Inboxed Minds: A Human Factors Analysis of In-Basket Messaging in Outpatient Psychiatry

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Outpatient psychiatry labor is visible to its institutions in, almost exclusively, one single form and shape: billable appointment slots on a clinic schedule. These are the units through which productivity, compensation, and staffing needs are defined. Every slot is assumed to contain the full scope of psychiatric care, including evaluation, diagnosis, treatment, documentation, and closure, all within the limits of the scheduled time. In this view, care appears orderly and complete, beginning and ending within the electronic calendar's grid.

In practice, much of psychiatric work takes place outside these. An entire layer of invisible work sustains patient care but receives no dedicated time, credit, or recognition. Psychiatrists spend large parts of their day returning phone calls, addressing pharmacy issues or clarification requests, initiating and monitoring prior authorizations, navigating insurance barriers, coordinating care with therapists and case managers, reviewing incoming records and lab results, and resolving scheduling conflicts.

The widespread implementation of the In-Basket Messaging health information technology compounds this layer of invisible tasks that are neither optional nor secondary to care: they are the glue that holds the clinical system together. Yet they remain absent from official metrics and unsupported by formal workflows.

The accumulation of invisible work steadily erodes the boundaries between clinical and personal time. Lunch breaks vanish, academic work is postponed, and evenings are consumed by message backlogs and unresolved coordination tasks. Each task may seem small, but together they form a parallel workload that is essential to patient safety and continuity yet institutionally invisible. The schedule shows completion, while the clinician's experience reveals an ongoing and unacknowledged obligation.

This divide exposes a deeper sociotechnical problem. The technical system, which includes the electronic health record (HER) and billing infrastructure, captures only what can be billed. The human system, composed of clinicians, absorbs everything else. What remains invisible to the institution is deeply tangible to the people doing the work.

Problem Statement and Significance

The growing burden of "invisible work" imposed by electronic health record (EHR) in-basket messaging has received increasing attention across medical specialties. Managing multiple asynchronous communication streams exceeds the bounds of distributed cognition designed into current workflows. The problem therefore exemplifies misalignment between the technical subsystem (EHR architecture) and the social subsystem (organizational workload expectations). In psychiatry, complex case management and highly individualized care coordination amplify the unseen workload managed via secure EHR messaging, where "message burden" encompasses both task load (quantitative volume) and mental workload (cognitive demands of context-switching and clinical decision-making). This study addresses these knowledge gaps by analyzing Epic Signal data from all outpatient psychiatry clinicians at one large academic medical center, mapping message volume, time spent, and after-hours activity to help make some of the invisible work visible and provide an evidence base for targeted interventions.

Literature Review

The growing burden of electronic health record (EHR) in-basket messaging has emerged as a critical challenge with mounting evidence linking message volume to clinician burnout and work-life imbalance. Recent literature reveals both the scale of this invisible workload, and some promising approaches to mitigation.

Quantifying the In-Basket Burden

Multiple studies have documented the dramatic growth of patient portal messaging and its impact on clinician workload. North et al. (2020) found that patient portal enrollment nearly doubled (from 33% to 62%) while message volume nearly tripled in some specialties, with physicians performing the majority of responses and substantial portions handled during evenings and weekends. The COVID-19 pandemic further exacerbated this trend, with Nath et al. (2021) reporting that patient medical advice requests more than doubled in primary care (105% increase) and total inbox time increased by 15-17% during the pandemic period.

Holmgren et al. (2022) demonstrated that weekly patient advice messages jumped from 8 to 16 per primary care physician post-COVID, while mean active EHR time increased by 6.5% for primary care physicians. Martinez et al. (2024) found that each additional 10 patient messages per quarter was associated with 12 minutes of extra after-hours EHR time, confirming that message volume directly translates to work-life boundary erosion.

The Documentation and In-Basket Connection

Arndt et al. (2017) provided landmark evidence that physicians spend 5.9 hours of an 11.4-hour workday on EHR tasks, including nearly 1 hour daily on in-basket management and clerical tasks. This "tethered to the EHR" phenomenon means that for every hour of direct clinical time, physicians spend nearly two hours on electronic and administrative labor. Yan et al. (2021) systematically reviewed 30+ studies and found consistent evidence that excessive EHR time, high message volume, and after-hours work are all correlated with provider burnout.

Burnout and Turnover Implications

The human and financial costs of this burden are substantial. Hamidi et al. (2018) found that physicians with burnout were more than twice as likely to plan on leaving their practice, with burnout accounting for 13-17% of physician departures and costing $15-55 million in recruitment costs over two years. Lou et al. (2022) demonstrated that while EHR workload metrics alone cannot reliably predict burnout, the combination of heavy after-hours use and high message volume significantly contributes to emotional exhaustion.

Clinician Perspectives and Coping Strategies

Qualitative studies reveal the psychological toll of constant message management. Lieu et al. (2019) found that primary care physicians often receive 70+ messages daily and feel "unbounded" by patient expectations for rapid responses. Physicians have developed numerous personal coping strategies, including one-touch processing rules and setting response time expectations, but many feel that message management remains a constant, stressful addition not accounted for in productivity metrics.

Murphy et al. (2019) synthesized clinician recommendations into five key areas: reducing low-value notifications, preventing message loss, improving inbox user interface, implementing team delegation, and providing protected time for inbox work. These findings highlight the need for both technological and organizational solutions.

Emerging Technological Solutions

Recent studies have evaluated AI-assisted approaches to in-basket management. Tai-Seale et al. (2024) and Garcia et al. (2024) both found that AI-generated message drafts achieved 20% utilization rates and significantly reduced clinician cognitive load and burnout scores, even when actual time savings were minimal. Small et al. (2024) demonstrated that AI-generated responses were rated as more empathetic and usable than human-authored ones in 69% of cases.

Ambient AI documentation tools have also shown promise. Balloch et al. (2024) found that AI scribes improved documentation quality while reducing consultation times by 26%, and Haberle et al. (2024) reported that Nuance DAX users showed improved work engagement and satisfaction with no negative impact on patient safety.

Workflow Redesign Successes

Organizational interventions have demonstrated measurable impact. Hadeed et al. (2025) implemented "Best Practice Standards" and "Routing Guides" that reduced physician message volume by 16% and carbon copy messages by 65%. Lukela et al. (2025) found that structured "portal practice sessions" (protected inbox time) led to 93% of physicians reporting improved ability to handle urgent messages and 88% reporting decreased after-hours work, despite minimal changes in objective after-hours metrics.

Liu et al. (2024) reported that an AI-assisted triage program resolved 31.9% of messages at the staff level before reaching physicians, demonstrating the potential for team-based approaches to reduce individual provider burden.

Psychiatry-Specific Gaps

While these studies span multiple specialties, the unique cognitive demands of psychiatric care involving complex medication management, crisis intervention, and emotionally nuanced communication remain underexplored. The combination of frequent patient communications, detailed documentation requirements, and the sensitive nature of mental health discussions creates distinct challenges that warrant specialty-specific evaluation and intervention strategies.

Sociotechnical and Human-Centered Design Framework

This study applies the sociotechnical systems framework central to human factors, recognizing that in-basket workload emerges from the dynamic interaction between EHR technology (the "technical" subsystem), organizational practice, provider role expectations, and patient demand (the "social" subsystem). Following Carayon's (2019) framework, in-basket workload is examined across four interconnected levels:

1. System Level: EHR architecture, triage protocols, and automation tools shape baseline load
2. Organizational Level: delegation policies, team structure, and time allocation affect message volume
3. Individual Level: provider role, clinical volume, and work patterns influence burden
4. Patient Level: population complexity, portal adoption, and message types shape communication frequency.

This multilevel perspective recognizes that interventions addressing in-basket overload must engage the entire work ecosystem. We operationalize in-basket workload as volume metrics (message counts), time metrics (in-basket and after-hours hours), and distributional metrics (Gini coefficient and Lorenz curve). The inequality metrics directly measure work system imbalance, where cognitive demands are unevenly distributed across providers, creating conditions where some individuals exceed their cognitive capacity while others operate below optimal efficiency.

Materials and Methods

Data Sources

Data was obtained from Epic Signal, an audit log and analytics tool embedded within the Epic electronic health record (EHR), to quantify in-basket activity among outpatient psychiatry clinicians at a large academic medical center. Signal extracts standardized metrics related to system use.

Two monthly datasets (July 2024–June 2025) were obtained:

1. A "Messages" extract summarizing counts of in-basket messages by provider
2. A "Time" extract detailing provider time spent on different EHR activities.

Population and Outcome Measures

This study was conducted at Penn Behavioral Health Outpatient Psychiatry Clinic (Philadelphia, PA), where providers operate in a unique organizational context without dedicated support staff for message triage, and must cross-cover colleagues' in-baskets during absences. Our study population included all psychiatric physicians (attendings, residents and fellows) and advanced practice providers with ambulatory schedules during the study period (July 2024–June 2025). Primary outcomes comprised in-basket message volume and time spent, total and after-hours work hours, intensity metrics (rates per week/appointment/scheduled hour), and workload inequality measures (Gini coefficient and Lorenz curves). Secondary outcomes included message subcategories and time distrubution.

Data Processing and Analysis

Data were imported from Excel exports using R, merged by provider identifier, and cleaned through standardized conversion, categorization, aggregation, anf feature engineering. Analyses were performed in R (v4.5.1) using descriptive statistics, comparative group analyses (Welch's t-tests/Wilcoxon rank-sum), and inequality measures (Gini coefficients). All data manipulation steps are fully reproducible (see inbasketosis.qmd).

Data Processing Pipeline: Epic Signal Analytics → Excel Export → R Processing → Analysis & Visualization

Results

Descriptive Statistics

The study cohort consisted of 64 providers from the Department of Psychiatry at an academic medical center. Table 1 presents comprehensive descriptive statistics across provider types, workload metrics, message patterns, and temporal characteristics.

Table 1: Table 1. Summary Statistics for Outpatient Psychiatry Clinic (July 2024 - June 2025)

Characteristic	n (%)	Range	Mean (SD)	Median (IQR)
Providers				
Attending Physician	26 (40.6)	—	—	—
Nurse Practitioner	4 (6.2)	—	—	—
Resident/Fellow	34 (53.1)	—	—	—
All	64 (100)	—	—	—
Workload				
Scheduled Appointments	28424 (—)	37.3–113.4	52.1 (13.0)	51.0 (19.6)

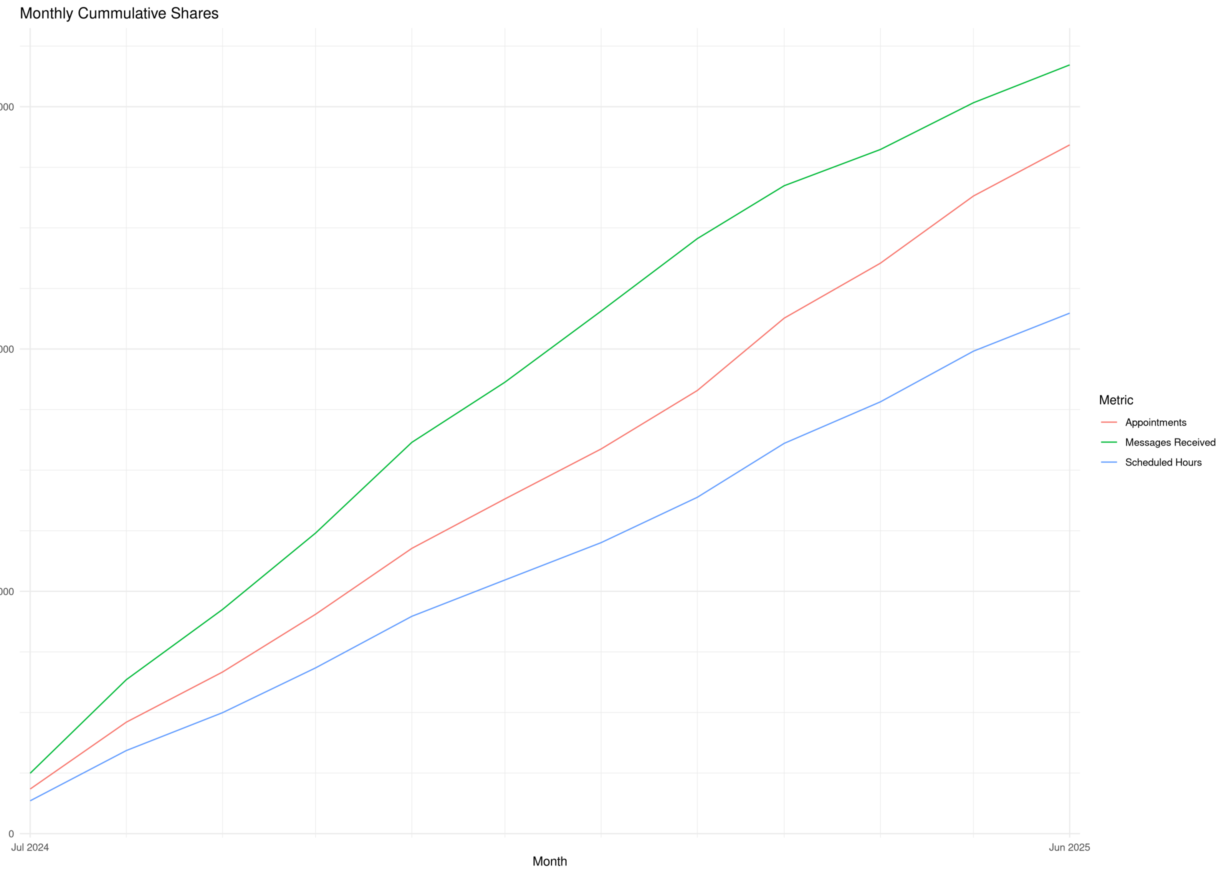
Characteristic	n (%)	Range	Mean (SD)	Median (IQR)
Scheduled	21480 (—)	40.0–40.0	40.0 (0.0)	40.0 (0.0)
Hours				
Digital				
In-Basket	1941.2 (12.4)	0.2–50.5	4.2 (6.1)	3.4 (2.0)
Hours				
After Hours	6605.2 (42.1)	0.0–46.2	11.6 (11.3)	8.9 (14.9)
Other	7128.0 (45.5)	0.7–90.2	19.0 (17.1)	13.0 (12.2)
All	15674.4 (100)	2.8–186.1	34.8 (26.9)	27.9 (20.6)
Minutes per Appointment				
In-Basket	183.0 (14.1)	0.0–9.6	2.9 (2.4)	2.9 (3.6)
Clinical	189.2 (14.5)	0.0–22.5	3.0 (3.4)	2.5 (3.9)
Review				
Notes/Letters	806.7 (62.0)	0.0–98.0	12.6 (15.0)	10.2 (16.3)
Orders	121.7 (9.4)	0.0–8.2	1.9 (1.7)	1.8 (2.7)
All	1300.7 (100)	0.0–129.7	20.3 (20.9)	18.5 (26.4)
Messages				
Medical Advice Request				
Counts	13841 (43.6)	0.0–367.1	27.6 (46.3)	23.0 (24.3)
Days to Complete	—	0.0–16.6	2.7 (3.7)	1.3 (2.2)
Minutes per Message	—	1.0–87.0	15.2 (16.1)	8.2 (11.8)
Patient Call				
Counts	6744 (21.3)	0.0–155.9	12.6 (21.1)	8.4 (8.4)
Days to Complete	—	0.0–17.0	3.2 (4.2)	1.5 (3.6)
Minutes per Message	—	3.7–375.0	37.4 (52.7)	23.6 (18.4)
Results				
Counts	5220 (16.5)	0.0–62.5	8.6 (12.8)	3.9 (7.9)
Days to Complete	—	0.0–29.0	4.4 (6.0)	2.5 (5.5)
Minutes per Message	—	2.5–1992.5	164.6 (398.4)	38.8 (86.2)
Rx Authorization				
Counts	5920 (18.7)	0.0–227.8	13.1 (32.1)	4.6 (9.9)
Days to Complete	—	0.0–5.4	0.4 (0.8)	0.2 (0.4)
Minutes per Message	—	3.1–375.0	52.2 (62.8)	32.2 (51.2)
All				
Counts	31725 (100)	0.0–757.0	61.9 (95.5)	45.1 (47.1)
Days to Complete	—	0.0–11.5	2.7 (3.0)	1.5 (3.0)
Minutes per Message	—	1.0–50.0	6.6 (8.2)	4.1 (4.4)

Table 1. Characteristics of 64 providers in the Department of Psychiatry (July 2024–June 2025). Data from Epic Signal Analytics. SD = standard deviation; IQR = interquartile range. All ranges,

Provider Distribution

The cohort included 26 attending physicians (40.6%), 4 nurse practitioners (6.2%), and 34 trainees (53.1%) including residents and fellows, representing the full spectrum of outpatient psychiatry providers at the institution.

Figure 1: In-Basket Hours by Provider

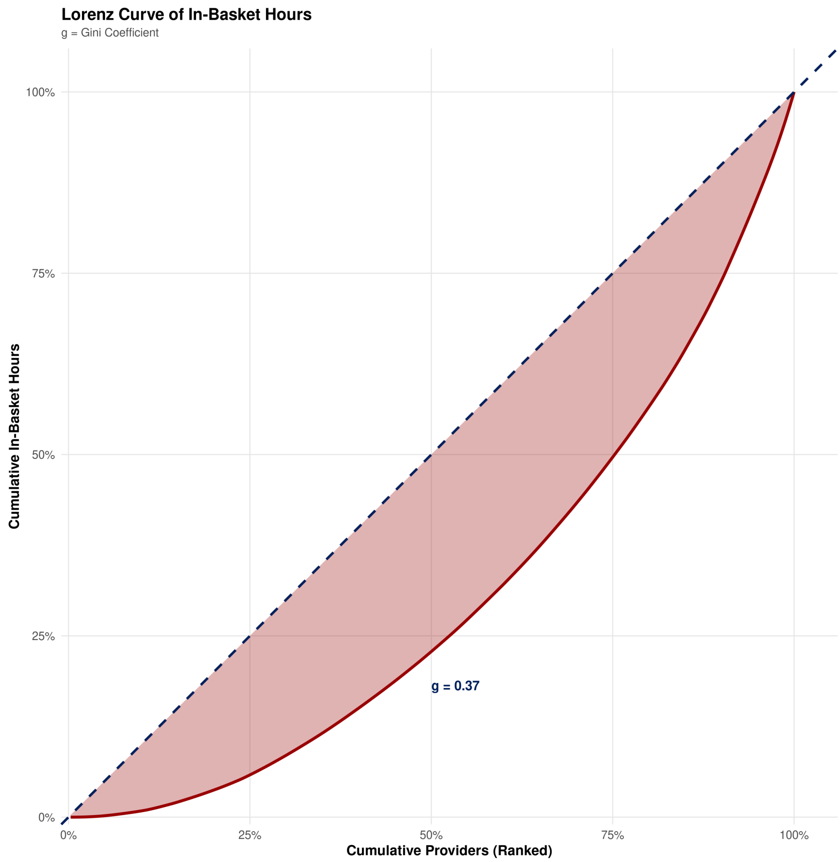


Workload and After-Hours Patterns

Providers spent an average of 1.3 hours per month on in-basket messaging activities (range: 0.1–6.3 hours), representing 12.4% of total digital workload. Critically, after-hours system usage constituted 42.1% of total digital workload, with providers averaging 4.1 hours per month outside standard clinical hours. This substantial spillover into personal time represents a major boundary erosion between work and life domains. Collectively, the 1,941 annual hours spent on in-basket messaging across all providers represents 1.2 full-time employees, $266,817 in professional revenue, or approximately 3,882 patient appointments.

Providers received an average of 19.6 messages per observation period (SD = 17.9), with medical advice requests representing the largest category (43.6% of total messages). Mean response times varied by message type: Medical Advice (2.7 days), Patient Calls (3.2 days), Results (4.4 days), and Rx Authorization (0.4 days).

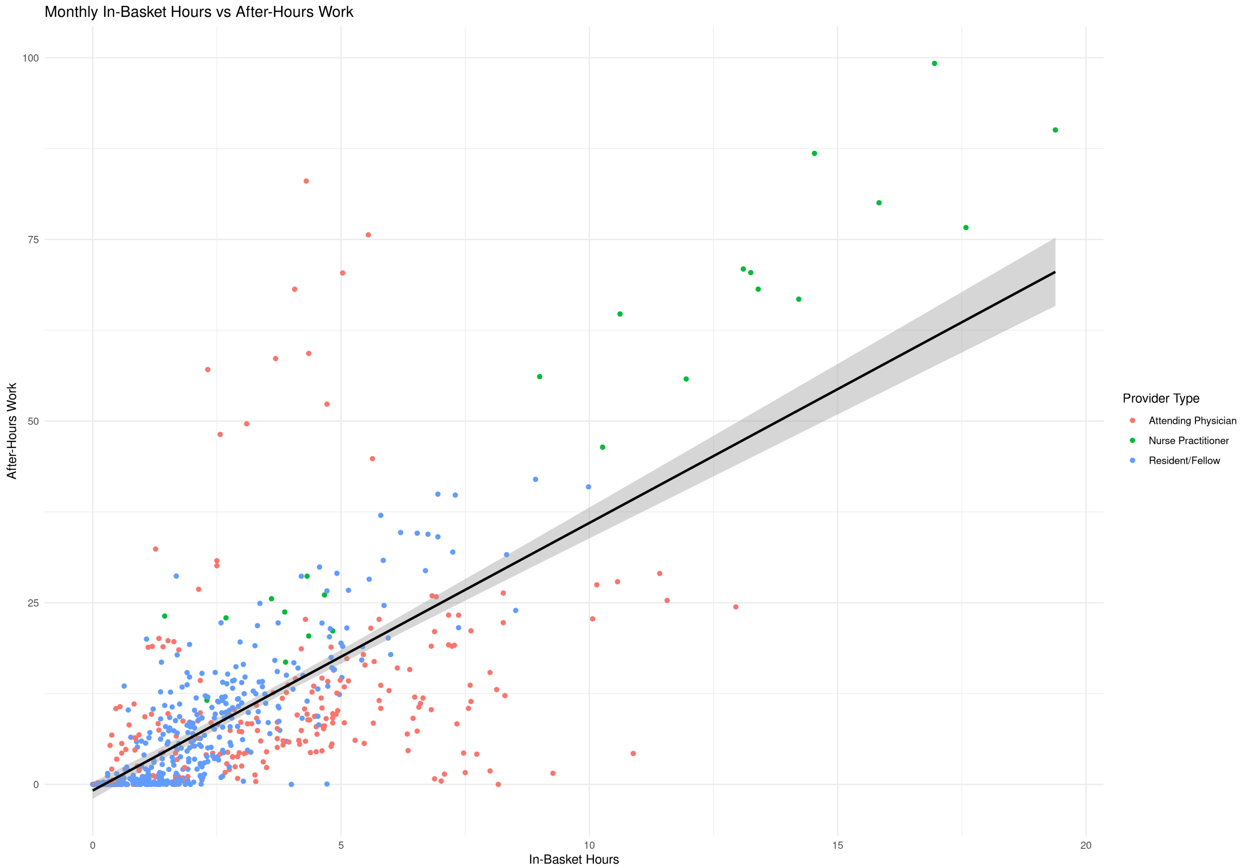
Figure 2: Inequality in Workload Distribution



Workload Distribution and Inequality

Workload distribution demonstrated significant variation, with total system time ranging from 0.4 to 36.9 hours annually per provider. Gini coefficient analysis revealed moderate inequality in workload distribution, with attending physicians bearing a disproportionate share of messaging burden compared to trainees.

Figure 3: Relationship Between In-Basket and After-Hours Work



Key Findings

The analysis revealed that, collectively, providers spent an astonishing 1,941 hours over the course of a year managing in-basket messages, a workload equivalent to employing 1.2 full-time clinicians (based on 54 working weeks per year, 40 hours per week, and 0.9 clinical effort). Framed differently, this messaging labor represented $266,817 in professional revenue (at a rate of $137 per hour), or the time needed to conduct nearly 3,882 30-minute patient appointments. The distribution of this messaging burden was far from equal. The Gini coefficient of 0.37 reflects a moderate concentration of workload, where a smaller subset of providers shouldered much of the overall in-basket responsibility. Notably, this messaging workload often bled into after-hours periods, with 42% of total EHR activity taking place outside of standard clinical hours. This significant spillover highlights a pervasive erosion of the boundary between work and personal life for many clinicians.

Discussion

Implementation and Optimization Challenges

Current productivity metrics focus exclusively on scheduled face-to-face encounters, creating a disconnect between actual work performed and work that "counts" for compensation. Recently implemented policies plan to use message completion timeliness in salary calculations, creating problematic incentives for clinican behavior. Epic Signal metrics represent only the tip of the iceberg, as they exclude telephone calls, paperwork, prior authorizations, and mental processing time, meaning actual invisible work burden is substantially higher than quantifiable through EHR audit logs alone.

Human Factors Interpretation

The observed patterns reveal fundamental work system imbalances that extend beyond simple workload management. The uneven distribution of messaging burden (Gini = 0.37) represents a classic work system imbalance where some providers exceed their cognitive capacity while others operate below optimal efficiency. This inequality creates conditions where the most experienced clinicians, who often handle the most complex cases, also bear disproportionate administrative burden, leading to cognitive overload and potential burnout.

The constant task-switching between patient care and messaging exemplifies the exponential cost increases predicted by mental workload theory (Wickens, 2008). Each context switch requires cognitive resources that could otherwise be devoted to clinical reasoning, creating a compounding effect where message management fragments attention throughout the day. The 42% after-hours work spillover further compounds this problem through the lens of attention restoration theory (Kaplan, 1995), where constant digital interruptions prevent the cognitive recovery necessary for sustained clinical performance.

Cross-coverage burden spikes represent a distributed cognition breakdown, where individual workload becomes unpredictable during colleague absences, disrupting the carefully calibrated work system balance. Finally, the speed versus quality pressure creates perverse incentives where financial penalties discourage the thorough clinical consideration that quality care requires.

The positive correlation between in-basket hours and after-hours work suggests that messaging burden spills beyond scheduled clinical time, creating persistent cognitive load that follows providers home and fragments attention, disrupting clinical reasoning throughout the day.

Problem-Solution Mapping

These human factors challenges demand targeted interventions grounded in sociotechnical design principles. For uneven workload distribution, real-time workload monitoring with automatic redistribution can restore work system balance by ensuring cognitive demands remain within individual capacity limits. Task-switching costs can be reduced by embedding messaging within patient context, allowing providers to maintain clinical focus while managing communications.

After-hours work spillover requires boundary management interventions, including protected in-basket time and response time limits that respect cognitive recovery needs. Message prioritization difficulty, reflecting information density overload, could be addressed through AI-powered urgency classification and visual cues that help providers quickly identify critical communications. Cross-coverage burden spikes demand distributed cognition solutions, such as shared team in-baskets with role-based access that maintain system continuity during absences.

Finally, the speed versus quality pressure requires fundamental incentive restructuring, replacing timeliness metrics with quality-weighted measures that reward thorough clinical consideration rather than penalize it.

Limitations and Future Research

This analysis has several limitations: the study is limited to a single department (psychiatry) at one institution, which may limit generalizability to other specialties and healthcare settings; the analysis relies on Epic Signal data, which does not capture all aspects of provider workload; the 12-month observation period may not capture seasonal variations or long-term trends; and the analysis focuses on quantitative metrics but does not capture qualitative aspects of message complexity, clinical urgency, or provider satisfaction. A critical next step involves qualitative interviews with high-burden providers to triangulate quantitative findings with lived experiences of cognitive load, task switching challenges, and work-life boundary management. Future research should include longitudinal studies examining seasonal variations and policy changes, multi-site studies across different specialties and organizational structures, and intervention studies testing AI-powered triage systems and workflow optimization strategies with rigorous evaluation of both quantitative outcomes and qualitative provider experience measures.

Conclusion

This analysis of in-basket messaging workload in outpatient psychiatry reveals both the scale of the challenge and opportunities for improvement. The moderate inequality in workload distribution (Gini = 0.37) and strong correlation between in-basket hours and after-hours work highlight the need for targeted interventions grounded in human factors principles. Addressing in-basket messaging burden requires a comprehensive approach including technological solutions, organizational changes, and policy reforms, with a focus on workflow optimization rather than crisis management. By making invisible work visible, we provide an evidence base for targeted interventions to contribute to more sustainable digital work environments in healthcare. Reducing in-basket burden is not just about doing digital work faster, but designing systems that honor human cognitive limits.

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