LEVERAGING TRANSACTIONAL BUSINESS DATA TO PREDICT EMPLOYEE WORKLOAD SATISFACTION IN OPERATIONS: AN EMPIRICAL STUDY – PART 1

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We examine whether transactional Enterprise Resource Planning (ERP) data can predict employee-perceived workload satisfaction in a metal-processing facility. Drawing on 127 working days of daily employee surveys across four logistics gates, we link each day's responses to operational records from four SAP tables: (COOIS) production confirmations, (LT060) external transport orders, (LT061) internal transport orders, and (MB51) material movements. Two gates register mean stress scores five to six times higher than a third. Internal transport activity correlates negatively with perceived problems at two gates, suggesting a buffering effect; at others, material volume rather than transport frequency seems to drive stress. Mid-week workload is consistently elevated. Our results confirm that ERP metrics can explain a bounded but meaningful portion of subjective workload variance, and that workplace-/ gate-level modeling substantially outperforms generalized approaches. These findings offer actionable insights for operations managers seeking to proactively monitor workplace social sustainability through data already available in existing information systems.

Keywords:
social sustainability,
business information systems,
employee satisfaction,
continuous improvement,
operations management

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1 Introduction

In the corporate context, sustainability refers to an organization's impact on the natural and social environment as well as its financial performance (Albers Mohrman and E. Lawler III 2014). Social sustainability, which is frequently framed as corporate social responsibility, thereby encompasses the people side of sustainability, such as human and labour rights, diversity, employee engagement, and supply chain responsibility (Missimer and Mesquita 2022; Nijhof et al. 2003). An important indicator for operationalizing social sustainability at the workplace is employee satisfaction, which is commonly understood as "a measure of how happy workers are with their job and working environment". Satisfied employees tend to be more committed and productive, while dissatisfaction can lead to low performance and absenteeism (Sageer 2012).

Although frequent employee surveys are beneficial for organizations - the frequency of feedback was found to be positively linked to both, performance and satisfaction (Mertens et al. 2021; Yaneva 2018) - systematic feedback collection remains uncommon in practice. In the DACH[1] region, 48% of companies conduct employee opinion surveys only every two years, and 17% annually (Maximilian Siessegger 2025). This sporadic approach risks overlooking short-term changes in employee satisfaction, hindering proactive social sustainability management.

Research identifies multiple determinants of employee satisfaction, including wages, leadership, promotion opportunities, work safety, and operational job characteristics such as working hours and task type and quantity (Myskova 2011; Sageer 2012). For day-to-day monitoring, short-term business process data is particularly relevant, as it offers insights into workload and tasks performed.

This paper addresses this gap in two ways. First, it extends a previously proposed idea for a Social Sustainability Insights Tool (Oettmeier et al. 2025) with a full empirical validation conducted at the logistic operations department of a manufacturing company. Second, it contributes to the emerging literature on people analytics in operations management by demonstrating how standard ERP transaction data can be used to build predictive models of employee workload

[1] D…Deutschland/Germany, A…Österreich/Austria, CH…Schweiz (DACH normaly includs also Liechtenstein)

perception together with seven hypothesis described in chapter 7. The central research questions are:

RQ1: *To what extent can subjective employee workload ratings be explained by objective ERP-derived operational metrics at the workplace (warehouse gate) level?*

RQ2: *Which operational factors correlate most strongly with perceived workload, and which warehouse gate-specific patterns provide actionable insights for continuous improvement?*

2 Related Work

2.1 Employee Satisfaction and Operational Workload

The literature broadly distinguishes between distal job satisfaction determinants - such as pay, career advancement, and organizational culture - and more proximal, task-related factors that fluctuate on shorter time horizons (Hackman and Oldham 1976; Myskova 2011). Demand-Control-Support (DCS) models (Karasek 1979) and the Job Demands-Resources (JD-R) framework (Bakker and Demerouti 2007) suggest that high task demands unaccompanied by adequate resources or autonomy are primary drivers of occupational stress and reduced satisfaction. In manufacturing and logistics contexts, empirical studies have linked objective workload metrics - such as order volumes, handling frequencies, and shift lengths - to subjective wellbeing outcomes (Lin and Mon 2025; Inegbedion et al. 2020).

Temporal patterns in workload have received comparatively less empirical attention. However, studies on production scheduling confirm that mid-week periods often accumulate higher order backlogs due to Monday start-up effects and end-of-week completion pressures (J. Buzacott and J. George Shanthikumar 1993). Such rhythmicity suggests that day-of-week may serve as a meaningful temporal control variable in workload models.

2.2 People Analytics and ERP-Driven Insights

People analytics - the collection and analysis of employee-related data to support evidence-based HR decision-making - has emerged as a significant research and practice domain (Opatha 2020). Recent work highlights the transformative potential of integrating diverse data sources, including operational metrics, to enhance satisfaction and retention (Ajiga et al. 2024; Snigdha and Singh 2024). ERP systems have increasingly incorporated people analytics dashboards to analyse staff attrition, hiring, and labour costs, demonstrating correlations between operational data and workforce metrics (Megan O'Brien 2021).

Empirical evidence also supports correlations between ERP system usability and employee satisfaction: studies on ERP implementations have found that streamlined workflows reduce stress and enhance satisfaction, while usability issues increase cognitive load and frustration (Bradley and Lee 2007; Dachawar et al. 2025). Overall, this study establishes a theoretical rationale for using ERP transaction data as a proxy for operational demands, yet no study has linked production order volumes, transport quantities, and material movements directly to daily satisfaction survey data at the production gate level.

3 Methodology

3.1 Research Design

This study is positioned within the Design Science Research (DSR) methodology of Peffers et al. (2007). The overall research program targets the development and validation of a Social Sustainability Insights Tool for ERP-based workplace monitoring. The problem identification, objectives definition, and initial design and development phases - including the conceptual architecture and requirements elicited from HR managers and data protection experts - were reported in prior work (Oettmeier et al. 2025). The present paper addresses the subsequent demonstration and evaluation phases: it demonstrates the feasibility of instantiating the tool's core mechanism - daily aggregation of ERP transactions and their alignment with workload survey data - in a real manufacturing setting and evaluates the explanatory and predictive value of this mechanism using quantitative analyses. The findings are fed into the design cycle..

3.2 Research Site and Survey Instrument

The study was conducted at a manufacturing facility that operates four distinct production warehouse logistics gates (referred to as Gates 3, 4, 5, and 6). Each gate represents a dedicated operational area with specific workflows involving inbound and outbound logistics as well as material handling. Employees at each gate complete as a group (not individually) a brief anonymized daily workload survey as part of the existing shopfloor management routine. The survey captures three dimensions on a 0 - 4 ordinal scale, where 0 denotes no workload and 4 denotes very high workload:

Routine Tasks (a): Perceived burden from standard, planned activities.

Irregular Tasks (u): Perceived burden from unplanned, ad-hoc activities.

Problems (p): Perceived frequency/severity of operational problems encountered.

3.3 ERP Data Sources and Feature Engineering

Operational data was extracted from three SAP transactions covering the same facility. Table 1 provides an overview of all data sources employed.

Table 1: Overview of data sources used in the analysis

Source	Records	Content	Role in Analysis
workload_ratings.csv	127	Daily employee workload ratings per gate (a, u, p)	Target variables
COOIS.csv	29,986	Production order confirmations by gate & date	Feature source (all gates)
LT22_061.csv	39,084	Internal warehouse transport orders	Feature source (Gates 5, 6)
LT22_060.csv	6,501	External transport orders (inbound/outbound)	Feature source (Gate 4)
MB51.csv	4,945	Material movement documents (goods receipts/issues)	Feature source (Gates 3, 4)
workplace.csv	129	Workstation-to-gate mapping table	Mapping reference
bom-assignment.csv	2,545	Bill-of-materials component assignments	Complexity reference

Source: Own

A key design decision was the adoption of gate-specific feature engineering. Given the structural heterogeneity of ERP data availability across gates - for instance, internal transport records (LT061) are exclusively associated with Gates 5 and 6, while external logistics records (LT060) are almost entirely attributable to Gate 4 - pooling all gates in a single feature space would introduce systematic missingness and mask gate-level dynamics. Table 2 summarizes the feature availability profile per gate.

Table 2: ERP data availability profile by production gate

Gate	Production Orders (COOIS)	Internal Transport (LT061)	External Transport (LT060)	Material Movements (MB51)
Gate 3	998 records	None	None	109 records
Gate 4	3,196 records	None	6,286 records	4,836 records
Gate 5	8,502 records	6,719 records	None	None
Gate 6	5,377 records	13,141 records	None	None

Source: Own

For each gate, daily-level features were aggregated from the raw transaction records: order count, transport count, total quantity (units or kilograms), and confirmed production quantity. Day-of-week was encoded as an ordinal integer (0 = Monday through 4 = Friday) and included as a temporal feature in all gate models. After matching ERP features to available survey days and removing rows where all operational features were zero, the final clean dataset comprised 127 survey days across all four gates.

3.4 Analytical Strategy

The analysis proceeded in three stages. First, descriptive statistics were computed for each satisfaction dimension by gate and by day-of-week to characterize the structural distribution of workload. Second, Pearson correlation coefficients were calculated between each operational feature and each target dimension (a, u, p) to identify the most informative predictors. Feature engineering extensions including lag variables and rolling means (3-day and 5-day windows) were systematically tested but yielded no statistically significant improvements in correlation coefficients.

4 Results

4.1 Descriptive Statistics by Gate

Table 3 presents the descriptive statistics for all three workload dimensions. Results are ordered by descending overall workload intensity defined as the arithmetic mean of the three satisfaction dimensions.

Table 3: Descriptive statistics of workload dimensions by gate (scale 0 = very low workload - 4 = very high workload; SD = standard deviation; N = 127 days)

Gate	Routine (a) µ ± SD	Irregular (u) µ ± SD	Problems (p) µ ± SD	Overall µ	N
Gate 3	1.65 ± 1.21	1.66 ± 1.18	1.56 ± 1.21	**1.62 (high-stress)**	127
Gate 4	1.61 ± 1.27	1.47 ± 1.26	1.47 ± 1.27	**1.52 (high-stress)**	127
Gate 6	1.02 ± 1.19	0.72 ± 1.28	0.46 ± 1.04	0.73	127
Gate 5	0.43 ± 0.83	0.21 ± 0.60	0.20 ± 0.62	**0.28 (low-stress)**	127

Source: Own

Gates 3 and 4 exhibit markedly elevated workload across all three dimensions, with mean overall scores of 1.62 and 1.52 respectively. In contrast, Gate 5 has a mean overall score of 0.28 - approximately one-sixth of Gate 3's level - despite hosting the highest production order volume of all gates (8,502 COOIS records; 31.1 confirmed orders per day on average). This dissociation between production volume and perceived workload points to fundamental differences in task characteristics and logistics support structures across gates. Gate 6 occupies an intermediate position with a mean overall score of 0.73, reflecting moderate workload with substantially higher variance in routine task ratings.

4.2 Day-of-Week Temporal Patterns

Table 4 presents mean overall workload by day-of-week for each gate. A consistent temporal pattern emerges across all four gates. The workload intensifies mid-week, peaking between Tuesday and Wednesday, and subsides toward Friday.

Table 4: Mean overall workload (arithmetic mean of a, u, p) by day-of-week per gate. Arrows indicate peak (↑) and trough (↓) days

Gate	Monday	Tuesday	Wednesday	Thursday	Friday
Gate 3	1.68	1.71	**1.75** ↑	1.46	1.41 ↓
Gate 4	1.58	**1.76** ↑	1.65	1.41	1.23 ↓
Gate 5	0.22	0.30	**0.49** ↑	0.26	0.12 ↓
Gate 6	0.60	**0.88** ↑	0.78	0.86	0.47 ↓

Source: Own

The Wednesday peak at Gates 3 and 5 and the Tuesday peak at Gates 4 and 6 are consistent with theoretical expectations from production scheduling literature. Monday's lower utilization (system start-up, deferred confirmations) is followed by mid-week accumulation of open orders and deliveries. The universal Friday decline may reflect reduced new-order initiation, deliberate managerial workload reduction ahead of the weekend, or the anticipation effect described in job satisfaction research. Fridays often yield more positive self-assessments regardless of objective workload (Kahneman et al. 2004).

4.3 Correlation Analysis by Gate

Table 5: Selected Pearson correlation coefficients between ERP features and workload dimensions per gate[2].

Gate	Feature	r (a)	r (u)	r (p)
Gate 3	Daily production order count	**+0.348***	**+0.390***	**+0.438***
	Confirmed production quantity	+0.299	+0.329	**+0.386***
	Material movement count	+0.072	+0.046	+0.048
Gate 4	Total material weight (kg)	**+0.314***	**+0.318***	**+0.313***
	External delivery volume	+0.177	+0.196	+0.157
	External transport count	+0.023	-0.034	-0.065
Gate 5	Internal transport volume (units from)	-0.082	-0.175	**-0.356***
	Internal transport count	-0.062	-0.176	**-0.339***
	Production order count	+0.120	-0.073	-0.028
Gate 6	Internal transport count	+0.161	-0.151	**-0.220***
	Internal transport volume	**+0.201***	-0.099	-0.189

Source: Own

[2] * indicates meaningful effect. a = routine tasks; u = irregular tasks; p = problems

Table 5 presents Pearson correlation coefficients between the most informative ERP features and each workload dimension per gate. Features with near-zero variance or less than 30 observations were excluded.

Several noteworthy patterns emerge from the correlation analysis. At Gate 3, feature "daily production order count" consistently shows the highest correlations with all three workload dimensions, peaking at r = +0.438 for problem perception - suggesting that higher daily order throughput is associated with more frequently reported operational disruptions. "Material movement count" adds negligible explanatory power, likely due to the limited number of observations (43 days with non-zero material movement count at Gate 3).

At Gate 4, feature "total material weight" emerges as the dominant predictor across all three dimensions (r = +0.31 to +0.32), while the raw count of external transports shows near-zero correlations. This asymmetry reveals an important volume-versus-frequency dynamic. It is the physical mass of goods processed rather than the number of transport events that appear to drive employee burden, plausibly because large shipments require extended handling, coordination, and physical effort.

The most striking finding concerns Gates 5 and 6: internal transport count/activity correlates negatively with problem perception (r = -0.356 and r = -0.220 resp.). Contrary to the intuitive expectation that more logistics activity means more work, higher internal transport throughput at these gates is associated with fewer reported problems. This suggests that timely and sufficient material provisioning may coincide with fewer reported work interruptions and wait states - a logistics buffer effect that we formalize as a testable hypothesis in Section 5. At Gate 6, the "internal transportation count" also shows a positive correlation with routine task ratings (r = +0.201), indicating that internal logistics work is classified as routine rather than problematic by these employees.

5 Discussion: Derived Hypotheses and Managerial Implications

5.1 Hypotheses Derived from Empirical Findings

The empirical results give rise to seven hypotheses that warrant confirmation in future studies with larger samples and ideally a control group design.

H1 (Logistics Buffer Hypothesis): Well-functioning internal logistics processes (LT061) reduce perceived workload, particularly problem perception. Evidence: Consistent negative correlations at Gates 5 ($r = -0.356$) and 6 ($r = -0.220$) suggest that timely material provisioning prevents work interruptions and ad-hoc problem-solving episodes.

H2 (Volume-over-Frequency Hypothesis): It is the physical volume of materials processed - not the frequency of transport events – that appear to drive employee workload. Evidence: At Gate 4, material weight (mb51_menge, $r \approx +0.31$) substantially predicts transport count (lt060_transporte, $r \approx 0.02$).

H3 (Mid-Week Stress Hypothesis): Mid-week (Tuesday to Wednesday) represents the peak workload period due to cumulative order and delivery pressure. Evidence: Confirmed across all four gates in Table 4, consistent with production scheduling theory (Buzacott & Shanthikumar 1993).

H4 (Task Character Hypothesis): Internal logistics tasks are perceived as substantially less burdensome than external logistics and material handling tasks, irrespective of volume. Evidence: Gate 5, with the highest production order volume, reports the lowest overall workload; Gates 3 and 4, which manage external material flows, report five to six times higher stress.

H5 (Task Heterogeneity Hypothesis): Gates with multi-source ERP profiles (i.e., heterogeneous task types) report higher workload than gates with focused operational profiles. Evidence: Gate 4 is the only gate active in three ERP data sources and reports the second-highest overall stress, while Gates 5 and 6 show cleaner operational focus and lower stress.

H6 (Data Coverage Hypothesis): ERP sources beyond those currently captured may correlate more strongly with perceived workload at Gate 3 than those used here. Evidence: Gate 3 has the highest mean workload (1.62) but the sparsest ERP coverage (998 COOIS records; no LT061/LT060 data), and observed correlations reach only $r = +0.44$.

H7 (Under-Utilization Hypothesis): Insufficient logistics activity - resulting in idle time and waiting - elevates perceived workload through boredom or frustration. Evidence: The negative LT061 correlation at Gates 5 and 6 may partially reflect the psychological burden of unproductive waiting when deliveries are delayed, complementing the logistics buffer mechanism in H1 or being moved to other Gates or position in company temporarily which could also lead to frustration.

5.2 Managerial Implications

The findings carry several concrete implications for operations managers seeking to leverage existing ERP data for social sustainability management. First, the identification of Gates 3 and 4 as structurally high-stress environments warrants targeted intervention. For Gate 4, the strong relationship between material volume and workload suggests that smoothing the incoming delivery schedule - for example, by negotiating more evenly distributed delivery windows with suppliers - could potentially reduce workload peaks. For Gate 3, the lack of ERP coverage suggests that the initial priority should be to improve data capture before continuing.

Second, the logistics buffer effect at Gates 5 and 6 (H1) suggests a cross-gate best-practice transfer opportunity. The internal transport scheduling practices that keep these gates well-supplied could be studied and partially adopted at Gates 3 and 4. Third, the consistent mid-week stress peak (H3) suggests that targeted workload relief measures - such as additional staffing, prioritized maintenance, or reduced ad-hoc task assignments - should be scheduled for Tuesday and Wednesday rather than distributed uniformly across the week.

Fourth, this study validates the feasibility of the Social Sustainability Insights Tool idea proposed in (Oettmeier et al. 2025). Even with existing ERP data and without any new IT infrastructure investments, it is possible to build gate-specific monitoring dashboards that flag workload-intensive operational configurations.

6 Limitations and Future Research

Several limitations of the present study must be acknowledged. First, the observation window of 127 working days (April to November 2024) covers only two-thirds of the annual calendar, excluding winter months and thus potentially seasonal variation in workload and satisfaction. A minimum of 24 months of continuous data collection is recommended before the predictive models are used for managerial decision-making.

Second, the survey instrument relies on self-reported ratings, which are susceptible to self-presentation bias, response habituation, and anchoring effects (Podsakoff et al. 2003). The convergence of individual employees' ratings into a single daily gate value conceals inter-individual variation that may be practically important. Future studies should consider supplementing subjective ratings with objective workload indicators such as absenteeism rates, task completion times, or quality error rates.

Third, data protection regulations - specifically the Swiss DSG (Bundesversammlung der Schweizerischen Eidgenossenschaft 2022) - constrain the use of personal employee attributes (age, experience, shift assignment, health data) that are theoretically important covariates in workload models. Future research should explore privacy-preserving aggregation techniques, such as differential privacy or federated learning, to enable the inclusion of such variables within legal constraints.

7 Conclusion

This paper provides the first empirical validation of the claim that transactional ERP data can serve as a meaningful, even if only partial, predictor of daily employee workload satisfaction in manufacturing operations - proving the answer to RQ1. The finding that internal transport activity (LT061) may function as a protective factor - reducing rather than increasing perceived problems at internal logistics gates - challenges the intuitive assumption that more operational activity always means more employee burden. The volume-over-frequency dynamic at the external materials gate and the consistent mid-week stress peak across all gates provide concrete, actionable signals that operations managers can integrate into shift planning and continuous improvement cycles. Therefore, RQ2 has also been answered.

By confirming both, the feasibility and the bounded nature of ERP-based workload prediction, this study advances the design science research program for workplace social sustainability tools and contributes to the intersection of people analytics, operations management, and information systems. The empirical evidence supports a workplace-specific, context-sensitive approach to deploying such tools rather than generic, facility-wide models. It underscores the importance of first improving data quality and ERP-to-gate assignment completeness at high-workload areas before attempting predictive monitoring.

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