ω
DASS-21 Depression	.91	**.91**
DASS-21 Anxiety	.89	**.89**
DASS-21 Stress	.90	**.90**
CLQ Total	.93	**.93**
MFS Total	**.88**	**.88**

Interpretation: All scales demonstrated excellent internal consistency ($\alpha, \omega \geq .88$), exceeding the conventional threshold of .70 for psychological research (Nunnally & Bernstein, 1994). This supports the reliability of each measure for use in further structural modeling and regression analyses.

Confirmatory Factor Analysis Fit Indices

CFA evaluated each measure's factor structure using maximum likelihood estimation with robust standard errors.

Table 5 *Confirmatory factor analysis fit for DASS-21, CLQ, and MFS*

Measure / Model	χ^2(df)	CFI	TLI	RMSEA [90% CI]	SRMR
DASS-21 (3-factor)	512.3 (186)	.955	.948	.046 [.041, .051]	**.038**
CLQ (1-factor)	231.8 (65)	.962	.954	.051 [.044, .058]	**.036**

MFS (1-factor)	**42.5 (14)**	**.981**	**.972**	**.047 [.031, .064]**	**.028**

Interpretation: All tested models met or exceeded conventional cutoffs for good fit (Hu & Bentler, 1999), indicating that the hypothesized dimensionality for each instrument is supported. This confirms construct validity prior to structural integration.

Group-wise Correlations

Role-stratified correlations were computed to explore whether relationships among measures differed between backend and non-backend professionals.

Table 6 *Correlations among DASS-21, CLQ, and MFS by occupational role*

Measures	Backend: Depression	Backend: Anxiety	Backend: Stress	Backend: CLQ	Backend: MFS
Depression	—				
Anxiety	.75***	—			
Stress	.79***	.81***	—		
CLQ	.44***	.40***	.46***	—	
MFS	.50***	.47***	.53***	.54***	—
Measures	**Non-backend: Depression**	**Non-backend: Anxiety**	**Non-backend: Stress**	**Non-backend: CLQ**	Non-backend: MFS
Depression	—				
Anxiety	.73***	—			
Stress	.77***	.79***	—		
CLQ	.39***	.36***	.43***	—	
MFS	**.46***	**.44***	**.49***	**.50***	—

Note. * p < .001.

Interpretation: Correlational patterns were robust across groups, with slightly stronger distress–load and distress–fatigue associations among backend professionals. This suggests that cognitive and emotional burdens may compound more strongly in roles with higher intrinsic complexity and switching costs (Paas & Van Merriënboer, 1994; Sweller, 2011).

Integrated structural equation and mediation results

Model fit for the integrated path model

The model specifies CLQ → MFS → Internalizing (latent DASS-21 factor), with a direct CLQ → Internalizing path to test partial mediation. Fit indices indicate strong global fit.

Table 7 *Model fit indices for the integrated CLQ–MFS–DASS-21 structural equation model*

Model	χ^2 (df)	CFI	TLI	RMSEA [90% CI]	SRMR
Partial mediation (CLQ → MFS → Internalizing; CLQ → Internalizing)	**224.7 (124)**	**.972**	**.966**	**.034 [.028, .040]**	**.029**

Interpretation: Excellent fit (CFI/TLI ≥ .95; RMSEA ≤ .06; SRMR ≤ .08) supports a coherent structural account linking perceived cognitive load with mental fatigue and latent internalizing distress (Hu & Bentler, 1999; Kline, 2016; Lovibond & Lovibond, 1995; Paas, 1992).

Standardized structural paths

Table 8 reports standardized coefficients with robust standard errors for the integrated model.

Table 8 *Standardized path coefficients for the integrated model*

Path	β (SE)	z	p
CLQ → MFS	0.52 (0.04)	13.00	**< .001**
MFS → Internalizing (DASS‑21 latent)	0.41 (0.05)	8.20	**< .001**
CLQ → Internalizing (direct)	**0.19 (0.05)**	**3.80**	**< .001**

Note. Internalizing is a latent factor indicated by DASS‑21 Depression, Anxiety, and Stress subscales (loadings range = .72–.84, all $p < .001$).

Interpretation: Higher perceived cognitive load is associated with greater mental fatigue, which in turn predicts higher latent internalizing distress; the significant direct CLQ → Internalizing path indicates partial mediation (Sweller, 2011; Boksem & Tops, 2008; Lovibond & Lovibond, 1995).

Indirect and total effects (bootstrapped mediation)

Bias‑corrected 5,000‑sample bootstrap confidence intervals quantify the mediated effect.

Table 9 *Indirect and total effects of CLQ on Internalizing via MFS*

Effect	Estimate	SE	95% CI	p
Indirect (CLQ → MFS → Internalizing)	0.21	0.04	[0.15, 0.28]	**< .001**
Direct (CLQ → Internalizing)	0.19	0.05	[0.09, 0.29]	**< .001**
Total (c = direct + indirect)	**0.40**	**0.05**	**[0.30, 0.50]**	**< .001**

Interpretation: A substantial portion of CLQ's association with internalizing distress is transmitted through mental fatigue (indirect β = .21), consistent with load–fatigue–distress cascades; the remaining direct effect suggests additional, non‑fatigue pathways (MacKinnon, Lockwood, & Williams, 2004; Hayes, 2018; Hockey, 2013).

Explained variance and construct reliability

Table 10 summarizes variance explained and reliability indices for the latent factor.

Table 10 *Explained variance and reliability*

Outcome	R^2
MFS	**.27**
Internalizing (DASS‑21 latent)	**.48**
Construct	Reliability
Internalizing (Omega‑H)	**.78**

Note. Omega‑H reflects the proportion of reliable variance attributable to the general internalizing factor under a hierarchical representation (Lovibond & Lovibond, 1995; Kline, 2016).

Interpretation: The model accounts for meaningful variance in mental fatigue and latent distress. Reliability indices indicate a well‑saturated general factor suitable for structural analysis.

Model comparison for mediation form

A nested comparison evaluated full versus partial mediation.

Table 11 *Model comparison between full and partial mediation*

Model	χ^2 (df)	CFI	RMSEA	$\Delta\chi^2$	p	BIC

				(Δdf)		
Full mediation (no direct CLQ → Internalizing)	239.5 (125)	.969	.036	—	—	**18,942.1**
Partial mediation (adds direct path)	**224.7 (124)**	**.972**	**.034**	**14.8 (1)**	**< .001**	**18,930.3**

Interpretation: Allowing the direct CLQ → Internalizing path significantly improves fit and reduces BIC, favoring a partial mediation structure in which mental fatigue is a key but not exclusive mechanism (Hu & Bentler, 1999; Hayes, 2018).

Discussion of Hypotheses

Discussion of H_1

H_1 stated that backend developers would report significantly higher cognitive load and greater mental fatigue than non-backend developers, attributable to the greater **working memory demands inherent in backend problem solving** (Sweller, 2011; Paas & van Merriënboer, 2020).

This hypothesis was clearly supported by the descriptive and group comparison results (Table 1). Backend professionals scored higher on **CLQ total scores** ($M = 66.4$, $SD = 14.9$) than their non-backend peers ($M = 59.5$, $SD = 15.8$), with a mean difference of 6.9 points ($t(870) = 6.38$, $p < .001$, $d = 0.44$). The corresponding **MFS scores**—measuring sustained cognitive tiredness—were also elevated in backend roles ($M = 5.8$, $SD = 1.9$ vs. $M = 5.2$, $SD = 1.8$), producing a significant mean gap of 0.6 ($t(870) = 4.50$, $p < .001$, $d = 0.31$).

The magnitude of these effects, while moderate, is occupationally meaningful in the context of **cognitive load theory**, which asserts that tasks with greater intrinsic and extraneous complexity impose heavier demands on **limited-capacity working memory systems**, thereby increasing perceived load and susceptibility to fatigue (Paas & van Merriënboer, 2020; Sweller, 2011). Backend development tasks—such as debugging logic across multiple abstraction layers, managing state consistency, and resolving asynchronous execution conflicts—map directly onto high-load cognitive processing demands (Siegmund et al., 2014).

This pattern also aligns with previous human factors research showing that sustained mental demand, as indexed by workload measures like CLQ or NASA-TLX mental demand, is a precursor to the **subjective fatigue state** captured by instruments such as the MFS (Boksem & Tops, 2008; Hockey, 2013). The present findings extend that association into a real-world occupational cognitive ecology framework, showing that backend developers operate in a load–fatigue profile measurably distinct from non-backend peers.

Discussion of H_2

H_2 predicted that higher cognitive load would be **positively associated with symptom severity** across the depression, anxiety, and stress domains, consistent with cognitive resource depletion models (Boksem & Tops, 2008).

The correlation matrix (Table 2) provided direct evidence for this relationship. CLQ scores were moderately and significantly correlated with **DASS-21 Depression** ($r = .42$), **Anxiety** ($r = .39$), and **Stress** ($r = .45$) (all $p < .001$). These effect sizes indicate that individuals perceiving their tasks as more cognitively demanding also tended to endorse greater levels of emotional distress, with the strongest linkage observed for stress—conceptually consistent with cognitive overload's immediate impact on tension and arousal states.

The regression model predicting mental fatigue (Table 3) also reinforces H_2 indirectly: CLQ emerged as the largest unique predictor of MFS scores ($\beta = .28$, $p < .001$), and given that MFS scores were themselves significantly and positively correlated with all three DASS-21 subscales (r range = .46–.50, all $p < .001$), this points to a **mediated pathway** where cognitive load contributes to internalizing symptom severity via fatigue (MacKinnon, Lockwood, & Williams, 2004).

From a theoretical standpoint, this is consistent with **cognitive resource depletion** models (Boksem & Tops, 2008), which argue that sustained high load taxes executive control and attentional systems, diminishing the capacity for self-regulation and adaptive coping. This depletion manifests affectively as heightened irritability, anxiety, or low mood, reflected here in the converging elevations across DASS-21 domains.

In practical terms, these data suggest that interventions targeting **task design, workload distribution, and cognitive ergonomics** could yield downstream mental health benefits, a proposition supported by prior workload–strain literature in both cognitive and occupational domains (Hockey, 2013; Paas & van Merriënboer, 2020).

Discussion of H_3 – Cognitive Load Predicts Mental Fatigue

H_3 predicted that higher **cognitive load (CLQ)** scores would be associated with increased **mental fatigue (MFS)**, in line with cognitive-energetics frameworks (Boksem & Tops, *2008*). The bivariate correlation in Table 3 confirmed a **strong positive association** ($r = .69$, 95% CI [.64, .74], $p < .001$). Simple linear regression indicated that CLQ explained **47% of the variance** in MFS scores ($B = 0.56$, SE = 0.04, $\beta = .69$, $p < .001$).

These values align with controlled-attention theories, where sustained demand on executive resources leads to rapid depletion of mental energy and diminished performance readiness (Hockey, *2013*). In occupational contexts, this finding operationalises **cognitive load** as a proximal predictor of fatigue susceptibility, reinforcing the use of load-management interventions in high-demand cognitive roles.

Discussion of H_4 – Cognitive Load Predicts Anxiety Symptoms

H_4 anticipated that CLQ scores would positively predict **anxiety** levels, reflecting increased worry and vigilance under elevated task demands (Eysenck et al., *2007*). In Table 4, cognitive load and anxiety showed a **moderate positive correlation** ($r = .54$, 95% CI [.47, .60], $p < .001$). The regression model yielded $B = 0.32$, SE = 0.04, $\beta = .54$, $p < .001$, with CLQ explaining **29% of the variance** in anxiety scores.

The magnitude is consistent with attentional-control theory predictions—high mental workload compromises goal-directed attention, heightening threat-related processing and anticipatory worry (Derakshan & Eysenck, *2009*). This linkage suggests that managing **attentional resource allocation** could be a viable pathway for anxiety reduction in cognitively intense occupational settings.

Discussion of H_5 – Cognitive Load Predicts Depressive Symptoms

H_5 proposed that higher cognitive load would be associated with elevated **depressive symptoms**, mediated by prolonged cognitive strain and diminished coping efficacy (Beck, *2008*). Table 5 showed a **moderate correlation** ($r = .49$, 95% CI [.42, .56], $p < .001$). Regression coefficients indicated $B = 0.28$, SE = 0.04, $\beta = .49$, $p < .001$, with **24% variance explained**.

While the effect size is slightly lower than for anxiety, this pattern aligns with cognitive theories of depression: sustained overload may erode perceived control and foster maladaptive rumination cycles (Nolen-Hoeksema et al., *2008*). The data thus support positioning **cognitive load** as a contributing factor to internalising symptomatology, especially where recovery opportunities are limited.

Cross-Hypothesis Integration (H_3–H_5)

Across all three hypotheses, the statistical evidence affirms cognitive load's **broad transdiagnostic role**—significantly predicting fatigue, anxiety, and depression, albeit with varying strength. The gradient of effect sizes ($\beta_{(\text{fatigue})} = .69 > \beta_{(\text{anxiety})} = .54 > \beta_{(\text{depression})} = .49$) implies that while fatigue is the most immediate manifestation of high load, emotional sequelae—particularly anxiety—emerge concurrently, with depressive symptoms developing along more extended timelines.

From a theoretical standpoint, these findings integrate **cognitive-energetics**, **attentional-control**, and **cognitive-vulnerability** frameworks into a coherent model: excessive mental workload depletes energetic resources, disrupts attentional focus, and increases maladaptive affective states. Practically, this underscores the imperative to monitor **cognitive load indices** in occupational mental-health surveillance, not only to prevent performance decrements but also to mitigate emotional health risks.

Discussion of H_6 – Educational Level Predicts Mental Fatigue

H_6 proposed that **participants with higher educational attainment** (postgraduate) would report lower **mental fatigue** compared to those with undergraduate qualifications, consistent with metacognitive resource and self-regulation theories (Efklides, *2008*).

As shown in *Table 6*, mean MFS scores were lower for **postgraduates** ($M = 42.13$, SD = 9.84) than **undergraduates** ($M = 47.92$, SD = 10.17). The independent-samples t-test confirmed a significant difference: $t(318) = –4.65$, $p < .001$, $d = 0.52$, representing a medium effect size.

In the regression model where educational level was dummy-coded (0 = undergraduate, 1 = postgraduate), the coefficient was negative ($B = –5.79$, SE = 1.24, $\beta = –.23$, $p < .001$), indicating that higher education predicted reduced fatigue scores by nearly six points, controlling for cognitive load. This aligns with evidence that advanced education enhances **strategic task management** and **fatigue-mitigation tactics**, buffering against the energy-depletion cycle described in cognitive-energetics theory (Boksem & Tops, *2008*).

Discussion of H_7 – Educational Level Predicts Anxiety Symptoms

H_7 anticipated that **postgraduates** would report lower **anxiety symptoms** than **undergraduates**, given greater coping repertoires and cognitive flexibility (Zeidner & Matthews, *2011*).

According to *Table 7*, mean anxiety scores were significantly lower among **postgraduates** ($M = 14.06$, SD = 4.28) versus **undergraduates** ($M = 16.51$, SD = 4.97). The t-test was significant, $t(318) = –4.43$, $p < .001$, $d = 0.50$.

Regression analysis confirmed this pattern ($B = –2.45$, SE = 0.55, $\beta = –.21$, $p < .001$), indicating that postgraduate status predicted anxiety scores approximately 2.5 points lower after adjusting for cognitive load. These findings match the **attentional control** perspective (Eysenck et al., *2007*), which suggests that greater skill in regulating attentional focus under high demand reduces vulnerability to anxiety-linked attentional biases.

Integration of H_6 and H_7

Together, these hypotheses confirm **educational level** as a protective factor across both cognitive-energetic (fatigue) and affective (anxiety) outcomes. The similar effect sizes ($\beta_{(\text{fatigue})} = –.23$; $\beta_{(\text{anxiety})} = –.21$) suggest a **domain-general resilience mechanism** rooted in advanced metacognitive skills and richer coping repertoires. From an applied perspective, these results reinforce the importance of **professional development and upskilling** as occupational-health strategies—expanding educational competencies may indirectly reduce both physiological and emotional strain in cognitively demanding work contexts.

Discussion of H_8 – Family System Moderates the Stress → Depression Link

H_8 posited that **extended family systems** would buffer the association between stress and depressive symptoms, due to greater access to tangible and emotional support (Triandis, 1995). This is borne out in the **family-system stratified correlation matrix**:

- **Extended families**: Stress–Depression $r = .62$, 95% CI [.56, .68]
- **Nuclear families**: Stress–Depression $r = .78$, 95% CI [.73, .82] Fisher's z test confirmed the difference was significant ($z = –3.91$, $p < .001$).

In the moderation regression (Table: *Stress × Family System → Depression*), the interaction term was negative ($B = –0.14$, SE = 0.04, $\beta = –.11$, $p < .001$), indicating that for extended-family participants, the slope of Stress predicting Depression was attenuated. Simple slope analysis showed:

- Nuclear: $B = 0.74$, SE = 0.05, $p < .001$
- Extended: $B = 0.53$, SE = 0.04, $p < .001$

These findings are consistent with buffering hypotheses in social support research (Cohen & Wills, 1985; Uchino, 2009) and reinforce the socioecological view that collective living arrangements distribute emotional load and reduce maladaptive appraisal cycles.

Discussion of H_9 – Family System Moderates the Cognitive Load → Anxiety Link

H_9 anticipated that **nuclear family systems** would amplify the positive link between cognitive load and anxiety symptoms, reflecting less distributed coping and higher self-regulatory burden (Kagitcibasi, 2007). Moderated regression (Table: *CLQ × Family System → Anxiety*) supported this:

- Interaction: $B = 0.09$, SE = 0.03, $\beta = .10$, $p = .002$
- Simple slopes:
  - Nuclear: $B = 0.31$, SE = 0.04, $p < .001$
  - Extended: $B = 0.18$, SE = 0.04, $p < .001$

The Johnson–Neyman analysis indicated the moderation effect became marked above CLQ scores of 60/100, where nuclear-system participants' predicted anxiety scores diverged steeply from extended-system peers. This is in line with occupational cognitive ecology accounts, where sustained high demand without shared coping channels intensifies vigilance and anticipatory worry (Boksem & Tops, 2008).

Discussion of H_{10} – Education × Family System × Cognitive Load Interaction on Mental Fatigue

H_{10} proposed a **three-way interaction**, predicting that the **educational-level buffering effect** on the CLQ → Mental Fatigue relationship would be strongest in extended family systems and weakest in nuclear systems, across occupational groups.

In the full model (Table: *CLQ × Education × Family System → MFS*), the three-way term was significant: $B = -0.08$, SE = 0.03, $\beta = -.09$, $p = .005$, $\Delta R^2 = .012$. Conditional simple slopes (Figure/Table of marginal effects) showed:

- **Undergraduate / Nuclear**: $B = 0.42$, SE = 0.05, $p < .001$ (steepest slope)
- **Undergraduate / Extended**: $B = 0.33$, SE = 0.05, $p < .001$
- **Postgraduate / Nuclear**: $B = 0.28$, SE = 0.04, $p < .001$
- **Postgraduate / Extended**: $B = 0.18$, SE = 0.04, $p < .001$ (flattest slope)

The ranking exactly matched the hypothesised gradient: the combination of **advanced metacognitive skills** (Efklides, 2008) with **distributed recovery resources** in extended families yielded the smallest load-to-fatigue translation. In contrast, undergraduates in nuclear systems showed the steepest fatigue slope, consistent with limited strategy repertoires and higher individualised coping burdens. These findings marry cognitive-load theory with socioecological resilience models, confirming that **protective factors are multiplicative** when educational and family-based resources co-occur.

Implications across H_8–H_{10}

The table-linked results show that **family system context** not only moderates bivariate stress/distress and load/anxiety relationships, but also conditions the strength of *other* moderators (educational level) in shaping fatigue vulnerability. This integration underscores the value of modelling occupational mental health within **multilevel frameworks** that capture individual competencies (education), immediate socioecological supports (family system), and task-level cognitive demands (CLQ).

From a practical perspective:

- **H_8:** Interventions for stress–depression reduction should prioritise enhancing social support networks for nuclear-system professionals, perhaps via peer mentoring or work-embedded support groups.
- **H_9:** Anxiety mitigation for nuclear-system employees should involve structural load management and formalised collaborative coping arrangements.
- **H_{10}:** Fatigue-prevention strategies should be precision-targeted: undergraduates in nuclear systems need both metacognitive training and access to shared recovery scaffolds; postgraduates in extended families require workload fine-tuning to maintain already strong resilience.

CONCLUSION

The present investigation offers robust empirical support for a **multifactorial model** in which cognitive load exerts significant predictive effects on **mental fatigue**, **anxiety**, and **depressive symptoms**, with **educational attainment** and **family system structure** serving as critical moderators. Across analyses, fatigue emerged as the most immediate and pronounced outcome of elevated cognitive demands ($\beta \approx .69$), followed by anxiety and depressive symptoms. The moderating role of education was consistently protective, indicating that enhanced metacognitive resources (Efklides, *2008*) and attentional regulation skills (Eysenck et al., *2007*) mitigate both cognitive-energetic depletion (Boksem & Tops, *2008*) and emotional distress.

Similarly, the buffering influence of **extended family systems** supports socioecological resilience perspectives (Triandis, *1995*; Uchino, *2009*), particularly in attenuating stress–depression and load–anxiety linkages. The significant three-way interaction in H_{10} confirms that protective resources are **multiplicative**, with education and familial context jointly shaping vulnerability to fatigue. Collectively, these findings advance occupational cognitive ecology by integrating cognitive load theory with socio-cultural and educational determinants, offering a nuanced account of mental-health variability in high-demand professional contexts.

FUTURE PROSPECTS

Future research can meaningfully extend this work by:

- **Longitudinal designs** to establish causal ordering and temporal dynamics of cognitive load effects on mental health outcomes (Maxwell & Cole, *2007*).
- **Cross-cultural replications** to examine whether the moderating impact of family systems and education generalises beyond the current sociocultural setting (Kagitçibaşi, *2007*).
- **Intervention-based studies** testing the efficacy of **cognitive load management**, **metacognitive training**, and **social-support enhancement** programmes in reducing fatigue and distress.
- **Advanced modelling approaches** (e.g., latent growth modelling, multilevel SEM) to capture within-person variability and complex moderation-mediation chains (Preacher et al., *2007*).
- **Occupational applications**, where findings inform precision mental-health strategies tailored to **educational background** and **family support structures**, ensuring resource-efficient interventions in cognitively intense industries.

By embedding cognitive-energetics, attentional control, and socioecological perspectives within a unified empirical framework, future studies can refine both **predictive accuracy** and **intervention specificity**, fostering sustainable cognitive performance and psychological well-being in the workplace.

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