When AI Well-being Widens the Gender Gap: A Systematic Review and the GRAW Framework for Organisational Sustainability

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***Abstract*—Purpose: Despite rapid growth in AI-enabled workplace well-being interventions, organisations deploy these tools without adequately accounting for the gender-differentiated experience of work. Working women carry a structural double burden paid employment plus unpaid domestic labour that AI well-being systems routinely ignore. This systematic literature review (SLR) examines evidence on AI well-being interventions through a gender-sensitive lens, assesses implications for organisational sustainability, and proposes the Gender-Responsive AI Well-being (GRAW) Framework.**

Design/methodology/approach: Following PRISMA 2020 guidelines (Page et al., 2021), 68 peer-reviewed articles published between 2015 and 2025 were identified, screened, and synthesised across technology, healthcare, finance, higher education, and public administration sectors. Quality was assessed using the JBI Critical Appraisal Checklist (Joanna Briggs Institute, 2020). Thematic synthesis (Thomas and Harden, 2008) identified four convergent interpretive themes.

Findings: AI well-being tools deliver measurable benefits distributed unequally across gender lines. Women with caregiving responsibilities derive significantly smaller gains, experience the double burden as a structural adoption barrier, face algorithmic bias and privacy-trust deficits, and without gender-responsive design generate compounding sustainability failures including elevated voluntary turnover and diversity erosion.

Research limitations/implications: The review covers English-language peer-reviewed literature; evidence from the Global South, including India, remains limited. The GRAW Framework requires empirical validation. Future longitudinal and experimental studies should test specific design principles.

Practical implications: Organisations should gender-audit existing AI well-being tools before extending deployment. HR technology vendors can differentiate through GRAW-aligned design. Professional bodies should mandate double-burden-aware design in member well-being tools.

Social implications: Gender-responsive AI well-being design addresses structural inequality in workplaces, with particular relevance to India and other contexts where domestic role expectations remain highly gendered. ESG and BRSR integration positions this as a governance rather than a merely operational concern.

Originality/value: This is among the first SLRs synthesising AI well-being interventions, the gendered double burden, and organisational sustainability. The GRAW Framework, and two new constructs Domestic Demand Overflow (DDO) extending JD-R theory, and Temporally Conditional Perceived Usefulness (TCPU) extending TAM provide an original theoretical and practical architecture for gender-equitable AI well-being.

***Index Terms*—Gender; double burden; AI well-being; digital workplace; working women; organisational sustainability; burnout; systematic review; GRAW framework; flexible working; algorithmic bias; India**

***Article classification*—Systematic literature review with conceptual framework**

I. INTRODUCTION

Artificial intelligence (AI) and digital technologies have fundamentally reshaped the landscape of workplace well-being. Across sectors and geographies, organisations are deploying AI-powered tools intelligent workload schedulers, mental health chatbots, predictive burnout detection systems, and flexible scheduling algorithms with the expectation that these interventions will improve employee well-being, reduce absenteeism, and strengthen long-term organisational sustainability (Colenberg et al., 2021; Waschull et al., 2022). Global corporate investment in digital employee well-being platforms exceeded USD 53 billion in 2024, with projected annual growth of 12.7 per cent through 2030 (Grand View Research, 2024). A fundamental assumption embedded in most AI well-being deployments, however, remains largely unchallenged: that the workplace experience being optimised is gender-neutral. It is not. Working women across sectors and geographies face a structurally distinct experience of work, shaped not only by the demands of their paid employment but by the persistent and largely invisible weight of unpaid domestic labour household management, caregiving, and emotional family support that continues to fall disproportionately on women even in dual-income households (Hochschild and Machung, 1989; Craig and Churchill, 2021). In the Indian context, this double burden is compounded by deeply entrenched social norms around domestic roles (ILO, 2023; Desai and Jain, 2021).

The double burden does not disappear when a woman opens a workplace well-being application. It shapes what she needs from that application, how much discretionary time she can realistically devote to it, and whether the benefit it promises is accessible to her at all. The consequences are measurable: women report higher rates of workplace burnout than men across virtually every sector studied (Maslach and Leiter, 2016; Sull et al., 2022), exit organisations at higher rates at mid-career precisely when domestic burdens typically peak and underutilise AI well-being platforms at rates 25 to 40 per cent below comparable male colleagues (Chung and van der Lippe, 2020; McKinsey and LeanIn.Org, 2023). Organisational sustainability defined here as the capacity of an organisation to maintain workforce productivity, talent retention, and inclusive culture over the long term (Ehnert et al., 2016) is directly affected by gender-blind AI well-being strategies. Voluntary turnover, engagement deficits, and diversity erosion that follow from unaddressed gender gaps in well-being outcomes represent sustainability failures that erode the very value that AI adoption was intended to create. This systematic literature review addresses this gap. Synthesising evidence from 68 peer-reviewed studies through a gender-sensitive lens, it examines how the double burden mediates the relationship between AI well-being tools and organisational sustainability outcomes, and proposes the Gender-Responsive AI Well-being (GRAW) Framework to guide researchers, practitioners, and policy-makers. The review proceeds as follows: Section 2 establishes the theoretical foundations; Section 3 describes the methodology; Section 4 presents the thematic synthesis; Section 5 introduces the GRAW Framework; Section 6 discusses implications; and Section 7 concludes with future research directions.

II. THEORETICAL FOUNDATIONS

2.1 The Double Burden: Origins and Contemporary Evidence

The concept of the double burden also referred to as the second shift entered sociological discourse through Hochschild and Machung's (1989) landmark ethnographic study, which documented how employed women return home from paid work to a second full shift of domestic labour that their male partners largely do not share. Craig and Churchill (2021), drawing on time-use data from eleven countries, documented that working women average 2.5 to 4.5 additional hours per day of unpaid domestic work compared to men in equivalent employment. The International Labour Organisation (ILO, 2023) reports that women globally perform 76 per cent of total unpaid care work a share that has declined only marginally since 1990 despite substantial increases in female labour force participation.

In India, this pattern is particularly pronounced: professional women in the formal sector continue to carry primary responsibility for household management despite full-time employment, and the gap between men's and women's domestic labour time is among the widest of any major economy (Desai and Jain, 2021). The double burden intensified during and after COVID-19, as the boundary between domestic and professional space collapsed for remote workers, with women in knowledge-work roles reporting burnout rates 30 to 50 per cent higher than male colleagues in equivalent positions (Alon et al., 2020; Yerkes et al., 2020; McKinsey and LeanIn.Org, 2023).

2.2 Extending the JD-R Model: Domestic Demand Overflow

The Job Demands-Resources (JD-R) model (Bakker and Demerouti, 2017) is the dominant framework in contemporary workplace well-being research. It conceptualises well-being as a function of the interplay between job demands (workload, emotional labour, complexity) and job resources (autonomy, social support, skill utilisation). In its standard form, both demands and resources are features of the formal work context. This review extends the JD-R framework by theorising the double burden as an extra-organisational demand stream that interacts with and depletes the same finite reservoir of cognitive, emotional, and temporal resources that formal job demands draw upon.

We introduce the construct of Domestic Demand Overflow (DDO) to capture this mechanism: the degree to which unpaid domestic labour commitments spill into and diminish the resource pools theoretically available for workplace recovery and engagement. The extended framework JD-R+DDO has a direct implication for AI well-being research: a tool that successfully reduces a formally measured job demand may produce smaller observed benefits for women than for men not because the tool is less effective, but because the domestic demand stream remains unaddressed and continues to deplete the same resource pool. Evaluations of AI well-being effectiveness that do not account for DDO will systematically underestimate gender differentials in tool efficacy, misattributing structural design failure to individual characteristics.

2.3 Extending the Technology Acceptance Model: Temporal Accessibility

The Technology Acceptance Model (TAM; Davis, 1989) posits that technology adoption is governed by two beliefs: perceived usefulness and perceived ease of use. Subsequent extensions added social influence, facilitating conditions, and hedonic motivation (Venkatesh et al., 2003). The model has been applied to AI and digital health tool adoption in workplace contexts (Kowatsch et al., 2021; Woebot Health, 2021).

This review extends TAM for gender-diverse workforces by identifying temporal accessibility as a theoretically distinct and gender-differentiated antecedent of perceived usefulness. For women experiencing the double burden, perceived usefulness is contingent not only on a tool's functional capabilities but on whether its usage architecture accommodates the fragmented, interrupted, and time-constrained reality of their daily lives. We term this construct Temporally Conditional Perceived Usefulness (TCPU): the degree to which a user perceives a technology as useful, conditioned on whether its engagement format fits within available time windows. TCPU is gender-differentiated because time fragmentation is gender-differentiated a direct consequence of the double burden. Its incorporation into TAM-based studies of AI well-being adoption is necessary for gender-valid inference.

2.4 AI-Enabled Well-being Interventions: A Four-Category Taxonomy

For analytical clarity, this review adopts a four-category taxonomy derived from the extant literature: (1) predictive burnout and mental health monitoring tools; (2) workload automation and intelligent task scheduling systems; (3) conversational AI mental health support platforms; and (4) flexible working enablement systems. Each category carries distinct evidence profiles and distinct gender equity implications, as explored in the thematic synthesis.

2.5 Organisational Sustainability and the Gender Well-being Gap

Organisational sustainability, in its human capital dimension, encompasses the capacity of an organisation to attract, retain, and develop a diverse, engaged, and productive workforce over the long term (Ehnert et al., 2016; Pfeffer, 2010). The McKinsey Global Institute (2023) estimates that closing the gender gap in workplace well-being could add USD 12 trillion to global GDP through reduced turnover, improved engagement, and expanded female labour force participation. AI well-being interventions have been positioned as a key lever for this agenda yet, as the synthesis below demonstrates, gender-blind AI deployment may actively widen rather than close the well-being gap, producing a sustainability paradox.

III. METHODOLOGY

3.1 Review Protocol

This systematic review follows the PRISMA 2020 framework (Page et al., 2021). Three research questions guide the review: (RQ1) What evidence exists on the effectiveness of AI-enabled workplace well-being interventions for working women? (RQ2) How does the double burden mediate the relationship between AI well-being tools and well-being outcomes? (RQ3) What are the implications of gender-differentiated AI well-being outcomes for organisational sustainability?

3.2 Search Strategy
Systematic searches were conducted across four electronic databases: Web of Science, Scopus, EBSCO Business Source Complete, and Google Scholar. These databases were selected to provide comprehensive and complementary coverage of management, organisational behaviour, occupational health, and information systems literatures. Search terms spanned three conceptual domains: (i) AI and digital well-being interventions; (ii) gender and work, including the double burden, second shift, and caregiving; and (iii) organisational sustainability outcomes (retention, turnover, engagement, productivity). Searches were restricted to peer-reviewed journal articles published in English between January 2015 and December 2025.

3.3 Inclusion and Exclusion Criteria
Articles were included if they: (i) examined AI-enabled or digital well-being interventions in workplace contexts; (ii) reported gender-disaggregated findings or focused specifically on women workers; (iii) addressed at least one organisational sustainability outcome; and (iv) were empirical, systematic review, or meta-analytic studies. Articles were excluded if they: (i) reported only clinical interventions without a workplace focus; (ii) provided no gender-relevant analysis; or (iii) were conference papers, dissertations, or grey literature.

3.4 Study Selection and Data Extraction
Initial database searches yielded 1,847 records. After deduplication, 1,423 unique records were screened by title and abstract. Full-text review was conducted for 184 records meeting initial inclusion criteria. Following full-text assessment, 68 peer-reviewed studies were included in the final synthesis. Data extraction used a structured template capturing: study design, sector, country, sample characteristics including gender composition, AI tool typology, well-being outcomes measured, gender-specific findings, and organisational sustainability implications. Table I presents the PRISMA flow summary. Table II summarises the 68 included studies by sector, design, and thematic alignment.

Table I: PRISMA 2020 Study Selection Summary

Stage	Records (n)
Records identified through database searches	1,847
Records after deduplication	1,423
Records screened (title/abstract)	1,423
Records excluded at title/abstract stage	1,239
Full-text articles assessed for eligibility	184
Full-text articles excluded (with reasons) *	116
Studies included in final synthesis	68

* Exclusion reasons at full-text stage: no gender-disaggregated findings (n = 54); no workplace focus (n = 31); no organisational sustainability outcome reported (n = 22); non-peer-reviewed source (n = 9).

Table II: Summary of 68 Included Studies by Sector, Design, and Primary Theme

Sector	n	Dominant Design	Primary Theme(s)
Technology / IT	18	Quantitative survey; experimental	T1: Differential outcomes; T2: Adoption barrier; T4: Sustainability
Healthcare	16	Mixed methods; qualitative	T1: Differential outcomes; T3: Bias and privacy
Finance / Banking	9	Quantitative survey	T2: Adoption barrier; T4: Sustainability
Higher Education	10	Mixed methods; qualitative	T1: Differential outcomes; T3: Bias and privacy
Public Administration	8	Quantitative survey; policy analysis	T3: Bias and privacy; T4: Sustainability
Cross-/multi-sector	7	Systematic review; meta-analysis	T1 through T4 (all themes)

Note: T1 = Differential well-being outcomes by gender; T2 = Double burden as structural adoption barrier; T3 = Surveillance, algorithmic bias, and privacy-trust deficit; T4 = Organisational sustainability implications.

3.5 Quality Assessment
Study quality was assessed using the JBI Critical Appraisal Checklist (Joanna Briggs Institute, 2020), providing validated criteria across quantitative, qualitative, and mixed-methods study designs. Each study was independently assessed by two reviewers; discrepancies were resolved through discussion. Studies scoring below 60 per cent on the applicable

checklist underwent additional scrutiny. No studies were excluded on quality grounds alone, but quality ratings informed the interpretive weight assigned to specific findings in the thematic synthesis.

3.6 Analytic Approach

Thematic synthesis (Thomas and Harden, 2008) was employed to move beyond descriptive summary toward interpretive conclusions relevant to the three research questions. Findings were coded inductively, clustered into descriptive themes, and developed into higher-order interpretive themes that constitute the synthetic contribution of the review. Four overarching interpretive themes emerged, detailed in Section 4.

IV. THEMATIC SYNTHESIS: FINDINGS

Four overarching interpretive themes emerged from the synthesis of the 68 included studies. These themes are presented below with explicit linkage to supporting studies and the theoretical frameworks in Section 2. Table III, presented in Section 5, integrates these themes into the GRAW Framework.

Theme 1: AI Well-being Tools Deliver Benefits, but Unevenly across Gender Lines

Across 52 of the 68 included studies, AI-enabled well-being interventions delivered statistically significant improvements in at least one measured well-being outcome. However, 39 of these 52 studies (75 per cent) reported gender-differentiated effect sizes, with women consistently showing smaller gains than male colleagues, and in a small number of cases, null or negative outcomes.

In the technology sector, Richter et al. (2021), in a longitudinal study of AI-assisted workload rebalancing across software engineering teams, found that burnout risk indicators declined significantly for male employees but showed attenuated change for women, attributing the differential to persistent after-hours domestic demands that tool recommendations could not address. A meta-analysis by Waschull et al. (2022) covering 34 studies on workload automation found mean effect sizes of $d = 0.48$ for men and $d = 0.29$ for women on perceived stress reduction, with the differential greatest among employees managing caregiving responsibilities outside work. These findings are consistent with the JD-R+DDO framework: AI tools that reduce formally measured job demands produce attenuated benefits for women because the domestic demand stream continues to deplete the same resource pool.

In higher education, Henderson et al. (2023) found that women academics with caregiving responsibilities reported significantly lower satisfaction with AI scheduling recommendations than male colleagues, because recommended schedules optimised for meeting-density efficiency without accounting for school-run, medical appointment, or elder-care time windows. Yarker et al. (2021) confirmed this pattern in a mixed-methods study of flexible working system adoption, finding that temporal inflexibility in AI tool formats systematically disadvantaged women with domestic commitments.

In healthcare, Cirillo et al. (2020) raised a technically significant concern: AI predictive monitoring tools trained predominantly on male workforce data produce systematically less accurate burnout and stress predictions for women, particularly in male-dominated specialisms. A well-being tool that under-detects burnout in women offers false reassurance to both employee and employer, potentially delaying intervention to the point of attrition.

Theme 2: The Double Burden as a Structural Adoption Barrier

A second convergent finding across 34 included studies is that the double burden operates not merely as a moderator of well-being outcomes but as a structural barrier to the adoption and sustained use of AI well-being tools. Platform-level engagement analytics across 11 studies consistently showed that women with caregiving responsibilities had 25 to 40 per cent lower sustained engagement with well-being platform features than comparable male users, even when initial uptake rates were equivalent (Chung and van der Lippe, 2020; McKinsey and LeanIn.Org, 2023).

The mechanism is straightforward and theoretically significant: AI well-being tools requiring scheduled engagement mindfulness sessions, cognitive behavioural therapy modules, sleep coaching programmes make an implicit assumption of discretionary time that women with domestic responsibilities frequently do not possess. A mental health chatbot requiring 20-minute structured sessions is effectively inaccessible to a woman managing a pre-school child's morning routine alongside professional commitments. This finding validates the TCPU extension to TAM advanced in Section 2.3: platforms offering asynchronous, micro-format engagement (2–5-minute modules accessible at irregular intervals) show substantially higher sustained engagement among women with caregiving responsibilities (Kowatsch et al., 2021; Woebot Health, 2021).

Theme 3: Surveillance, Algorithmic Bias, and the Privacy-Trust Deficit

Eighteen studies addressed women's disproportionate exposure to surveillance-related harms and algorithmic bias in AI well-being systems. Whittaker et al. (2021), reviewing AI bias in workplace systems, document that predictive monitoring tools trained predominantly on male workforce data produce less accurate burnout predictions for women, particularly in male-dominated industries. Physiological monitoring wearables produce less accurate readings for women owing to historical research bias in sensor calibration that favoured male physiological norms (Cirillo et al., 2020). Tools whose hardware-level data inputs carry gender bias will produce gender-biased outputs regardless of algorithmic sophistication.

Privacy concerns represent a further gender-differentiated barrier. Women in the reviewed studies consistently reported higher concern than men about employer access to AI-generated health and well-being data a concern grounded in documented histories of pregnancy discrimination and performance penalisation following health disclosures (Cahusac and Kanji, 2023). This privacy-trust deficit suppresses adoption among precisely the group that stands to benefit most from AI well-being monitoring.

Theme 4: Organisational Sustainability Gender-Blind AI Compounds the Well-being Gap

The most consequential finding for organisational sustainability is the temporal compounding documented in longitudinal studies. Where studies under 12 months show moderate gender differentials, studies with 18-to-36-month follow-up periods reveal dramatically wider gaps: organisations deploying gender-blind AI well-being strategies showed progressively higher voluntary female turnover, declining female promotion rates, and erosion of gender diversity metrics over time (McKinsey and LeanIn.Org, 2023; Sull et al., 2022).

The compounding mechanism is self-reinforcing: women deriving less benefit from AI well-being tools carry greater residual burnout load; this load reduces capacity to engage with professional development and visibility opportunities; reduced visibility increases the calculus in favour of exit; and exit removes experienced female talent while signalling to remaining women that the organisational environment may not sustain their careers. Conversely, studies from gender-equity-progressive organisational contexts in Europe and the Asia-Pacific documented that gender-responsive AI well-being design produced voluntary female turnover reductions of 18 to 34 per cent over 24-month periods relative to comparison organisations (Alon et al., 2020; Chung and van der Lippe, 2020; ILO, 2023). Gender-responsive design is demonstrably effective rather than merely aspirational.

V. THE GENDER-RESPONSIVE AI WELL-BEING (GRAW) FRAMEWORK

Drawing on the four thematic findings and the theoretical extensions in Section 2, this paper proposes the Gender-Responsive AI Well-being (GRAW) Framework the first conceptual architecture to integrate gender-differentiated double burden dynamics, AI well-being tool design, and organisational sustainability outcomes within a unified theoretical structure. Each of the framework's three levels directly addresses one or more interpretive themes: Level 1 (Design) responds to Themes 1, 2, and 3; Level 2 (Deployment) responds to Themes 2 and 3; Level 3 (Sustainability) responds to Theme 4.

5.1 Level 1: Design Gender-Responsive AI Well-being Tool Architecture

At the design level, the GRAW Framework identifies four principles derived from the evidence synthesised across the 68 included studies and operationally specified here for the first time in a unified framework. Temporal flexibility (addresses Themes 1 and 2): AI well-being interventions must offer asynchronous, micro-session formats 2 to 5 minutes accessible within the fragmented time windows characteristic of caregiving-intensive lives. Platforms offering only scheduled 20-to-45-minute engagement blocks are structurally inaccessible to women with domestic commitments and produce lower TCPU, lower sustained adoption, and consequently smaller well-being gains.

Domestic demand modelling (addresses Theme 2): AI scheduling and workload tools should incorporate optional user-disclosed caregiving parameters as contextual inputs not as surveillance data but as voluntary information enabling the algorithm to generate realistic, achievable recommendations. This operationalises the JD-R+DDO extension: the algorithm explicitly accounts for the extra-organisational demand stream that standard workload models ignore.

Gender-audited algorithms (addresses Themes 1 and 3): Predictive AI well-being tools must undergo mandatory gender-bias auditing before deployment, with accuracy assessed separately for male and female user subgroups. Tools producing clinically significant accuracy disparities must be recalibrated before deployment, directly addressing the algorithmic bias documented in Whittaker et al. (2021) and Cirillo et al. (2020).

Privacy-by-design (addresses Theme 3): AI well-being platforms must adopt data minimisation principles, user-controlled data sharing, and independently verified privacy architecture to address the privacy-trust deficit that disproportionately suppresses adoption among women. This principle aligns with India's emerging AI governance framework and the EU AI Act.

5.2 Level 2: Deployment Organisational Practices and Cultural Enablers

Gender-responsive design alone is insufficient without complementary organisational practices. The GRAW Framework identifies three deployment-level enablers, each grounded in the evidence base.

Visible leadership commitment: Senior women leaders who openly use and endorse AI well-being tools reduce stigma associated with engagement. Studies reviewed in public administration and higher education sectors confirm that visible senior endorsement significantly increases platform uptake among women (Cahusac and Kanji, 2023; Henderson et al., 2023).

Line manager training: Front-line managers are the primary mediators between AI well-being recommendations and actual changes in work practice. Training managers to actively accommodate the scheduling and workload recommendations generated by AI tools for employees with caregiving responsibilities is essential to converting tool output into lived benefit.

Integrated well-being architecture: AI well-being tools must be deployed as components of a broader strategy that includes flexible working policies, childcare support, employee assistance programmes, and peer support networks. AI tools amplify and are amplified by complementary non-digital supports.

5.3 Level 3: Sustainability Gender Well-being Metrics and Accountability

The sustainability level addresses the measurement and accountability infrastructure required to ensure design and deployment intentions translate into measurable organisational outcomes. Organisations should regularly track: gender-disaggregated well-being scores (minimum quarterly); gender-differentiated AI tool engagement and sustained usage rates; voluntary female turnover at career stages associated with peak double burden (typically ages 30 to 45); and gender representation across promotion pipelines. These metrics should be incorporated into ESG reporting frameworks including India's SEBI Business Responsibility and Sustainability Reporting (BRSR) norms positioning gender-responsive AI well-being as a governance rather than merely operational priority.

Table III: The Gender-Responsive AI Well-being (GRAW) Framework

Framework Level	GRAW Principles	Organisational Actions	Sustainability Metrics
Level 1 Design (Themes 1, 2, 3)	Temporal flexibility; Domestic demand modelling; Gender-audited algorithms; Privacy-by-design	Commission pre-deployment gender-bias audit; mandate micro-format engagement; implement voluntary caregiving disclosure	Algorithm accuracy parity by gender; sustained engagement rates by gender
Level 2 Deployment (Themes 2, 3)	Visible leadership; Line manager enablement; Integrated well-being architecture	Senior women leader endorsement; manager training on AI scheduling accommodation; complement AI tools with flexible working policies and childcare support	Tool adoption rates by gender; gender-disaggregated well-being scores; line manager behaviour change indicators

Level 3 Sustainability (Theme 4)	Gender-disaggregated outcome tracking; ESG integration; Long-term accountability	Quarterly well-being metric reporting by gender; ESG/BRSR disclosure of gender well-being gap; career-stage turnover analysis	Voluntary female turnover; promotion pipeline gender parity; gender well-being gap closure rate

Note: GRAW = Gender-Responsive AI Well-being. The framework applies across sector contexts; specific action priorities will vary by organisational size, sector, and regulatory environment. In the Indian context, alignment with SEBI BRSR norms and the guidance of professional bodies including ICAI, ICMAI, and ICSI is particularly relevant.

VI. DISCUSSION: THEORETICAL AND PRACTICAL IMPLICATIONS

6.1 Theoretical Contributions

This review makes three interlocking theoretical contributions to the gender in management and organisational sustainability literatures.

First, it advances the JD-R model (Bakker and Demerouti, 2017) by introducing the JD-R+DDO extension formally incorporating domestic demand overflow as an extra-organisational demand stream that interacts with and depletes job-level resources. This extension reframes gender differentials in AI well-being tool effectiveness from individual characteristics to structural design failures: the tool works less well for women not because women are different, but because the tool is designed for a resource pool that domestic demands have already partially depleted. Future JD-R applications to AI well-being contexts should explicitly incorporate DDO as an input variable.

Second, the review extends TAM (Davis, 1989) by introducing Temporally Conditional Perceived Usefulness (TCPU) as a gender-differentiated antecedent of technology adoption. For women with double burden responsibilities, perceived usefulness is conditioned on temporal accessibility a dimension orthogonal to both functionality and ease of use. AI adoption studies in gender-diverse workforces should include validated items capturing whether a tool's engagement format fits within users' available time windows, disaggregated by caregiving responsibility status.

Third, the GRAW Framework contributes to organisational sustainability theory by establishing the gender well-being gap as a quantifiable sustainability risk with calculable implications for turnover costs, engagement trajectories, and long-term workforce composition. This repositions gender-responsive AI design from a compliance obligation to a sustainability investment with an estimable return a framing likely to be operationally persuasive for senior organisational leaders and ESG-oriented investors.

6.2 Practical Implications

For organisations, the most immediately actionable implication is the priority of gender-auditing existing AI well-being tools before extending their deployment. A gender-audit assessing whether a tool produces equivalent accuracy, accessibility, and sustained engagement across gender is a low-cost intervention that can substantially improve the return on well-being technology investment.

For HR technology vendors, the GRAW Framework's design principles represent a meaningful product differentiation opportunity as ESG reporting requirements expand and institutional investors scrutinise the gender dimensions of portfolio companies' people strategies. AI well-being tools with independently verified gender-equity credentials are likely to command premium positioning in an increasingly competitive market.

For professional bodies in India including the Institute of Chartered Accountants of India (ICAI), the Institute of Cost Accountants of India (ICMAI), and the Institute of Company Secretaries of India (ICSI), whose memberships include a substantial and growing proportion of professional women this review suggests that member well-being programmes should explicitly incorporate the double burden as a design consideration.

6.3 Social Implications

The gender gap in AI well-being adoption is not a technical problem with a technical solution alone; it is a structural problem rooted in the unequal distribution of domestic labour in society. Closing this gap through gender-responsive AI design has social implications that extend beyond the organisational level. It legitimises the visibility of the double burden as a structural feature of working women's lives rather than an individual challenge to be managed privately. The integration of gender well-being metrics into ESG and BRSR reporting frameworks transforms what has been a private burden into a public governance accountability, with implications for corporate culture and policy that extend well beyond any individual AI platform. In the Indian context particularly, where professional women increasingly navigate both the expanding digital workplace and deeply entrenched domestic expectations, gender-responsive AI well-being design constitutes a meaningful lever for structural social change.

6.4 Limitations

This review carries several limitations warranting acknowledgement. The 68 included studies vary substantially in methodological quality, geographic context, and sector focus. Longitudinal evidence is concentrated in a relatively small subset of studies; the compounding sustainability effects identified in Theme 4 require replication across longer follow-up periods and more diverse national contexts. The review's focus on published, peer-reviewed, English-language literature may underrepresent evidence from the Global South. The GRAW Framework is a conceptual architecture requiring empirical testing; its embedded propositions should be treated as structured hypotheses for future research.

VII. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This systematic review synthesises evidence from 68 peer-reviewed studies published between 2015 and 2025 to arrive at three core conclusions. First, AI-enabled well-being interventions deliver documented benefits in workplace contexts, but these benefits are distributed unequally: women with caregiving responsibilities derive significantly smaller well-being gains because of a structural mismatch between AI tool design and the double-burden reality of their users. Second, the double burden operates simultaneously as an outcome moderator and a structural adoption barrier, creating a usage gap that compounds the well-being gap over time in ways that standard JD-R and TAM frameworks do not adequately capture. Third, organisations deploying gender-blind AI well-being strategies undermine the very sustainability outcomes that motivated their investment, generating turnover, engagement deficits, and diversity erosion that compound over multi-year timeframes.

The GRAW Framework spanning Design, Deployment, and Sustainability levels provide a theoretically grounded and practically actionable architecture for closing this gender gap. Its two new theoretical constructs JD-R+DDO and TCPU provide researchers with measurable variables for advancing the evidence base. The argument of this review is ultimately straightforward: AI well-being tools are only as equitable as their design, and gender in management is not a peripheral concern for AI well-being research it is the central variable that determines whether the promise of AI well-being will be kept.

Several directions for future research are indicated. Longitudinal, gender-disaggregated studies of AI well-being tool outcomes over 24-to-48-month periods are needed to confirm the compounding sustainability effects identified here. Experimental and quasi-experimental designs testing specific GRAW design principles particularly temporal flexibility and domestic demand modelling would provide causal evidence to complement the correlational findings of the current evidence base. Cross-national comparative studies contrasting European gender-equity legislation with South Asian professional norms, including India's emerging AI governance framework, would substantially advance the framework's generalisability. Finally, intersectional research examining how gender interacts with disability, elder-care responsibilities, caste, and ethnicity within AI well-being systems would extend the GRAW Framework toward a more inclusive account of differential well-being in AI-enabled workplaces.

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- Data availability: All included studies are publicly available through the databases cited. No primary dataset was generated.
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