Designing Work That Doesn't Break People: Translating Work Design Theory into AI Systems

Abstract and Executive Summary

Abstract
Knowledge work is increasingly characterized by high cognitive demands, constant digital interruption, and meeting-heavy coordination. Yet most "productivity" systems still optimize what is easiest to count (activity, responsiveness, and output volume) rather than what organizations ultimately need: high-quality outcomes delivered at a pace people can sustain. This whitepaper synthesizes research on SMART work design, cognitive load theory, attention fragmentation, and digital overload — and translates these bodies of evidence into a privacy-first product system for "work reshaping" AI. The proposed design emphasizes job crafting nudges, workload pacing, and recovery cycles that reduce needless cognitive load without surveillance. It also introduces a productivity-versus-sustainability measurement model that links work redesign interventions to business outcomes (quality, error rates, cycle time, and retention) while directly measuring human sustainability (mental workload, recovery, and burnout risk). [1]

Executive Summary
The strategic claim is straightforward: **work design is a controllable driver of performance and well-being**, and AI can be designed to *change* work conditions rather than simply *measure* worker activity. SMART Work Design provides a research-grounded structure for redesigning jobs across five dimensions (stimulating work, mastery, agency, relational work, and tolerable demands). [2]

Cognitive load theory explains why knowledge workers break when "work" is designed as a constant stream of context switching and coordination overhead: working memory is limited, and performance suffers when tasks impose unnecessary processing demands ("extraneous" load). [3]

Research on task switching, interruptions, and attention residue shows that fragmentation has real performance costs. Task alternation produces switch costs (time and accuracy penalties), and incomplete task transitions leave "attention residue" that reduces performance on the next task. [4]

Field and lab evidence also shows a central paradox in digital work: people often compensate for interruptions by working faster, but at a psychological cost (greater stress, frustration, and perceived time pressure). [5]

Meeting overload adds a second layer of fragmentation: meetings disrupt deep work, create transition costs, and can require "recovery" time to re-engage with task work — particularly after poor-quality or irrelevant meetings. [6]

Traditional productivity metrics fail because they reshape behavior around proxies (Goodhart/Campbell-style distortions), and because knowledge work outputs are inherently difficult to quantify without encouraging performative work. [7]

This paper proposes a product system ("RUDY AI") that operationalizes these insights with three core mechanisms:
1) **Work design diagnostics** (SMART-based) that identify work conditions driving overload; 2) **work reshaping recommendations** that reduce extraneous load and fragmentation while increasing autonomy and mastery; and 3) **privacy-first measurement** that uses voluntary self-report and role-appropriate quality metrics (not keystroke monitoring) to validate improvements and guide controlled experiments. [8]

Literature Review

SMART work design as a system-level lever
SMART Work Design is positioned as a practical synthesis of work design research that helps organizations redesign jobs for both well-being and performance, with "SMART" standing for: stimulating work, mastery, agency, relational work, and tolerable demands. [2]
In the model's supporting research and documentation, SMART is not framed as employee self-optimization. It is framed as *work redesign* — a shift away from "fix-the-worker" tactics toward changing job characteristics that drive stress and disengagement. [9]

Cognitive load theory and the limits of working memory
Cognitive load theory begins from a capacity constraint: tasks draw on limited cognitive processing resources, and learning/performance suffers when demands exceed those limits. [3]
A foundational implication is that organizations can improve performance not only by increasing effort, but by **removing unnecessary load** — the workplace analog of reducing "extraneous" instructional load (e.g., poorly designed information flows, unclear goals, unnecessary meetings, and constant interruptions). [10]

Attention fragmentation: task switching, interruptions, and attention residue
Controlled experiments show that switching between tasks incurs measurable costs (time and performance), supporting a view of task switching as involving executive control stages (e.g., goal shifting and rule activation). [11]
In workplace-like task designs, "attention residue" explains why moving from one task to another can degrade performance when the first task remains cognitively active (unfinished, unresolved, or emotionally salient). [12]
Workplace field observations also describe pervasive fragmentation. In one detailed observational study, information workers were found to switch work events frequently (reported as averaging every three minutes in prior work referenced by the paper), and interruptions were a common feature of work "spheres." [13]
Lab evidence further indicates that people can respond to interruptions by accelerating

task execution, but with increased stress and frustration — underscoring that "speed" is not the same as "healthy productivity." [5]

Digital overload: information overload and technostress

Information overload has a long research history in organizational and information systems scholarship, describing conditions where information supply exceeds human processing capacity, degrading decision quality and well-being. [14]

Technostress research extends this lens, emphasizing that technology can create both "techno-distress" and "techno-eustress," and that design choices in systems and organizational practices shape which predominates. [15]

In applied management literature, communication overload is increasingly treated as an organizational design issue, not merely an individual time-management problem; even large-scale surveys reported in managerial outlets point to substantial perceived excess communication volume. [16]

Meeting overload, meeting recovery, and meeting hangovers

Meeting science research suggests meetings are essential coordination mechanisms but can create direct and indirect costs when poorly designed. Work on "meeting recovery" frames the transition time needed after meetings to regain focus and reduce fatigue, linking meeting outcomes (effectiveness, satisfaction, relevance) to recovery needs. [17]

Managerial evidence also describes the "meeting hangover" phenomenon: lingering negative affect and reduced focus following poorly run meetings, with impacts lasting beyond the meeting itself. [18]

Decision fatigue: evidence, debate, and design implications

Sequential decision quality deterioration is often discussed as "decision fatigue," but the evidence base is mixed and contested across contexts. A prominent field study of judicial decisions reported substantial within-day variation consistent with depletion or defaulting dynamics, with higher favorable decisions after breaks. [19]

That interpretation has been challenged in subsequent critique and replied to in follow-up correspondence, illustrating that causality and mechanisms are complex in naturalistic "sequential decision" datasets. [20]

More recent large-scale field evidence in healthcare has reported no supportive pattern for decision fatigue in that setting, reinforcing the need to treat decision fatigue as a plausible risk under certain conditions rather than a universal law. [21]

For product design, the implication is conservative: do not assume a single depletion mechanism; instead, treat heavy decision load and lack of breaks as **risk factors** for lower decision quality and higher stress, to be tested empirically. [22]

Theoretical Framework

This framework integrates four research-backed propositions into a single product-ready model.

Work design sets the "cognitive operating conditions."

SMART Work Design frames work characteristics as upstream determinants of outcomes such as engagement and burnout risk. In system terms, it describes how job structure shapes the baseline balance of resources (agency, mastery, relational support) and demands (tolerable vs excessive), influencing both performance and well-being. [2]

Cognitive load is not merely "busy-ness" — it is capacity consumption.
Cognitive load theory's practical value in work design is that it distinguishes between load that is inherent to the task and load that is imposed by how work is organized and presented. Design choices that increase unnecessary processing demands reduce available capacity for problem-solving, learning, and quality execution. [10]

Fragmentation creates hidden costs that output metrics miss.
Task switching costs and attention residue make performance non-linear: two hours of uninterrupted deep work are not equivalent to two hours fragmented into micro-sessions by meetings and notifications. [23]
Furthermore, evidence that people work faster under interruptions but experience higher stress implies that output volume can rise while sustainability collapses — a classic measurement trap. [5]

Recovery is a "performance technology," not a perk.
Meeting recovery research argues that transition time and recovery after meetings are part of how people sustain performance across a day, especially when meetings are ineffective or irrelevant. [17]
More broadly, micro-break evidence indicates that short breaks can improve well-being outcomes and (in many cases) performance, supporting the idea that recovery cycles can be designed rather than left to individual willpower. [24]

Why traditional productivity metrics fail in this context
Metrics reshape behavior. MIT research on metrics and "pitfalls" emphasizes that measurement systems can generate counterproductive actions and unintended consequences; organizations often "become exactly what they seek to measure." [25]
Managerial research likewise notes that metrics are necessary but can undermine strategy when they become targets, encouraging gaming and narrowing focus. [26]
And when work is cognitive and judgment-based, even identifying valid output measures is difficult — knowledge workers decide what to do and when, and effort can be partially invisible to managers. [27]
This motivates a shift from "more output" to **sustainable productivity**, explicitly defined as aligning performance outcomes with employee well-being rather than treating them as competing objectives. [28]

Productization

Productization (how RUDY AI implements this)
RUDY AI is designed as a *work design* system, not a worker surveillance system. Its core promise is to **reshape work conditions** (job structure, meeting norms, pacing, recovery) to improve both performance quality and sustainability.

Product system architecture

RUDY AI follows a three-layer architecture:

Diagnosis layer: SMART × Load × Fragmentation map
RUDY AI converts work signals into a structured "work design map" in three representations:

1) **SMART profile** (stimulating, mastery, agency, relational, tolerable demands). [29]
2) **Cognitive load risk profile**, focused on *avoidable extraneous load* (unclear goals, redundant coordination, poor information flow). [10]
3) **Fragmentation profile** (meeting density, transition costs, interruption exposure) grounded in established switching-cost and fragmentation research. [30]

Intervention layer: work reshaping recommendations
The intervention layer is intentionally behavioral and structural — it changes defaults, sequences, and coordination patterns rather than merely reporting dashboards. This design aligns with technostress research emphasizing that stress outcomes depend on system and organizational design, not only individual coping. [15]

Learning layer: privacy-first experimentation and adaptation
RUDY AI updates its recommendations by learning from outcomes (quality, cycle time, recovery metrics) and user feedback — but does so using **controlled experiments and aggregate insights**, not individual surveillance scoring. This aligns with "sustainable productivity" guidance warning that activity monitoring can be misinterpreted as policing unless transparency, trust, and employee benefit are explicit. [28]

Translating theory into product features

Job crafting nudges (agency and mastery without role drift)
Job crafting research frames employees as active "crafters" of task, relational, and cognitive boundaries, with interventions shown (in meta-analytic evidence) to increase job crafting behaviors and improve engagement and some forms of performance. [31]
RUDY AI operationalizes this by offering constrained, role-safe nudges such as:

- **Task shaping**: "Batch similar requests into one response window" to reduce switching costs. [32]
- **Mastery loops**: "Add a 5-minute 'definition of done' step" to reduce rework and ambiguity (extraneous load). [33]
- **Relational crafting**: "Route questions through a rotating 'office hours' channel" to preserve support while reducing interrupt-driven fragmentation. [34]

Workload pacing (cognitive load budgeting)
Cognitive load theory implies that performance improves when unnecessary load is minimized and when intrinsic load is managed through sequencing and scaffolding. [33]
RUDY AI instantiates this via:

- **Cognitive load budgeting**: limits "high-load events" (complex decisions, deep design reviews) per day; schedules high-load tasks when users report highest focus windows. [35]
- **Coordination throttles**: recommends asynchronous alternatives when meeting density exceeds recovery thresholds (meeting recovery research). [6]
- **Complexity-aware interruption policy**: for complex tasks, defaults to "protected focus blocks" because interruptions disproportionately harm complex decision-making. [36]

Recovery cycles (micro-breaks, transition time, and meeting recovery)
Micro-break meta-analysis indicates that short breaks can improve well-being and can benefit performance, while workplace studies emphasize the need for transition/recovery around meetings. [37]
RUDY AI implements:

- **Meeting recovery buffers**: automatically suggests 5–15 minute buffers after high-cognitive-load meetings (especially low-quality meetings) and tracks whether buffers reduce fatigue and improve subsequent task execution. [6]
- **Micro-break prompts**: "two-minute reset" prompts tied to user-defined signs of overload, designed as opt-in well-being supports rather than mandatory compliance. [24]
- **Detachment protection**: "end-of-day closure" rituals (capture next action + park unfinished thoughts) to reduce after-hours cognitive carryover; framed as reducing attention residue and enabling recovery. [38]

Meeting overload controls (designing better coordination)
Meeting overload is treated as an organizational design problem: poor meetings create hangovers and reduce engagement; meeting recovery time becomes necessary when meeting quality is low or relevance is low. [39]
RUDY AI provides:

- **Meeting necessity classifier (privacy-first)**: based on meeting metadata (duration, attendees, frequency) and post-meeting quick ratings, not content capture. [40]
- **Asynchronous-by-default templates**: replaces status meetings with structured async updates when feasible, preserving relational needs through deliberate check-ins rather than constant sync. [41]

Decision load reduction (testing, not assuming, decision fatigue)
Because decision fatigue evidence is mixed across contexts, RUDY AI treats decision load as a measurable risk and tests whether reducing decision density improves quality and well-being in each organization. [42]
Features include:

- **Decision batching**: consolidates low-stakes approvals into scheduled windows to minimize constant cognitive switching. [4]

- **Default design**: proposes reversible defaults for low-risk decisions and escalates only when quality risk is high, reducing extraneous decision effort. [43]

Measurement of Cognitive Load Without Surveillance

Measurement of cognitive load (without surveillance) must satisfy three constraints simultaneously: validity, privacy, and business relevance. The research consensus in mental workload measurement emphasizes multiple measurement categories (subjective, performance-based, psychophysiological), with subjective measures often regarded as highly valid and sensitive for workload. [44]

A privacy-first measurement stack

Tier 1: Voluntary micro-check-ins (gold standard for privacy + interpretability)
RUDY AI uses opt-in, short prompts derived from established mental workload instruments (e.g., TLX-style factors such as mental demand, time pressure, effort, frustration). [45]
These prompts are triggered by *work events* (post-meeting, after a focus block), but completion is always voluntary and user-controlled.

Tier 2: Work-product quality and error proxies (role-specific, non-invasive)
Because interruptions and overload can preserve "speed" while harming stress and quality, RUDY AI prioritizes outcome metrics such as:

- **Error rates / defect escape** in engineering or operations workflows. [46]
- **Rework** (e.g., revision cycles, reopened tickets) as a proxy for unclear requirements and extraneous load. [47]
- **Peer review quality** (structured rubrics) rather than volume of output. [48]

Tier 3: Aggregated work-pattern metrics (metadata only, no content capture)
At team level, RUDY AI can compute metrics such as:

- Meeting density and average transition time availability (from calendars). [17]
- Fragmentation indicators derived from task switching research (e.g., number of distinct work "spheres" touched per day using task system categories, not app monitoring). [13]
  These are used for work redesign, not performance evaluation.

Burnout and sustainability measurement

Burnout is defined (in occupational framing) as a syndrome resulting from chronic workplace stress that has not been successfully managed, characterized by exhaustion, cynicism/mental distance, and reduced professional efficacy. [49]
RUDY AI treats burnout risk as a sustainability KPI that must be reduced alongside quality improvements. Evidence in systematic review/meta-analysis links burnout to lower quality and safety outcomes in demanding settings (healthcare), supporting the broader claim that burnout is not merely a personal cost — it is a quality risk. [50]

Productivity vs sustainability framework

Drawing on the “sustainable productivity” framing: organizations must reconcile outputs with inputs (human energy, well-being, and engagement), and avoid activity monitoring that appears as policing; data should be used transparently to support employees and improve work design. [28]

RUDY AI uses a two-axis evaluation model:

- **Productivity (P)**: quality-adjusted output and timeliness (not sheer volume). [51]
- **Sustainability (S)**: workload, recovery, and burnout risk (short-term strain + long-term health). [52]

Operationally, the goal is to move teams toward a quadrant of **high P / high S**, rather than optimizing P while degrading S (the common failure mode under proxy metrics). [53]

Hypotheses + Measurable Constructs

Hypotheses + measurable constructs translate the theory into testable claims. Each hypothesis is designed to be falsifiable, measurable, and tied to business outcomes.

Work design and job crafting hypotheses

H1 (SMART redesign effect): Teams receiving SMART-informed work redesign recommendations will show improved sustainability (lower mental workload and burnout risk) and improved productivity (higher output quality and lower error rates) compared to control teams. [54]
Constructs: SMART profile shifts (survey), mental workload (micro-check-ins), burnout (validated burnout scales aligned with WHO framing), quality metrics (role-specific). [55]

H2 (job crafting nudge effect): Job crafting nudges will increase job crafting behaviors and work engagement, and will improve contextual performance, relative to control. [31]
Constructs: job crafting frequency (self-report), engagement, contextual performance ratings where available. [56]

Fragmentation and multistream work hypotheses

H3 (fragmentation reduction improves quality): Reducing context switching and enabling cleaner task transitions will improve quality and reduce time-to-completion variance for complex work. [57]
Constructs: switch-cost proxies (meeting density + task switching indicators), quality metrics, rework rate, self-reported focus. [58]

Meeting overload and recovery hypotheses

H4 (meeting recovery buffers reduce fatigue): Introducing recovery buffers after meetings will reduce meeting fatigue/hangover and improve post-meeting task resumption effectiveness. [6]

Constructs: post-meeting fatigue (micro-check-in), time-to-first-meaningful-work after meetings (self-report or workflow event timing), perceived meeting effectiveness and relevance. [40]

Digital overload and technostress hypotheses

H5 (communication overload reduction lowers technostress): Reducing communication overload (volume, fragmentation, expectation of immediacy) will reduce technostress and improve perceived control and well-being. [59]
Constructs: perceived techno-distress, perceived control/agency (SMART "agency"), workload micro-check-ins, after-hours interruption frequency (metadata only). [60]

Metrics and management hypotheses

H6 (sustainability-adjusted metrics outperform output-only metrics): A sustainability-adjusted productivity model (quality + timeliness + human sustainability) will better predict retention risk and quality outcomes than output-only activity metrics. [61]
Constructs: retention/turnover intention, quality outcomes, burnout and workload, activity volume metrics (for comparison only, not as targets). [62]

KPI Mapping and Controlled Experiment Design

KPI mapping must connect interventions to both business value and human sustainability, while avoiding proxy-metric traps.

KPI model

Primary KPI families (to be selected per role/function):

Quality and error KPIs (business-critical)
- Defect escape / incident rates; quality audit scores; customer satisfaction where relevant. [63]
- Rework rate (reopened tickets, revision cycles) as a proxy for extraneous load and unclear work design. [47]

Throughput and flow KPIs (without rewarding speed at all costs)
- Cycle time and flow efficiency (time in active work vs blocked/coordination time), interpreted alongside sustainability metrics. [64]

Sustainability KPIs (human capital protection)
- Mental workload (short micro-check-ins based on workload constructs). [44]
- Meeting fatigue / hangover indicators and recovery sufficiency. [6]
- Burnout risk (validated measures aligned with occupational burnout definitions). [65]

Leading indicators (diagnostic, not evaluative)
- Meeting density, back-to-back meeting rates, and buffer time availability. [17]
- Fragmentation signatures (task switching proxies), interpreted cautiously because fragmentation can be necessary in some roles. [66]

Controlled experiment design

Controlled experiment design should match the sociotechnical nature of work. The recommended approach is a staged cluster randomized design to reduce spillover.

Experimental design (A/B tests)
- **Unit of randomization:** team (cluster randomization), not individuals, to avoid contamination via shared meeting norms and coordination behaviors. [67]
- **Arms:**
- Control: measurement-only + generic well-being resources.
- Treatment A: SMART diagnostic + job crafting nudges. [68]
- Treatment B: A + pacing + recovery cycles (meeting buffers + micro-break prompts). [37]
- Treatment C (optional): B + meeting redesign automation (async substitution recommendations). [69]

Timeline:
- Baseline (2–4 weeks): collect voluntary workload measures + KPI baselines. [70]
- Intervention (8–12 weeks): deliver nudges and structural recommendations; maintain measurement. [71]
- Follow-up (4+ weeks): assess persistence, rebound effects, and sustainability. [72]

Primary evaluation method:
- Difference-in-differences at team level for quality and sustainability outcomes; preregister hypotheses and analysis plan to reduce interpretive flexibility (especially important in fatigue research where effects can be context-dependent). [73]

Safeguards against metric gaming:
- Do not use experimental metrics for compensation or performance evaluation during the study. This follows metric-pitfall research emphasizing distortions when metrics become targets. [43]

Ethical Considerations and References

Ethical considerations must treat AI work systems as sociotechnical interventions with power implications, not neutral analytics tools.

Privacy-first, non-surveillance commitments

1) **Data minimization and metadata preference:** Use calendar/task metadata and voluntary self-report, not keystrokes, screenshots, or always-on monitoring. This aligns with sustainable productivity guidance warning that activity monitoring can be experienced as policing unless clearly employee-benefiting and transparent. [28]
2) **Employee control and purpose limitation:** Individuals control personal workload data visibility; managers receive only de-identified, aggregated insights intended for work redesign, not individual evaluation. [28]
3) **Transparency of recommendations:** Users can see why a recommendation was made

(e.g., “meeting density exceeded recovery threshold”), reducing opacity and supporting trust. [74]

Avoiding algorithmic management harms

Algorithmic management research emphasizes that AI systems can reshape power dynamics, introduce opacity, and intensify data capture pressures; work systems therefore must be designed with accountability and worker agency at the center. [75] RUDY AI’s design goal is to be an “algorithmic *work redesign* assistant,” not an “algorithmic manager”: it optimizes *work conditions* (meeting norms, pacing, clarity), not individual surveillance-based performance scoring. [76]

Fairness and inclusion

Workload, interruptions, and meeting burdens are not evenly distributed. Therefore:
- RUDY AI should audit recommendations for disparate impacts (e.g., caregiving schedules, time-zone inequities, role-based meeting load). [77]
- Interventions should prioritize structural fixes (meeting norms, role clarity, staffing) rather than requiring individual coping strategies as the first-line solution. [9]

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