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AI-Supported Early Detection of Burnout and Depression in Social Work Professionals: Effort-Reward Imbalance, Emotional Labor, and the Differential Mediating Role of Surface Acting

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ABSTRACT

Background. Social work professionals constitute one of the most psychologically vulnerable occupational groups, characterized by sustained exposure to emotionally demanding client interactions, chronic resource scarcity, and structural organizational pressures. Although effort-reward imbalance (ERI) is an established predictor of burnout and depression, the mechanisms through which it produces psychological harm—and the potential of artificial intelligence (AI) to support early detection—remain underexplored.

Aim. This study examined surface acting, a form of emotional labor, as a mediator linking ERI to emotional exhaustion and depression, and derived implications for a conceptual AI-based monitoring framework.

Method. A cross-sectional online survey was conducted with $N = 98$ social work professionals in Germany (M age = 36.9 years, $SD = 8.6$; 68.4% female). Instruments comprised the Effort-Reward Imbalance Scale, the Maslach Burnout Inventory–Emotional Exhaustion subscale, the Patient Health Questionnaire-9, and the Surface Acting subscale of the Emotional Labor Scale. Parallel mediation models were estimated using bias-corrected bootstrapping with 5,000 resamples.

Results. ERI strongly predicted both emotional exhaustion ($\beta = .88$, $p < .001$) and depression ($\beta = .87$, $p < .001$). Surface acting partially mediated the ERI–exhaustion pathway (indirect $\beta = .11$, 95% CI [.01, .22]) but did not mediate the ERI–depression pathway (indirect $\beta = -.003$, 95% CI [−.11, .10]).

Conclusion. Emotional labor contributes to the exhaustion pathway but not the depression pathway, indicating that the two outcomes arise through partly distinct mechanisms. This differential pattern carries direct implications for the design of AI-supported early detection systems, which should track the shared resource-depletion trajectory rather than assume a single mediating mechanism.

Keywords: burnout, depression, social work, emotional labor, surface acting, effort-reward imbalance, artificial intelligence

INTRODUCTION

It is Tuesday afternoon in a community mental health center in Frankfurt. A social worker—seven years into a career she once described as her calling—sits across from a client in acute crisis, her third in five hours. Her voice is calm, her posture attentive, her affect carefully modulated to project both warmth and professional authority. Internally, however, she is running on empty: her concentration is fraying, a low-grade headache has settled behind her eyes, and for the second consecutive week she has skipped lunch. She does not label what she is experiencing as burnout. She calls it Tuesday.

This vignette, while fictional in detail, reflects a structural reality that pervades the helping professions with particular severity in social work. The global prevalence of burnout among social workers is estimated at between 35% and 75% depending on the subsector, measurement instrument, and national context, with consistently higher rates in child protection, psychiatric aftercare, and migration counseling (Maslach & Leiter, 2016; Kim

& Ji, 2009). Depression, frequently comorbid with professional burnout, affects approximately one in four social work practitioners at clinically significant levels across international studies (Siebert, 2004; Stalker et al., 2007). Yet early detection and prevention remain structurally underdeveloped: most social workers who experience clinically relevant psychological distress neither seek help proactively nor receive systematic organizational screening (Sousa et al., 2018).

The German context intensifies this challenge considerably. The social work sector in Germany employs approximately 420,000 qualified professionals and faces structural pressures including chronic underfunding, high caseloads, and persistent undervaluation relative to comparable professions in education and healthcare (Bundesagentur für Arbeit, 2023). Occupational health surveillance is largely absent or inconsistently implemented at the organizational level, and self-reporting of mental health difficulties carries strong stigma within a professional culture that implicitly demands resilience and self-sacrifice (Pazer, 2024a). These conditions converge to produce a workforce highly susceptible to undetected psychological deterioration over extended time periods—with individual, organizational, and societal costs that remain difficult to quantify precisely because the deterioration itself so often goes undetected.

Understanding the specific psychological mechanisms through which occupational stressors translate into burnout and depression in this population is therefore a matter of both theoretical importance and urgent practical consequence. A substantial body of research has established effort-reward imbalance (ERI)—the mismatch between subjectively experienced work demands and perceived occupational rewards—as a central predictor of burnout and poor mental health among caring professionals (Siegrist, 1996; van Vegchel et al., 2005). However, comparatively less attention has been directed toward the mediating mechanisms through which this imbalance produces psychological harm, and whether those mechanisms are identical across distinct health outcomes. Emotional labor—the management of expressed emotions to fulfill occupational role requirements, as theorized by Hochschild (1983) and elaborated by Grandey (2000) and Morris and Feldman (1996)—represents a theoretically compelling and empirically underexplored candidate mediator in the social work context, given the constitutive centrality of relational emotional performance to social work practice.

Moreover, a structurally underexamined research gap concerns the integration of emerging artificial intelligence (AI) technologies into occupational health prevention frameworks for the helping professions. Recent years have witnessed an accelerating development of AI applications capable of detecting psychological distress through behavioral biomarkers, natural language patterns, speech analysis, and physiological indicators (Luxton, 2020; Torous et al., 2020). These developments open novel possibilities for continuous, low-threshold, and stigma-reducing monitoring of occupational mental health, yet their application to the specific context of social work—and the empirical evidence base required to inform such systems—remains at a nascent stage.

Against this backdrop, the present study pursues the following central research question: To what extent does surface acting as a form of emotional labor mediate the relationship between effort-reward imbalance and the dual outcomes of burnout and depression among German social work professionals, and is the mediating mechanism equivalent across both outcomes? The answer carries direct implications not only for theoretical models of occupational health in the helping professions, but for the evidence-based design of AI-supported early detection systems. By situating empirical mediation analysis within a broader discourse on technological prevention architectures, this article aims to contribute simultaneously to occupational health psychology, social work research, and applied AI scholarship.

THEORETICAL BACKGROUND

Burnout in Social Work: Definition, Prevalence, and the Job Demands-Resources Model

The conceptualization of burnout has undergone considerable theoretical refinement since Freudenberger's (1974) initial description of the phenomenon among volunteer workers in alternative care settings. The dominant framework in contemporary research remains Maslach and Jackson's (1981) tridimensional model, which defines burnout as a syndrome constituted by emotional exhaustion, depersonalization, and a reduced sense of personal accomplishment. Emotional exhaustion—the depletion of the emotional resources required for sustained empathic engagement—occupies the central position in this model as the primary driver from which depersonalization and reduced accomplishment are theorized to follow (Maslach et al., 1996). For social work professionals, whose occupational role is constitutively defined by relational engagement with clients in states of vulnerability, distress, or systemic exclusion, emotional exhaustion carries both phenomenological and functional significance of particular gravity.

The Job Demands-Resources (JD-R) model developed by Demerouti et al. (2001) and subsequently extended by Bakker and Demerouti (2017) offers the most comprehensive structural account of burnout as an organizational phenomenon. The model posits two fundamental processes: a health-impairment process, through which chronic exposure to demanding job characteristics without adequate resources depletes psychological capital and produces burnout; and a motivational process, through which resources function as buffers and enablers of engagement. In the social work context, demands include emotional intensity, role ambiguity, high caseload, and secondary traumatic stress, while resources typically encompass supervisory support, autonomy, and institutional recognition—resources that are systematically undersupplied in many social work organizations (Bakker et al., 2004; Hobfoll, 2001). The consistent finding that subjective appraisal of demand-resource imbalance predicts burnout outcomes over and above objective workload indicators suggests that the psychological interpretation of workplace conditions, rather than their mere objective presence, constitutes the operative mechanism (van Vegchel et al., 2005; Alarcon, 2011).

Depression as a Comorbid Condition in Occupational Health

The conceptual and nosological relationship between burnout and depression has been a subject of ongoing theoretical and empirical debate. Whereas early contributions by Maslach and colleagues positioned burnout as a work-specific syndrome categorically distinct from the generalized symptomatology of depressive disorder, subsequent research has challenged this differentiation on both empirical and theoretical grounds (Bianchi et al., 2015; Schonfeld & Bianchi, 2016). Meta-analyses examining the overlap between validated burnout and depression measures consistently report correlation coefficients in the range of .51 to .68, suggesting substantial shared variance while not precluding meaningful construct distinction (Koutsimani et al., 2019). The conceptualization of the relationship as sequential rather than synonymous—with burnout functioning as a proximal antecedent of clinical depression when sustained without intervention—has received empirical support from prospective longitudinal investigations.

From a clinical standpoint, the comorbidity of burnout and depression in social work populations is of significant epidemiological and practical concern. Siebert's (2004) survey of NASW members in the United States found that 19% reported a personal history of clinical depression, with notably elevated rates among those working in high-intensity subsectors. In the German context, Lehr et al. (2010) documented that helping professionals with high burnout scores had a substantially elevated risk of a subsequent depressive episode within a 12-month period. The trajectory of professional mental health deterioration is theorized to operate via several mechanistic pathways: the erosion of cognitive resources reduces affective regulatory capacity; the progressive withdrawal from meaningful work eliminates sources of positive reinforcement; and the social isolation frequently accompanying advanced burnout deprives individuals of the interpersonal support that constitutes a principal buffer against depressive onset (Nolen-Hoeksema et al., 2008; Hakanen & Schaufeli, 2012). Critically, the fact that burnout and depression may share an antecedent yet diverge in their proximal mechanisms motivates the present study's examination of whether a single emotional-labor pathway operates equivalently across both outcomes.

Emotional Labor as a Mechanism of Psychological Depletion

The concept of emotional labor, as theoretically introduced by Hochschild (1983) in her seminal sociological study of airline attendants, refers to the management of felt and displayed emotions in accordance with occupational role requirements. Hochschild distinguished two fundamental regulatory strategies: surface acting, in which the worker alters external emotional expression without modifying the underlying affective state; and deep acting, in which the worker engages in active internal psychological work to genuinely modify subjective feeling states in alignment with role demands. The psychological consequences of these strategies differ substantially: surface acting has been consistently and robustly associated with emotional exhaustion, depersonalization, and poor subjective wellbeing, while deep acting shows more nuanced and context-dependent associations with health outcomes (Grandey, 2003; Hülsheger & Schewe, 2011).

The theoretical link between surface acting and burnout operates most coherently through the lens of the resource depletion perspective articulated by Grandey (2000) and elaborated in the Conservation of Resources (COR) framework of Hobfoll (1989, 2001). Surface acting places sustained demands on self-regulatory resources—particularly attentional control and emotional suppression—that share a limited pool with the resources required for empathic attunement, reflective practice, and client-centered relationship maintenance. When the performance of emotional labor is chronic, intensive, and inadequately resourced, the resulting depletion creates conditions for emotional exhaustion that directly parallel the central dimension of burnout (Hülsheger & Schewe, 2011; Zapf, 2002 as cited in Hülsheger & Schewe, 2011). In social work, emotional labor occupies a particularly complex and structurally inescapable position: the emotional performances required of social workers are governed not primarily by organizational display rules aimed at customer satisfaction, but by normative professional ethics of empathy, non-judgment, and client dignity that constitute the ethical foundation of the discipline (Dominelli, 2014). Notably, the resource-depletion account predicts a tighter mechanistic coupling between surface acting and exhaustion than between surface acting and depression, since exhaustion is the proximal product of regulatory-resource loss whereas depression involves additional cognitive-affective processes—a theoretical asymmetry the present study tests directly.

Artificial Intelligence in Occupational Mental Health Monitoring

The application of artificial intelligence methodologies to the early detection of psychological distress represents one of the most rapidly developing frontiers at the intersection of technology, psychology, and public health. Broadly defined, AI-based mental health monitoring systems leverage machine learning algorithms to identify patterns in behavioral, physiological, linguistic, and temporal data that reliably precede or co-occur with clinically significant psychological deterioration (Luxton, 2020; Torous et al., 2020). Existing applications range from passive monitoring systems that analyze smartphone usage patterns, keystroke dynamics, and social media behavior (Chow et al., 2017; Saeb et al., 2015), to active systems that employ natural language processing to analyze the semantic and affective content of professional output (Coppersmith et al., 2015; Guntuku et al., 2017), to multimodal platforms combining physiological sensor data with validated self-report instruments in real-time feedback architectures (Mohr et al., 2017).

The theoretical promise of AI-based occupational health monitoring for high-risk groups such as social workers lies in several mutually reinforcing advantages: continuous, unobtrusive monitoring enables detection of gradual deterioration trajectories that periodic clinical assessment cannot capture; personalization through adaptive algorithms addresses the heterogeneity of burnout and depression presentations; and algorithmically triggered psychoeducational feedback introduces a novel point of preventive contact that does not require clinical consultation—a significant advantage in cultures characterized by help-seeking stigma (Luxton, 2020; Pazer, 2024b). However, the evidence base remains nascent, and the specific empirical parameters required to inform responsible system design—including which validated constructs most effectively serve as early warning indicators, and whether the same indicator predicts multiple outcomes equally well—require systematic investigation. The present study addresses this gap empirically.

Research Hypotheses

Drawing on the foregoing theoretical foundations, the following hypotheses are advanced. H1: Effort-reward imbalance will positively and significantly predict emotional exhaustion (H1a) and depressive symptomatology (H1b). H2: Surface acting will function as a partial mediator of the relationship between effort-reward imbalance and emotional exhaustion (H2a) and between effort-reward imbalance and depression (H2b), such that the bootstrap confidence interval for the indirect effect excludes zero. H3: The empirically identified mediation pathways will provide a theoretically coherent foundation for the design of AI-supported early detection systems targeting occupationally specific psychological risk indicators in social work.

METHOD

Study Design

The present investigation employed a cross-sectional, correlational online survey design. This design was selected as methodologically appropriate for the initial examination of the hypothesized mediation pathways, providing the analytic basis for path-analytic procedures while enabling efficient, platform-independent data collection from a geographically dispersed professional population. The inherent limitations of cross-sectional designs with respect to causal inference and temporal precedence are acknowledged and addressed systematically in Section 5.3.

Sample and Recruitment

Participants were recruited through online professional networks and social-media-based communities for social work professionals. Eligibility required current employment in a qualified social work role (state-recognized Sozialarbeiter/in or Sozialpädagoge/in) and a minimum of six months of continuous professional practice. Participants were informed of voluntary participation, anonymity, data-protection compliance with the GDPR, and the right to withdraw at any time without disadvantage.

The final analytic sample comprised N = 98 participants (68.4% female, 29.6% male, 2.0% diverse; M age = 36.9 years, SD = 8.6, range 24–55). Mean weekly working hours were M = 37.6 (SD = 3.1). The majority held a Bachelor's degree in Social Work (72.4%), with 27.6% holding a Master's degree. Occupational subsectors represented included child and youth welfare (33.7%), psychiatric social work (17.3%), addiction counseling (16.3%), migration and integration services (16.3%), and other fields (16.3%).

Measures

Effort-Reward Imbalance (ERI). The Effort-Reward Imbalance Scale (Siegrist et al., 2004) was used to assess the subjective balance between perceived occupational demands and experienced rewards, expressed as an effort-reward ratio; values exceeding 1.0 indicate demand-reward imbalance. A sample item from the effort subscale is: “I have constant time pressure due to a heavy work load.” The instrument has demonstrated good internal consistency in prior validation studies (α = .84; Siegrist et al., 2004).

Emotional Exhaustion (MBI-EE). Burnout was operationalized through the Emotional Exhaustion subscale of the Maslach Burnout Inventory (Maslach et al., 1996), comprising nine items rated on a seven-point frequency scale (0 = never to 6 = every day). Higher scores indicate greater exhaustion. A sample item is: “I feel emotionally drained from my work.” The subscale shows excellent internal consistency across validation samples (α = .89; Maslach et al., 1996).

Depression (PHQ-9). Depressive symptomatology was assessed using the Patient Health Questionnaire-9 (Kroenke et al., 2001), a nine-item validated screening instrument. Items are rated on a four-point frequency scale (0 = not at all to 3 = nearly every day), with total scores ranging from 0 to 27. A cutoff of $\geq$ 10 indicating moderate-to-severe depression is well established (Kroenke et al., 2001). The instrument demonstrates excellent reliability in validation research (α = .87; Kroenke et al., 2001).

Surface Acting (ELS-SA). Surface acting was measured using the Surface Acting subscale of the Emotional Labor Scale (Grandey, 2003). Items are rated on a five-point Likert scale. A sample item is: “I put on a mask in order to express the right emotions for my job.” The subscale shows satisfactory internal consistency in validation research (α = .81; Grandey, 2003). Because the present dataset comprised validated composite scale scores rather than item-level responses, the reliability coefficients reported here reflect the instruments' established psychometric properties (see Note to Table 1).

Statistical Analysis

Data analysis proceeded in three sequential phases. First, descriptive statistics were computed for all study variables, including means (M) and standard deviations (SD). Second, bivariate Pearson correlations among all study variables were calculated to establish the pattern of intercorrelations prerequisite to mediation analysis.

Third, the mediation hypotheses (H2a, H2b) were tested in two parallel simple mediation models with effort-reward imbalance as predictor, surface acting as mediator, and emotional exhaustion and depression as the respective outcomes, following the regression-based framework of Hayes (2018; PROCESS Model 4). All variables were standardized prior to analysis, and bias-corrected bootstrapping with 5,000 resamples was used to generate 95% confidence intervals (CIs) for indirect effects; a bootstrap CI excluding zero indicates statistical significance. Direct effects were tested at the α = .05 threshold. To examine the risk for common-method bias (Podsakoff et al., 2003), Harman's single-factor test was performed; its limited diagnostic value in a four-variable composite-score dataset is discussed in Section 5.3.

RESULTS

Descriptive Findings

Table 1 presents descriptive statistics for all study variables. Effort-reward imbalance scores indicated pervasive demand-reward imbalance, with a mean ERI ratio of M = 1.36 (SD = 0.21); 96.9% of participants exceeded the critical threshold of 1.0, a strikingly high proportion consistent with the structurally strained conditions documented for German caring professions (van Vegchel et al., 2005). Mean emotional exhaustion scores (M = 24.98, SD = 7.54) fell in the moderate-to-high range, with 43.9% of participants meeting or exceeding the frequently used clinical burnout indication cutoff of ≥ 27 (Maslach et al., 1996). Depression scores revealed clinically significant depressive symptomatology (PHQ-9 ≥ 10) in 42.9% of the sample—a prevalence markedly exceeding population-level norms (Kroenke et al., 2001) and consistent with the elevated risk profile of helping professionals. Surface acting showed moderate mean levels (M = 3.27, SD = 0.79), consistent with prior research in comparable populations (Grandey, 2003; Hülsheger & Schewe, 2011).

Table 1 Descriptive Statistics and Instrument Reliability (N = 98)

Scale	Items (n)	*M*	*SD*	*α*
Effort-Reward Imbalance (ERI)	16	1.36	0.21	.84
Surface Acting (ELS-SA)	4	3.27	0.79	.81
Emotional Exhaustion (MBI-EE)	9	24.98	7.54	.89
Depression (PHQ-9)	9	8.93	4.74	.87

Note. N = 98. M = arithmetic mean; SD = standard deviation; α = Cronbach's alpha. ERI values reflect the effort-reward ratio; values > 1.0 indicate imbalance. Because the dataset comprised validated composite scores, α values are reported from the instruments' published validation studies rather than recomputed from item-level data in the present sample.

Correlational Findings

Table 2 presents the Pearson intercorrelation matrix. Consistent with H1a and H1b, effort-reward imbalance was strongly and positively associated with both emotional exhaustion (r = .88, p < .001) and depression (r = .87, p < .001), providing robust bivariate support for both components of H1. Surface acting showed significant positive associations with effort-reward imbalance (r = .67, p < .001), emotional exhaustion (r = .68, p < .001), and depression (r = .58, p < .001). The correlation between the two outcome variables was very high (r = .90, p < .001), consistent with—and exceeding—the burnout-depression comorbidity range reported by Koutsimani et al. (2019). All intercorrelations were in the theoretically anticipated direction; the notably elevated magnitudes are addressed in the limitations.

Table 2 Pearson Intercorrelation Matrix (N = 98)

Variable	*M*	*SD*	1	2	3	4
1. Effort-Reward Imbalance	1.36	0.21	—			

2. Surface Acting	3.27	0.79	.67**	—		
3. Emotional Exhaustion	24.98	7.54	.88**	.68**	—	
4. Depression (PHQ-9)	8.93	4.74	.87**	.58**	.90**	—

Note. N = 98. Values are Pearson correlation coefficients. M and SD denote arithmetic mean and standard deviation. ERI = Effort-Reward Imbalance; MBI-EE = Maslach Burnout Inventory–Emotional Exhaustion; PHQ-9 = Patient Health Questionnaire-9. ** $p < .01$ (two-tailed).

Main Analysis: Mediation of the ERI–Burnout and ERI–Depression Pathways

The results of the two parallel mediation models are presented in Table 3. With respect to Outcome 1 (emotional exhaustion), the direct effect of effort-reward imbalance remained strong and significant after the inclusion of surface acting ($\beta = .77$, $p < .001$, 95% CI [.65, .89]), indicating partial rather than full mediation. The effect of ERI on surface acting was substantial ($\beta = .67$, $p < .001$, 95% CI [.52, .82]), and surface acting in turn predicted emotional exhaustion while controlling for ERI ($\beta = .16$, $p = .011$, 95% CI [.04, .29]). The bias-corrected bootstrap confidence interval for the indirect effect excluded zero ($\beta = .11$, 95% CI [.01, .22]), confirming a statistically significant—though modest—partial mediation. H2a was thus supported, with the qualification that the lower confidence bound lies close to zero and the proportion of the total effect carried by the indirect path was approximately 12.6%.

Parallel analyses for the ERI–depression pathway revealed a markedly different pattern. The direct effect of effort-reward imbalance on depressive symptomatology remained strong after the inclusion of the mediator ($\beta = .88$, $p < .001$, 95% CI [.74, 1.01]). However, surface acting did not significantly predict depression while controlling for ERI ($\beta = -.005$, $p = .94$, 95% CI [−.14, .13]), and the indirect effect of ERI on depression through surface acting was not statistically significant, with a bootstrap confidence interval spanning zero ($\beta = -.003$, 95% CI [−.11, .10]). H2b was therefore not supported. In summary, surface acting functioned as a statistically significant partial mediator of the pathway from effort-reward imbalance to emotional exhaustion, but not of the pathway to depression; H1a and H1b were both confirmed by the strong and significant total and direct effects of ERI on both outcomes, whereas the mediating role of emotional labor was specific to the exhaustion pathway.

Table 3 Parallel Mediation Results: Direct and Indirect Effects (N = 98)

Pathway	***β***	***p***	**95% CI**
Outcome 1: Emotional Exhaustion (MBI-EE)			
Direct: ERI → MBI-EE	.77	< .001	[.65, .89]
Direct: ERI → Surface Acting (SA)	.67	< .001	[.52, .82]
Direct: SA → MBI-EE (controlling ERI)	.16	.011	[.04, .29]
Indirect: ERI → SA → MBI-EE	.11	—	[.01, .22]
Outcome 2: Depression (PHQ-9)			
Direct: ERI → PHQ-9	.88	< .001	[.74, 1.01]
Direct: ERI → Surface Acting (SA)	.67	< .001	[.52, .82]
Direct: SA → PHQ-9 (controlling ERI)	−.01	.94	[−.14, .13]
Indirect: ERI → SA → PHQ-9	−.00	—	[−.11, .10]

Note. β = standardized regression coefficient; CI = confidence interval based on bias-corrected bootstrapping with 5,000 resamples (Hayes, 2018). SA = Surface Acting; ERI = Effort-Reward Imbalance; MBI-EE = Maslach Burnout Inventory–Emotional Exhaustion subscale; PHQ-9 = Patient Health Questionnaire-9. Dashes (—) in the *p*-value column for indirect effects indicate use of bootstrap CIs rather than parametric significance tests. All variables were standardized prior to analysis. Direct effects tested at $\alpha = .05$.

DISCUSSION

Summary and Theoretical Integration

The present investigation set out to examine whether surface acting as a form of emotional labor mediates the associations between effort-reward imbalance and the dual outcomes of burnout and depression among German social work professionals, and whether this mechanism operates equivalently across both outcomes. The findings yielded a differentiated answer. Effort-reward imbalance was a powerful predictor of both emotional exhaustion ($\beta = .88$ total effect) and depressive symptomatology ($\beta = .87$ total effect). Surface acting emerged as a statistically significant—though modest—partial mediator of the ERI–exhaustion pathway (indirect $\beta = .11$, 95% CI [.01, .22]), but did not mediate the ERI–depression pathway, where the indirect effect was indistinguishable from zero ($\beta = -.003$, 95% CI [−.11, .10]). The mechanism through which occupational imbalance translates into psychological harm thus appears to be partly outcome-specific rather than uniform.

These findings integrate coherently with, and refine, the theoretical landscape established in Section 2. Within the framework of the JD-R model (Demerouti et al., 2001; Bakker & Demerouti, 2017), the results extend the model's health-impairment pathway by identifying emotional labor as a specific mechanism linking demand-resource imbalance to exhaustion. The asymmetry is itself theoretically informative and consistent with the resource-depletion logic of COR theory (Hobfoll, 1989, 2001): surface acting most directly taxes the self-regulatory resources whose depletion constitutes emotional exhaustion, whereas depressive symptomatology evidently arises in this sample predominantly through the direct burden of effort-reward imbalance rather than through the specific channel of emotional performance. In other words, suppressing felt emotion behind a professional facade appears to feed exhaustion more than it feeds depression, while the experience of chronic imbalance itself drives depressive symptoms along a more direct route. The partial and small magnitude of the exhaustion mediation indicates, moreover, that the great majority of the ERI effect on burnout—roughly seven-eighths of the total effect—operates through pathways other than surface acting, pointing to additional mechanisms such as cognitive rumination, secondary traumatic stress, and sleep disruption that warrant investigation.

The very high correlation between emotional exhaustion and depression ($r = .90$) is consistent in direction with the position advanced by Bianchi et al. (2015) and Schonfeld and Bianchi (2016) that these constructs share a common affective-depleting pathway, although its magnitude exceeds the typical meta-analytic range (Koutsimani et al., 2019) and likely reflects, in part, features of the present dataset discussed in Section 5.3. Interpreted cautiously, the pattern supports a conceptualization of the social work mental-health risk profile as an integrated and mutually reinforcing cluster. For AI-based monitoring this has a concrete design implication: rather than assuming a single mediating mechanism that drives all outcomes, detection architectures should track the shared underlying resource-depletion trajectory while remaining sensitive to the possibility that distinct indicators (e.g., emotional-labor signatures) carry differential predictive value for burnout versus depression.

Practical Implications and a Conceptual AI-Based Framework for Early Detection

The practical significance of these findings extends across multiple levels of intervention. At the individual level, the finding that surface acting contributes to the exhaustion pathway identifies emotional-labor management as a specifically actionable target for burnout prevention. Psychotherapeutic and coaching approaches focused on authentic emotional expression, emotional self-awareness, and the development of deep-acting competencies—rather than continued reliance on surface suppression—represent evidence-grounded clinical priorities. That surface acting did not mediate the depression pathway tempers, however, any expectation that emotional-labor interventions alone would substantially reduce depressive symptomatology; the latter appears more tightly bound to effort-reward imbalance itself.

At the organizational level, the consistent finding that effort-reward imbalance drives both outcomes powerfully and largely directly reinforces the structural imperative of organizational intervention. Sustainable prevention in the helping professions cannot rely on individual resilience enhancement alone; it must address the structural determinants of occupational imbalance through caseload management, professional recognition structures, supervisory resource provision, and institutional acknowledgment of the emotional-labor demands inherent in social work. Because depression in this sample was driven predominantly by imbalance rather than by emotional labor, structural rebalancing of effort and reward may be the single most consequential lever for reducing depressive risk.

Of particular applied significance is the implication for AI-based early detection. The empirical identification of effort-reward imbalance as the dominant signal construct, and of surface acting as a secondary, outcome-specific contributor, provides theoretically grounded parameters for occupational mental-health monitoring algorithms. A conceptual AI framework for early detection in social work might operate across three integrated, sequentially escalating layers. The first layer, passive behavioral monitoring, would continuously analyze objective behavioral indicators accessible through professional digital environments—keystroke dynamics, email response latency, calendar patterns, and meeting attendance—using change-point detection against individual baselines (Saeb et al., 2015; Chow et al., 2017). The second layer, natural language processing analysis, would apply validated algorithms to optional, anonymized samples of professional written communication to detect lexical markers of exhaustion and dysphoric affect (Coppersmith et al., 2015; Guntuku et al., 2017); the present finding that emotional-labor signatures are more tightly coupled to exhaustion than to depression suggests that such linguistic markers—flat affect, terse communication, reduced expressive variability—may have greater sensitivity for burnout than for depressive risk, an asymmetry that algorithm developers should encode rather than ignore. The third layer, adaptive validated self-report, would integrate abbreviated forms of the validated instruments into a mobile interface triggered at algorithmically identified high-risk time points, aligning with the ecological momentary assessment paradigm (Mohr et al., 2017). Questions of ethical governance, GDPR Article 9 compliance, worker consent, and algorithmic transparency must be addressed with rigor equal to the technical validation process itself.

Limitations

Several limitations constrain the interpretation and generalizability of the present findings. First and most fundamentally, the cross-sectional design precludes any causal inference regarding the directionality of the observed associations. The data are equally consistent with alternative causal models—including the possibility that individuals with depressive tendencies perceive greater occupational imbalance. Resolution requires longitudinal panel designs with repeated-measure assessment at a minimum of three time points, enabling cross-lagged structural models that can disambiguate temporal precedence.

Second, the relatively modest sample size (N = 98) limits statistical power for detecting small indirect effects and produces wide bootstrap confidence intervals; the lower bound of the significant exhaustion-mediation interval lay close to zero, and the non-significant depression mediation should not be read as definitive evidence of no effect but rather as an absence of detectable mediation at the present power. Replication in larger samples is needed.

Third, the non-probabilistic, online recruitment strategy introduces self-selection bias of indeterminate magnitude and direction, so the generalizability of these findings to the full population of German social work professionals should be treated as provisional. The high proportion of participants exceeding the ERI imbalance threshold (96.9%) may partly reflect a sample enriched for occupational strain.

Fourth, all study variables were assessed through self-report in a single session, creating conditions for common-method bias (Podsakoff et al., 2003). Harman's single-factor test indicated that one component accounted for a large share of the variance; this value, however, is of limited diagnostic value in a dataset comprising only four highly intercorrelated composite scores, where high shared variance is expected on substantive grounds and the test cannot distinguish method variance from genuine construct overlap. The unusually high intercorrelations among study variables—including the r = .90 between exhaustion and depression—nonetheless counsel interpretive caution and may reflect shared method variance, conceptual overlap among the measured constructs, or characteristics of the data source. Future investigations should incorporate multi-method assessment, including supervisor ratings, behavioral indicators, and physiological measures.

Fifth, because the dataset comprised validated composite scores rather than item-level responses, sample-specific internal-consistency coefficients could not be computed, and the reliabilities reported derive from the instruments' published validation studies. Relatedly, the analysis does not account for theoretically relevant moderators—resilience, emotion-regulation competence, sleep quality, supervisory support, team cohesion, professional seniority, and family status—that may substantially qualify the identified associations and constitute important targets for future research.

Outlook

The findings open multiple productive directions. Most immediately, longitudinal panel studies tracking the temporal development of effort-reward imbalance, emotional labor, burnout, and depression across multiple time points are required to establish the directional architecture of the relationships identified here and to determine whether the differential mediation observed cross-sectionally holds prospectively. Lagged mediation models with at least three measurement points would clarify the precise temporal dynamics through which surface acting feeds exhaustion and would strengthen the causal foundations for the AI detection framework proposed in Section 5.2.

At the methodological frontier, experimental intervention studies that systematically target emotional-labor management—through deep-acting training, emotion-regulation coaching, or mindfulness-based professional development—and assess downstream effects on burnout and depression would provide the strongest available causal evidence, and would directly test the prediction, suggested by the present differential finding, that such interventions should reduce exhaustion more than depression. Quasi-experimental designs exploiting natural variation in organizational support provision offer a complementary avenue trading experimental control for ecological validity.

With respect to the AI framework, the priority concerns psychometric calibration of behavioral and linguistic biomarker signals against criterion-validated assessment in ecological momentary assessment studies within naturalistic professional environments. The present study's identification of effort-reward imbalance as the dominant predictor and surface acting as an outcome-specific contributor suggests that monitoring systems should weight imbalance-related signals heavily while treating emotional-labor signatures as differentially informative across outcomes. The broader vision underlying this research is one in which the structural invisibility of occupational psychological suffering in the helping professions—the experience of the social worker for whom Tuesday is burnout without a name—becomes systematically detectable, proactively addressable, and ultimately preventable through the responsible integration of behavioral science and artificial intelligence. The present study provides an empirically grounded, theoretically coherent foundation for this vision.

Statements and Declarations

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Conflict of Interest

The author declares that there are no competing financial or non-financial interests that could be perceived to have influenced the work reported in this article.

Ethics Approval

The study was conducted in accordance with the ethical principles of the World Medical Association Declaration of Helsinki (World Medical Association, 2013) and the guidelines of the Deutsche Gesellschaft für Psychologie (DGPs) and the Berufsverband Deutscher Psychologinnen und Psychologen (BDP) for non-interventional survey research. As the study involved exclusively voluntary, anonymous self-report data collection without experimental intervention, clinical interaction, or collection of sensitive personal identifiers, formal review by an institutional ethics committee was not required under applicable regulations.

Informed Consent

Participants received written pre-survey information describing the study objectives, the voluntary nature of participation, the anonymity of all collected data, compliance with the GDPR, and the right to withdraw at any time without disadvantage. Submission of a completed survey was treated as constituting informed consent to participation.

Data Availability Statement

The dataset analyzed in this study is available from the corresponding author upon reasonable request. Data have not been publicly archived owing to the sensitivity of mental health-related items and participant privacy considerations.

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Use of Generative AI

Generative AI tools were used for language editing, structural organization, and stylistic refinement of portions of this manuscript, as well as for assistance with the statistical computation and tabulation of results. All scientific content, theoretical reasoning, analytical decisions, interpretation of results, and intellectual conclusions remain the sole responsibility of the author.

REFERENCES

1. Alarcon, G. M. (2011). A meta-analysis of burnout with job demands, resources, and attitudes. Journal of Vocational Behavior, 79(2), 549–562. https://doi.org/10.1016/j.jvb.2011.03.007
2. Awa, W. L., Plaumann, M., & Walter, U. (2010). Burnout prevention: A review of intervention programs. Patient Education and Counseling, 78(2), 184–190. https://doi.org/10.1016/j.pec.2009.04.008
3. Bakker, A. B., & Demerouti, E. (2017). Job demands-resources theory: Taking stock and looking forward. Journal of Occupational Health Psychology, 22(3), 273–285. https://doi.org/10.1037/ocp0000056
4. Bakker, A. B., Demerouti, E., & Verbeke, W. (2004). Using the job demands-resources model to predict burnout and performance. Human Resource Management, 43(1), 83–104. https://doi.org/10.1002/hrm.20004
5. Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173
6. Bianchi, R., Schonfeld, I. S., & Laurent, E. (2015). Burnout-depression overlap: A review. Clinical Psychology Review, 36, 28–41. https://doi.org/10.1016/j.cpr.2015.01.004
7. Bundesagentur für Arbeit. (2023). Berufssteckbrief: Sozialarbeit und Sozialpädagogik. https://berufenet.arbeitsagentur.de
8. Chow, P. I., Fua, K., Huang, Y., Bonelli, W., Xiong, H., Barnes, L. E., & Teachman, B. A. (2017). Using mobile sensing to test clinical models of depression, social anxiety, state affect, and social isolation among college students. Journal of Medical Internet Research, 19(3), e62. https://doi.org/10.2196/jmir.6820
9. Coppersmith, G., Dredze, M., Harman, C., & Hollingshead, K. (2015). From ADHD to SAD: Analyzing the language of mental health on Twitter through self-reported diagnoses. In Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology (pp. 1–10). https://doi.org/10.3115/v1/W15-1201

10. Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. Journal of Applied Psychology, 86(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499
11. Dominelli, L. (2014). Globalising social work in a context of global crises. In C. Noble, H. Strauss, & B. Littlechild (Eds.), Global social work (pp. 15–30). Sydney University Press.
12. Freudenberger, H. J. (1974). Staff burn-out. Journal of Social Issues, 30(1), 159–165. https://doi.org/10.1111/j.1540-4560.1974.tb00706.x
13. Grandey, A. A. (2000). Emotional regulation in the workplace: A new way to conceptualize emotional labor. Journal of Occupational Health Psychology, 5(1), 95–110. https://doi.org/10.1037/1076-8998.5.1.95
14. Grandey, A. A. (2003). When “the show must go on”: Surface acting and deep acting as determinants of emotional exhaustion and peer-rated service delivery. Academy of Management Journal, 46(1), 86–96. https://doi.org/10.2307/30040678
15. Guntuku, S. C., Yaden, D. B., Kern, M. L., Ungar, L. H., & Eichstaedt, J. C. (2017). Detecting depression and mental illness on social media: An integrative review. Current Opinion in Behavioral Sciences, 18, 43–49. https://doi.org/10.1016/j.cobeha.2017.07.001
16. Hakanen, J. J., & Schaufeli, W. B. (2012). Do burnout and work engagement predict depressive symptoms and life satisfaction? A three-wave seven-year prospective study. Journal of Affective Disorders, 141(2–3), 415–424. https://doi.org/10.1016/j.jad.2012.02.043
17. Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (2nd ed.). Guilford Press.
18. Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. American Psychologist, 44(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513
19. Hobfoll, S. E. (2001). The influence of culture, community, and the nested-self in the stress process: Advancing conservation of resources theory. Applied Psychology, 50(3), 337–421. https://doi.org/10.1111/1464-0597.00062
20. Hochschild, A. R. (1983). The managed heart: Commercialization of human feeling. University of California Press.
21. Hülsheger, U. R., & Schewe, A. F. (2011). On the costs and benefits of emotional labor: A meta-analysis of three decades of research. Journal of Occupational Health Psychology, 16(3), 361–389. https://doi.org/10.1037/a0022876
22. Kim, H., & Ji, J. (2009). Factor structure and longitudinal invariance of the Maslach Burnout Inventory. Research on Social Work Practice, 19(3), 325–339. https://doi.org/10.1177/1049731508318550
23. Koutsimani, P., Montgomery, A., & Georganta, K. (2019). The relationship between burnout, depression, and anxiety: A systematic review and meta-analysis. Frontiers in Psychology, 10, Article 284. https://doi.org/10.3389/fpsyg.2019.00284
24. Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. Journal of General Internal Medicine, 16(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x
25. Lehr, D., Schmitz, E., & Hillert, A. (2010). Bewältigungsmuster und psychische Gesundheit: Eine clusteranalytische Replikationsstudie. Zeitschrift für Arbeits- und Organisationspsychologie, 52(1), 3–16. https://doi.org/10.1026/0932-4089.52.1.3
26. Luxton, D. D. (2020). An introduction to AI in mental health care. In D. D. Luxton (Ed.), Artificial intelligence in behavioral and mental health care (pp. 1–26). Academic Press. https://doi.org/10.1016/B978-0-12-420248-1.00001-5
27. MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. Multivariate Behavioral Research, 39(1), 99–128. https://doi.org/10.1207/s15327906mbr3901_4
28. Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. Journal of Organizational Behavior, 2(2), 99–113. https://doi.org/10.1002/job.4030020205
29. Maslach, C., & Leiter, M. P. (2016). Understanding the burnout experience: Recent research and its implications for psychiatry. World Psychiatry, 15(2), 103–111. https://doi.org/10.1002/wps.20311
30. Maslach, C., Jackson, S. E., & Leiter, M. P. (1996). Maslach Burnout Inventory manual (3rd ed.). Consulting Psychologists Press.

31. Mohr, D. C., Zhang, M., & Schueller, S. M. (2017). Personal sensing: Understanding mental health using ubiquitous sensors and machine learning. Annual Review of Clinical Psychology, 13, 23–47. https://doi.org/10.1146/annurev-clinpsy-032816-044949
32. Morris, J. A., & Feldman, D. C. (1996). The dimensions, antecedents, and consequences of emotional labor. Academy of Management Review, 21(4), 986–1010. https://doi.org/10.5465/amr.1996.9704071861
33. Nolen-Hoeksema, S., Wisco, B. E., & Lyubomirsky, S. (2008). Rethinking rumination. Perspectives on Psychological Science, 3(5), 400–424. https://doi.org/10.1111/j.1745-6924.2008.00088.x
34. Pazer, S. (2024a). Burnout in sozialen Berufen: Strukturelle Determinanten und psychotherapeutische Implikationen. Zeitschrift für Sozialarbeit, 12(1), 45–63.
35. Pazer, S. (2024b). Künstliche Intelligenz in der psychotherapeutischen Nachsorge. Soziale Arbeit Digital, 3(2), 112–128.
36. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
37. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
38. Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). Mobile phone sensor correlates of depressive symptom severity in daily-life behavior. Journal of Medical Internet Research, 17(7), e175. https://doi.org/10.2196/jmir.4273
39. Schonfeld, I. S., & Bianchi, R. (2016). Burnout and depression: Two entities or one? Journal of Clinical Psychology, 72(1), 22–37. https://doi.org/10.1002/jclp.22229
40. Siegrist, J. (1996). Adverse health effects of high-effort/low-reward conditions. Journal of Occupational Health Psychology, 1(1), 27–41. https://doi.org/10.1037/1076-8998.1.1.27
41. Siegrist, J., Starke, D., Chandola, T., Godin, I., Marmot, M., Niedhammer, I., & Peter, R. (2004). The measurement of effort-reward imbalance at work: European comparisons. Social Science & Medicine, 58(8), 1483–1499. https://doi.org/10.1016/S0277-9536(03)00351-4
42. Siebert, D. C. (2004). Depression in North Carolina social workers: Implications for practice and research. Social Work Research, 28(1), 30–40. https://doi.org/10.1093/swr/28.1.30
43. Sousa, M., Ribeiro, J., & Paiva, T. (2018). Help-seeking behaviour and mental health in social workers. European Journal of Social Work, 21(4), 527–538. https://doi.org/10.1080/13691457.2017.1320543
44. Stalker, C. A., Mandell, D., Frensch, K. M., Harvey, C., & Wright, M. (2007). Child welfare workers who are exhausted yet satisfied with their jobs. Child & Family Social Work, 12(2), 182–191. https://doi.org/10.1111/j.1365-2206.2006.00455.x
45. Torous, J., Myrick, K. J., Rauseo-Ricupero, N., & Firth, J. (2020). Digital mental health and COVID-19: Using technology today to accelerate the curve on access and quality tomorrow. JMIR Mental Health, 7(3), e18848. https://doi.org/10.2196/18848
46. van Vegchel, N., de Jonge, J., Bosma, H., & Schaufeli, W. (2005). Reviewing the effort-reward imbalance model: Drawing up the balance of 45 empirical studies. Social Science & Medicine, 60(5), 1117–1131. https://doi.org/10.1016/j.socscimed.2004.06.043
47. World Medical Association. (2013). World Medical Association Declaration of Helsinki: Ethical principles for medical research involving human subjects. JAMA, 310(20), 2191–2194. https://doi.org/10.1001/jama.2013.281053