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CARPENTERS' WORKDAY: BETWEEN VALUE-ADDING WORK AND PHYSICAL STRAIN

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ABSTRACT

Productivity improvement efforts in construction often rely on Work Sampling (WS) to increase Direct Work (DW) and reduce Wasted Work (WW). Such time-based metrics rarely account for how shifts in activity change workers' physical workload. This study examines the descriptive relationship between work categories and observed physical workload in a carpentry team on a Norwegian project. Over five workdays, a dual-coding WS protocol recorded activity type (DW, Indirect Work (IW), WW) and workload. Overall, DW accounted for 41.31% of observations, IW 47.89%, and WW 10.80%. Workload was predominantly Moderate (45.79%), with substantial shares in High (29.39%) and Low (24.83%). Descriptive linear fits showed a positive association between DW and High workload shares (R^2 = 0.28), and an inverse association between WW and High workload shares (R^2 = 0.36). Daily questionnaires indicated mental load peaked on the day with the highest WW, linked to organisational challenges. Findings suggest efforts to increase DW may create a denser physical workload profile for carpenters, requiring parallel ergonomic and work structuring measures.

KEYWORDS

Work structuring, waste, value, work sampling, ergonomics.

INTRODUCTION

The construction industry is a cornerstone of the global economy, yet productivity growth has historically lagged behind that of the manufacturing and service sectors. Unlike manufacturing, which often benefits from highly controlled production lines, construction remains fundamentally reliant on heavy, manual, and repetitive labour performed under complex and variable site conditions. In Norway, Statistics Norway (n.d.) shows a clear divergence over the last 25 years: productivity in the general market-based mainland economy has increased by approximately 30%, while production per man-hour in the construction and civil engineering sector has declined by roughly 10%. This pattern has intensified the debate on how to accurately measure and improve workface efficiency, driving a renewed focus on Lean Construction methodologies that seek to optimise flow and eliminate non-value-adding activities.

A common method for diagnosing inefficiency in site production is Work Sampling (WS), a statistical method introduced by Tippett (1935, cited in Barnes, 1949) and later formalised by Barnes (1949). In the broader Lean Construction literature, workface analysis is fundamentally rooted in distinguishing between value-adding and non-value-adding time. However, as Kalsaas (2013) notes, construction work is far more diverse than traditional assembly-line

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manufacturing, requiring categorisation frameworks that reflect this complexity. Consequently, taxonomies vary widely across studies, which can complicate direct cross-study comparisons (Josephson & Björkman, 2013). For instance, Kalsaas (2013) divides construction work into categories such as direct work, indirect work (physical preparation), planning/coordination, and observable waste, while more recent studies like Görsch et al. (2022) classify activities into Value-Adding (VA), Value-Supporting (VS), and Non-Value-Adding (NVA) states.

To operationalise these core Lean concepts for observational analysis, this study adopts the taxonomy recently utilised in several contemporary WS studies, aggregating tasks into Direct Work (DW), Indirect Work (IW), and Wasted Work (WW) (Pérez et al., 2024; Salling et al., 2022; Wandahl et al., 2021). In this context, DW aligns with VA transformation, IW covers VS support tasks, and WW captures observable NVA waste. Meta-analytic evidence using this framework indicates that DW often constitutes a limited share of working time, with Wandahl et al. (2021) reporting a global average of 43.6%. A common implication drawn from such results is that productivity can be improved by increasing the share of DW, primarily by reducing WW.

However, analyses that focus solely on how time is allocated treat labour time as a uniform resource, thereby overlooking differences in physical workload across activity states. Abdelhamid and Everett (2002) showed that construction tasks frequently involve moderate-to-high metabolic demands, which are rarely captured by standard time-based productivity metrics. DW activities, such as mounting drywall or framing, can be physically demanding, whereas WW activities, such as waiting or empty travel, are often less physically intensive.

Kalsaas (2013) further suggests that parts of what is classified as non-value-adding time may function as implicit recovery for workers. From this perspective, reducing low-intensity intervals and increasing time spent in production tasks may increase exposure to high physical workload by reducing opportunities for recovery during the shift. This points to a potential trade-off: improvements in time-based productivity metrics may be accompanied by greater physical strain, which in turn may be associated with fatigue, increased injury risk, and longer-term workforce outcomes (Hwang & Lee, 2017).

Despite this concern, there is limited quantitative research that integrates time allocation and physical workload within the same observational framework. This paper addresses this gap by examining the relationship between work categories and observed physical workload in a construction setting.

While the efficiency-ergonomics trade-off is a universal concern across the construction industry, the mechanical demands of different trades vary significantly. To explore this phenomenon empirically, this study investigates the following research questions through a targeted quantitative case study of a carpentry crew:

- **RQ1:** How is working time distributed between Direct Work, Indirect Work, and Wasted Work?
- **RQ2:** How is working time distributed across different levels of physical workload?
- **RQ3:** How do interval-level work category shares co-vary with observed physical workload levels?
- **RQ4:** To what extent does observed physical workload correspond with workers' self-reported experience of strain?

THEORETICAL FRAMEWORK

WORK SAMPLING AS AN EMPIRICAL BASELINE

Work Sampling (WS) estimates time allocation by aggregating many random, momentary observations into proportions (Barnes, 1949). Because the output is proportions, WS is well

suited for benchmarking time allocation patterns against other projects and trades. A commonly used rule-of-thumb for estimating proportions with 95% confidence and ±5% precision is on the order of a few hundred observations (≈384) (Farooq et al., 2017), which provides a practical reference for whether a dataset is likely to stabilise at the category level.

FROM CATEGORY SHARES TO PATTERNS OVER THE DAY

DW, IW, and WW are typically treated as improvement targets and reported as overall shares (Salling et al., 2022; Wandahl et al., 2021). However, two methodological extensions are particularly relevant for the present study. First, simple regression-style analyses have been used to summarise how WS category shares co-vary with other measures at the interval level (Wandahl et al., 2023). Second, "day curves" visualise how category composition changes across the shift, highlighting that similar weekly averages can arise from very different temporal structures (Neve et al., 2022). These approaches motivate analysing not only weekly totals but also within-day co-variation and the timing/fragmentation of high-production periods.

WORK SAMPLING AND ALTERNATIVE MONITORING APPROACHES

While WS is widely used to estimate time allocation, comparing results across studies is notoriously difficult due to varying definitions of value-adding and non-value-adding categories (Josephson & Björkman, 2013). Furthermore, traditional interval-based WS has limitations; it provides aggregate snapshots but can easily miss high-frequency, short-duration activity changes or micro-interruptions that disrupt the workflow (Görsch et al., 2022). To address these limitations, recent Lean Construction literature has explored alternative and complementary monitoring approaches, including methodological advances in WS applications (Robinson, 2010). For instance, quantitative continuous workflow analysis has been proposed to better visualise and uncover the root causes of process interruptions (Görsch et al., 2022).

Additionally, alternative lean interventions, such as First-Run Studies (FRS), are frequently employed to closely evaluate standard work, identify bottlenecks, and continuously improve processes at the micro-level by testing and refining operations before full-scale production (Hackett et al., 2015). However, even with these varied monitoring approaches, the primary focus often remains on time efficiency rather than the physiological and psychological cost of the work.

LINKING VALUE-ADDING TIME TO PHYSICAL AND PSYCHOLOGICAL WORKLOAD

The WS taxonomy is defined from a production perspective, but different categories carry systematically different physical and mental demands. Ergonomic and human factors research highlights the intense physiological toll of construction. For example, Abdelhamid and Everett (2002) used continuous measurements of oxygen uptake and heart rate to demonstrate that typical construction tasks frequently fall into moderate-to-heavy metabolic intensity ranges. More recently, studies utilising objective wearable health devices have corroborated these high physical demands, linking sustained exposure to heavy manual labour with increased fatigue and long-term musculoskeletal risks (Hwang & Lee, 2017).

Furthermore, the push for productivity not only increases physical strain but also elevates cognitive demands. Excessive mental workload and worksite stressors have been shown to reduce workers' situational awareness, induce cognitive tunnel vision, and increase the likelihood of accidents (Chen et al., 2016; Sneddon et al., 2006). Because core production tasks (DW) often inherently require higher metabolic and cognitive output, compressing or removing low-intensity intervals (WW or IW) to increase production may inadvertently make the workday more physically and mentally "work-dense," pushing workers closer to their physiological and psychological limits.

THE EFFICIENCY–RECOVERY PROPOSITION

Kalsaas (2013) argues that parts of what is operationally labelled "waste" may function as implicit recovery through micro-pauses, waiting, and other low-intensity gaps embedded in the day. Combining that argument with the physiological differentiation above yields a testable proposition: periods with higher DW shares and lower WW shares should coincide with higher observed workload intensity within the day. This proposition motivates the paper's use of interval-level co-variation summaries to examine whether "efficient" periods (high DW / low WW) align with a denser physical workload profile in practice.

METHODS

A quantitative case study was conducted at a 465-unit student housing project in Oslo, Norway, executed under a turnkey contract. In terms of Lean maturity, the project did not utilise a full-fledged Last Planner System® (LPS) down to the daily production control level. However, several core LPS elements were actively used to manage physical production. This included a formal planning hierarchy (Master, Phase, Lookahead, and Weekly Work Plans), collaborative pull planning using digital sticky-note sessions for critical phases like interior work, and 3-week lookahead planning that actively evaluated the seven prerequisites for making tasks ready.

The observed sample comprised a single carpentry crew of 11 workers (including two apprentices) responsible for self-performed tasks, such as erecting inner walls, shaft walls, and facade panelling. These tasks were inherently physically demanding; for instance, the inner wall construction required the manual handling of 33 kg drywall boards and sustained overhead work to navigate pre-installed ceiling utilities.

Data was collected using a random-interval, sweep-based Work Sampling (WS) design. The unit of analysis was the individual worker observation, defined as a single, simultaneous registration of both the worker's activity category and their corresponding physical workload level. Interval start times were randomly generated in advance using a Python script, with lunch breaks excluded from the sampling frame. A complete "sweep" (interval) involved locating and observing all available workers once.

Activities were classified into six categories: Production, Transport, Preparation, Conversation, Walking, and Waiting, which were subsequently aggregated into Direct Work (DW), Indirect Work (IW), and Wasted Work (WW). Simultaneously, physical workload was visually assessed. To control for observer bias, data were collected by a single trained observer utilising a strict six-level observational scale inspired by Abdelhamid and Everett (2002). Prior to site entry, this scale was contextualised into a predefined visual rubric with concrete anchor examples (e.g., "arms above shoulder height" for Heavy Load) co-developed with the project's carpentry foreman. The six levels were later aggregated into Low, Moderate, and High workload for analysis. To reduce systematic order or route bias, the observer varied the access points and the sequence of traversing the work zones between sweeps.

The observation plan targeted 20 intervals per day, Monday–Thursday, and 15 intervals on Friday. The study yielded $N = 854$ valid observations, comfortably exceeding the recommended statistical threshold ($N = 510$) for 95% confidence and ±5% precision. The average duration of a sweep was 10.2 minutes.

Because sweeps were initiated at random intervals averaging roughly 20 to 30 minutes apart, it is important to acknowledge the limitations of this sampling frequency. As Görsch et al. (2022) note, interval-based snapshots may miss high-frequency, short-duration activity changes or micro-interruptions embedded in the workflow. However, because this study aimed to establish descriptive, shift-level covariation between aggregate work category shares and aggregate physical strain – rather than diagnosing continuous root-cause workflow interruptions – this sampling strategy is statistically sufficient to support the baseline conclusions.

To triangulate the observational data, an anonymous, end-of-day questionnaire was administered to the crew. The survey consisted of five items rated on a 1–6 scale, covering perceived physical load, mental load, productivity, fatigue, and factors affecting productivity. A total of 44 responses were collected; non-responses were primarily due to worker absence or time constraints at the end of the shift. Finally, interval-level linear fits were used as descriptive summaries of the covariation between work-category shares and workload shares across intervals

RESULTS

The data collection campaign yielded a total of $N = 854$ valid observations over five working days. The sample size is above the level typically used to estimate proportions with approximately ±5% precision.

TEMPORAL DISTRIBUTION OF WORK (RQ1)

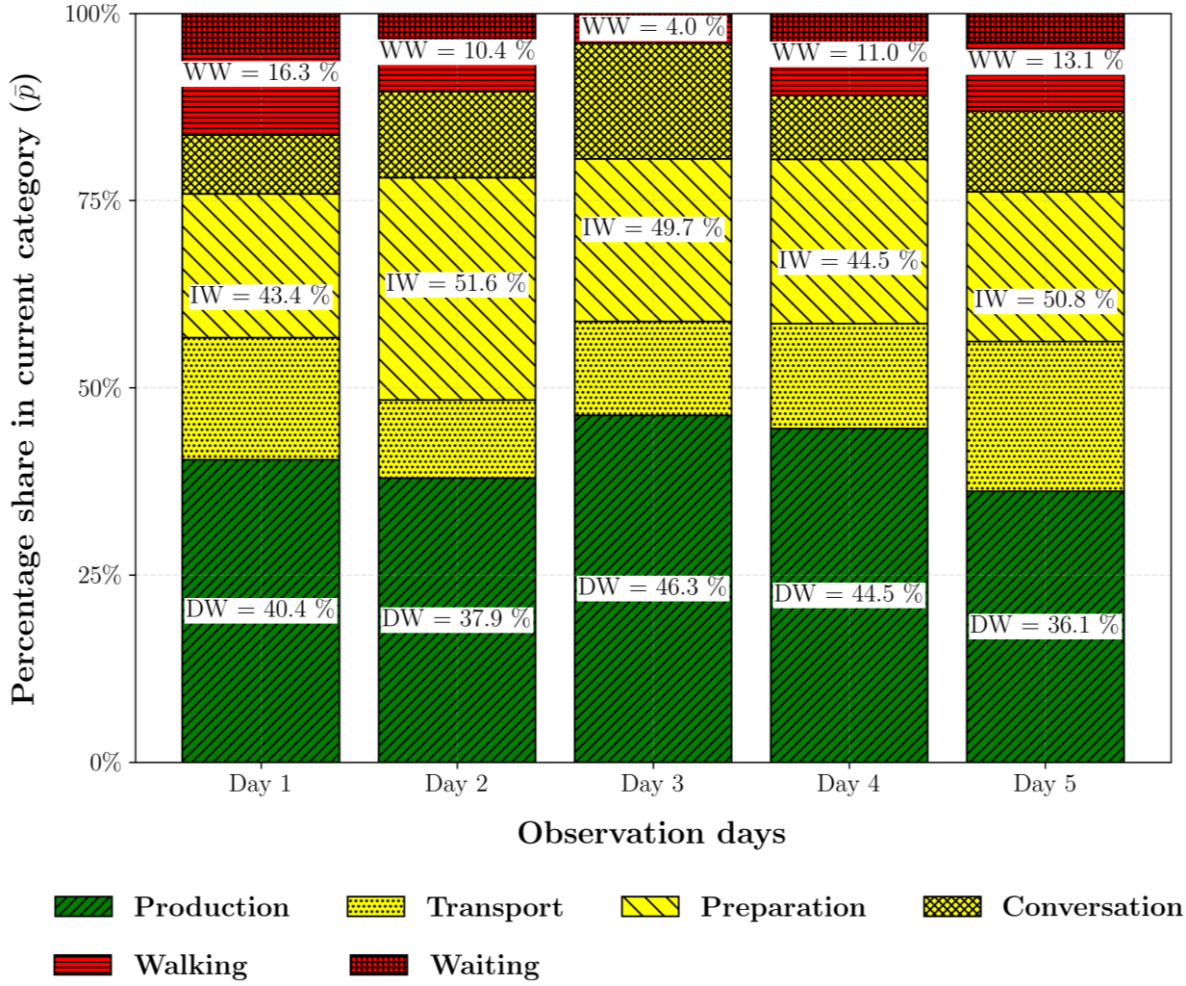

Figure 1: Daily distribution of time across work categories

Across the full dataset, the carpentry team spent:

- Direct Work (DW): 41.31%
- Indirect Work (IW): 47.89%
- Wasted Work (WW): 10.80%

The DW share is close to the global average reported by Wandahl et al. (2021) (43.6%), suggesting that the observed work pattern is comparable to typical construction operations. IW

accounted for the largest share of time, driven primarily by preparation and transport activities. WW was comparatively low relative to many WS studies, indicating limited idle time and waiting in this case.

As shown in Figure 1, the daily variation was substantial. Day 3 recorded the highest DW share (46.29%) and day 5 the lowest (36.1%). Day 3 also had the lowest WW, in contrast to the highest on day 1 (16.3%).

PHYSICAL WORKLOAD PROFILE (RQ2)

Simultaneously with activity classification, the physical intensity of each observation was recorded. The results show that the carpenters' workday was predominantly moderate in intensity but retained a substantial component of heavy labour.

- **Low workload:** 24.83% (e.g., standing, writing)
- **Moderate workload:** 45.79% (e.g., walking, handling light tools)
- **High workload:** 29.39% (e.g., heavy lifting, overhead work)

The temporal distribution of load, shown in Figure 2, mirrored the productivity profile. Day 3, identified above as the most productive day, also recorded the highest proportion of High workload (36.6%). Conversely, Day 1 recorded the highest proportion of Low Load (36.5%), coinciding with the high waste levels on that day.

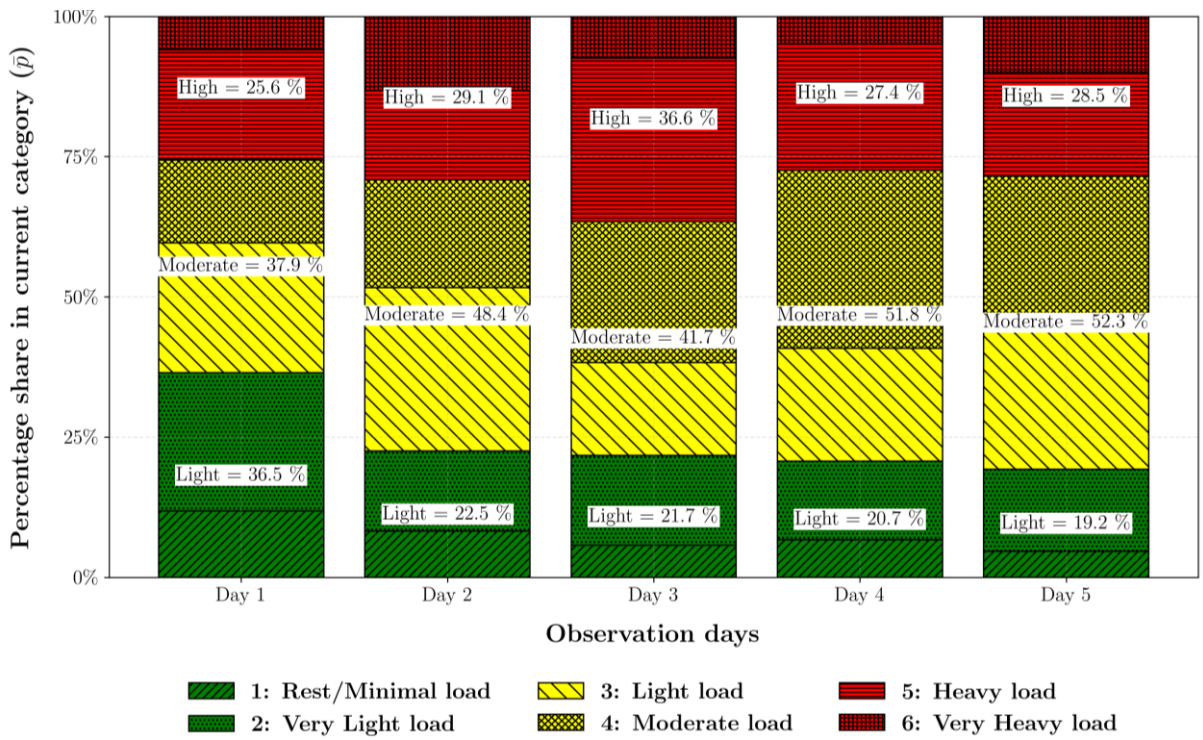

Figure 2: Daily distribution of physical workload levels

Covariation Between Work Categories and Workload (RQ3)

To summarise how interval-level work-category shares covaried with workload shares, linear fits were calculated across intervals and are reported descriptively.

Direct Work (DW) and High Physical Workload

The interval-level fit indicated a positive association between the share of Direct Work and the share of observations classified as High physical workload ($R^2 = 0.28$). Figure 3 shows an upward trend for High workload as DW share increases. Descriptive fit: $Y_{High} = 0.521 \cdot X_{DW} + 10.34$. Within this fitted relationship, higher DW shares correspond to higher fitted

High-load shares; this should be interpreted as within-case covariation rather than a causal effect estimate. Interpreted within this descriptive fit, a 10 percentage-point higher DW share corresponds to a 5.2 percentage-point higher fitted High-load share.

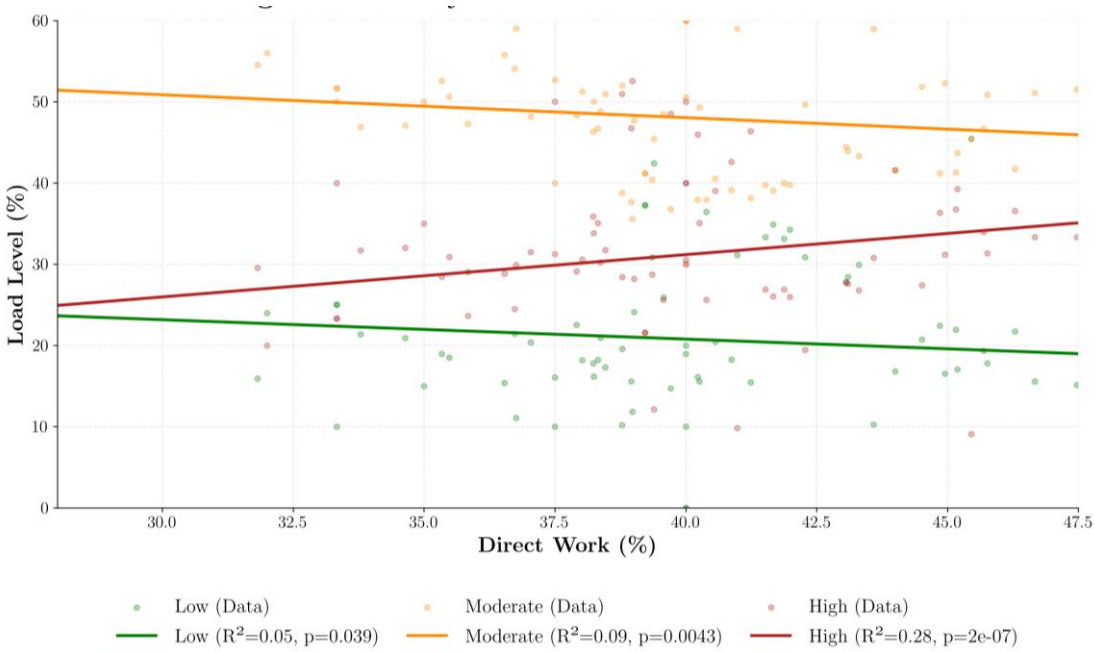

Figure 3: Linear Regression – Direct Work vs. Workload

Wasted Work (WW) and High physical workload

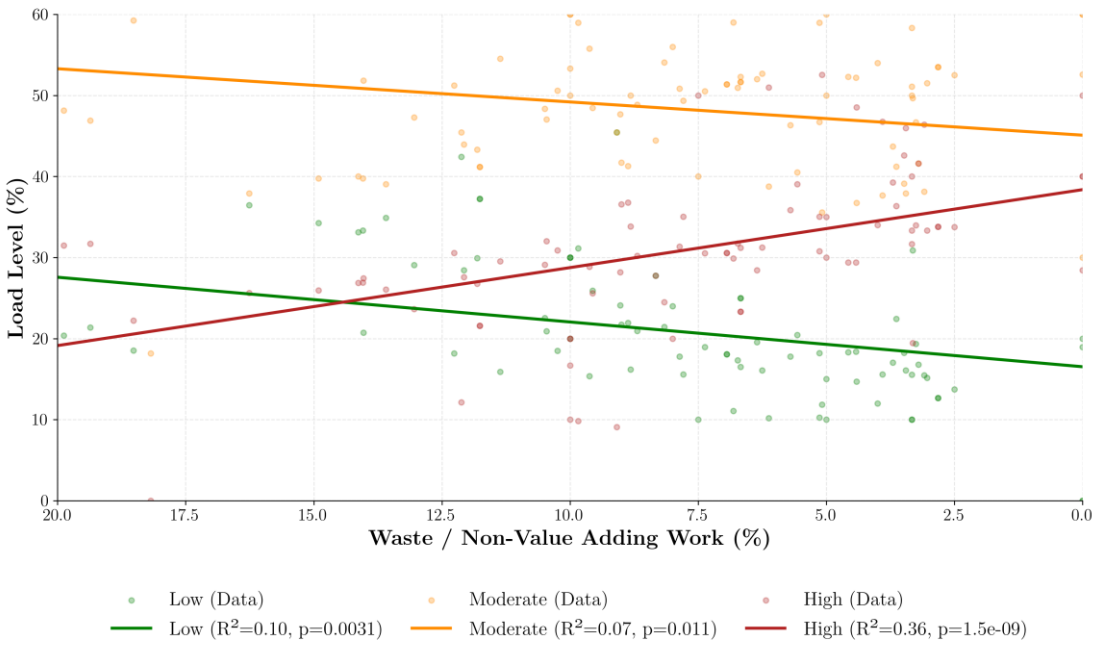

Figure 4: Linear Regression – Wasted Work vs. Workload

WW share was inversely associated with High workload share across intervals ($R^2 = 0.36$). Figure 4 shows a downward trend for High workload as the WW share increases. Descriptive fit: $Y_{High} = -0.962 \cdot X_{WW} + 38.37$. As above, this is reported as within-case co-variation; because the variables are bounded proportions, the fitted slope should not be interpreted as a transferable or causal effect size.

SUBJECTIVE VALIDATION (RQ4)

The end-of-day questionnaires (*N = 44*) were used to compare observed patterns with workers' reported experience.

- **Physical fatigue** was highest on Day 5 (median of 4 on a 6-point scale). While Day 3 had the highest proportion of High workload, Day 5 combined sustained load with cumulative fatigue across the week.
- **Mental load** was highest on Day 1 (median of 4.5), coinciding with the highest WW share (16.3%) and the lowest DW share. Reported drivers included organisational conditions such as crowding and waiting for other trades. On the remaining days, the median mental load was 2 – 3.

Taken together, these results indicate that higher DW periods coincide with higher observed physical workload, while higher WW periods coincide with higher reported mental load in this case.

DISCUSSION

THE EFFICIENCY–ERGONOMICS TRADE-OFF IN CONTEXT

The work pattern observed in this case is not unusual in WS terms. The Direct Work share (41.31%) is close to the global average reported by Wandahl et al. (2021) (43.6%), which suggests that the setting is broadly comparable to many construction WS case studies rather than an extreme outlier. At the same time, the dataset shows that productivity-oriented composition shifts are not physiologically neutral: intervals with higher Direct Work shares coincided with higher shares of observations classified as High workload ($R^2 = 0.28$).

This is consistent with the physiological literature that motivates the study. Abdelhamid and Everett (2002) show that common construction production tasks frequently fall in moderate-to-heavy intensity ranges when assessed using physiological measures. If Direct Work is disproportionately made up of such tasks, then a positive DW–High workload co-variation is exactly what would be expected – even if the WS taxonomy itself is defined from a production perspective rather than an ergonomic one.

To make the magnitude tangible, consider the hypothetical situation where collaborative pull planning and make-ready processes successfully eliminate delays, raising the crew's Direct Work from roughly 40% of the day to 60%. In this case, the fitted within-case relationship suggests what that shift would look like physically: the share of time rated High workload would move from roughly 31% to roughly 42%. That is about 11 percentage points more of the working time spent at high physical intensity. Over a standard work week, this corresponds to a markedly higher cumulative biomechanical load – with less opportunity for recovery – which is the type of exposure profile linked in the occupational health literature to fatigue and elevated risk of work-related musculoskeletal disorders when sustained (Hwang & Lee, 2017). The point is not that a Lean intervention will necessarily produce that exact change, but that the pattern observed here implies a real potential for time-based efficiency gains to coincide with a denser physical workload profile.

"WASTE" AS LOW-INTENSITY RECOVERY

The inverse co-variation between Wasted Work share and High workload share ($R^2 = 0.36$) aligns with Kalsaas' (2013) argument that some time labelled as "waste" in operational taxonomies may function as implicit recovery for workers. In practical terms, intervals characterised by waiting, standing, or walking without materials are usually far less physically demanding than core production tasks. In this dataset, the threshold comparison supports the same story: when WW ≤ 5%, the share of High workload increases to 36.4%, compared with

the weekly average of 29.39%. That pattern is consistent with the idea that removing low-intensity gaps can make the day more "work-dense" physically.

This does not mean that waste should be preserved for its own sake. Although the findings suggest that Wasted Work provides implicit physical recovery, its coincidence with peak mental load indicates that operational delays generate cognitive frustration. To resolve this trade-off, recovery must be decoupled from waste. If improvement efforts reduce these low-intensity intervals, recovery has to be handled deliberately rather than accidentally. Otherwise, part of the "gain" in time-based productivity metrics may be paid for through increased physical strain.

LEAN MATURITY AND THE WEEKLY RHYTHM

The observed weekly rhythm, characterised by high Wasted Work (WW) and mental stress at the beginning of the week, followed by a mid-week peak in Direct Work (DW), resembles patterns typical of conventional construction sites. However, it is important to contextualise this within the project's Lean maturity. Although the project utilised collaborative pull planning for critical phases and 3-week lookaheads with make-ready checks, it did not implement a full-fledged Last Planner System® down to daily production control. The early-week friction suggests a gap between macro-level phase planning and micro-level shift execution. Translating the weekly work plan into daily tasks still generated operational friction (delays, crowding, and coordination issues), leading to peak mental load. Once these initial weekly hurdles were resolved, DW peaked mid-week, bringing with it the highest share of High physical workload. This demonstrates that even when upstream Lean planning elements are present, operational-level execution can still concentrate physical and mental strain into specific phases of the week.

IMPLICATIONS FOR LEAN-ORIENTED IMPROVEMENT

Lean Construction initiatives commonly use DW, IW, and WW or similar as diagnostic categories and targets for improvement. This study suggests that, in manual trades, using those categories without an ergonomic lens can be misleading. If higher DW is achieved mainly by compressing or eliminating low-intensity periods (often categorised as WW), the likely outcome is a higher share of the day spent in physically demanding states. A practical implication is that productivity improvement work should be paired with work structuring that manages workload density, for example, through task rotation, alternation between heavier and lighter tasks, planned micro-breaks, and ergonomic measures that reduce the physical intensity of production activities. Without that parallel effort, the "better" DW numbers may coincide with higher cumulative strain.

To truly align with Lean continuous improvement, production system design should shift from merely maximising time-based DW to optimising the physiological sustainability of the work. Rather than treating ergonomic interventions as an afterthought, work structuring should be integrated directly into the planning hierarchy. For instance, deliberately sequencing high-strain and low-strain tasks within lookahead plans, or addressing ergonomic constraints during collaborative pull planning, would ensure that continuous improvement targets true value generation rather than just increased human exertion.

TRADE-SPECIFIC CONTEXT

Because this study relies on a single-trade sample (carpentry), the specific percentages of DW and High workload cannot be universally generalised to all construction workers. The observed workload profile is heavily influenced by trade-specific tasks, such as the manual handling of heavy drywall boards (often exceeding 30kg) and sustained overhead work due to pre-installed ceiling utilities. Other trades, such as electricians or heavy equipment operators, possess entirely different biomechanical exposures and mobility patterns, which would likely yield a different covariation between DW and physical strain. Future research should apply this dual-coding framework across multiple trades to establish a comparative baseline.

METHODOLOGICAL NOTE: WHAT THE FITS DO AND DO NOT CLAIM

The use of interval-level regression-style fits follows recent WS work that uses simple models to summarise relationships in observational data. However, the present fits are reported descriptively for a reason: both the work categories and workload levels are shares constrained to sum to 100% within an interval, and this closed structure can mechanically induce or amplify correlations. The fits are therefore best read as compact summaries of within-case co-variation, not as transferable effect sizes or causal estimates. Complementing such summaries with temporal patterning (for example day curves as proposed by Neve et al., 2022) can be useful because it keeps attention on how the workday is structured, not only on weekly averages.

CONCLUSION

This study examined how work-category composition covaries with observed physical workload in a construction workday using a dual-coding work-sampling approach combined with a brief end-of-day questionnaire. In this case, intervals with higher Direct Work shares tended to coincide with higher shares of observations classified as High workload, while intervals with higher Wasted Work shares tended to coincide with lower High workload shares. The questionnaire responses broadly aligned with the observational patterns, with physical fatigue highest towards the end of the week and mental load highest on the day characterised by the highest Wasted Work share.

These findings suggest that efforts to increase Direct Work in manual trades may, in some circumstances, be accompanied by a denser physical workload profile unless work structuring and ergonomic measures are addressed in parallel. However, these conclusions must be interpreted in light of several methodological limitations. First, the reliance on a single-case, single-trade sample means the observed patterns reflect specific carpentry tasks rather than universally generalisable exposures. Second, the 20-to-30-minute random interval sampling method provides aggregate snapshots but cannot capture high-frequency micro-interruptions. Third, physical workload was assessed via visual observation and subjective self-reporting, which lacks the precision of continuous physiological monitoring. Finally, because the data consists of proportions that must sum to 100%, this mathematical structure can mechanically induce correlations. Therefore, these statistical fits should be read as descriptive patterns within this specific case, rather than causal or transferable effects.

Future research could strengthen this line of inquiry through multi-site and longitudinal designs that combine work sampling with objective measures (for example, wearable sensors), and by examining how specific improvement measures change both time allocation and physical workload over time.

REFERENCES

Abdelhamid, T. S., & Everett, J. G. (2002). Physical demands of construction work: A source of workflow Unreliability. *IGLC10*.

Barnes, R. M. (1949). Motion and time study (3rd ed.). John Wiley & Sons.

Chen, J., Song, X., & Lin, T. (2016). Revealing the "invisible gorilla" in construction: Estimating construction safety through mental workload assessment. Automation in Construction, 63, 173–183. https://doi.org/10.1016/j.autcon.2015.12.008

Farooq, H., Zekavat, P. R., & Moon, S. (2017). While loop algorithm to enhance the efficiency of work sampling method in performance measurement: International Symposium on Automation and Robotics in Construction. *Proceedings of the 34th International Symposium on Automation and Robotics in Construction and Mining (ISARC 2017)*, 6–13. https://doi.org/10.22260/ISARC2017/0001

Görsch, C., Al Barazi, A., Seppänen, O., & Abou Ibrahim, H. (2022). Uncovering & visualizing work process interruptions through quantitative workflow analysis. *IGLC30*, 142–152. https://doi.org/10.24928/2022/0116

Hackett, V., Pasquire, C., Stratton, R., & Knight, A. (2015). The use of First Run Studies to develop standard work in liquefied natural gas plant refurbishment. *IGLC23*, 671–680.

Hwang, S., & Lee, S. (2017). Wristband-type wearable health devices to measure construction workers' physical demands. *Automation in Construction*, 83, 330–340. https://doi.org/10.1016/j.autcon.2017.06.003

Josephson, P.-E., & Björkman, L. (2013). Why do work sampling studies in construction? The case of plumbing work in Scandinavia. *Engineering, Construction and Architectural Management*, 20(6), 589–603. https://doi.org/10.1108/ECAM-12-2011-0108

Kalsaas, B. T. (2013). Measuring Waste and Workflow in Construction. *IGLC21*.

Neve, H., Wandahl, S., Lindhard, S., Teizer, J., & Lerche, J. (2022). Learning to see value-adding and non-value-adding work time in renovation production systems. *Production Planning and Control*, 33(8), 790–802. https://doi.org/10.1080/09537287.2020.1843730

Pérez, C. T., Wandahl, S. & Arildsen, M. (2024). Relationship Between Time Spent in Production Work Activities and Production Workspaces. *IGLC32*. https://doi.org/10.24928/2024/0189

Robinson, M. A. (2010). Work sampling: Methodological advances and new applications. *Human Factors and Ergonomics in Manufacturing & Service Industries,* 20(1), 42–60. https://doi.org/10.1002/hfm.20186

Salling, S., Pérez, C. T. & Wandahl, S. (2022). Breakdown Work Sampling. *IGLC30*. https://doi.org/10.24928/2022/0125

Sneddon, A., Mearns, K., & Flin, R. (2013). Stress, fatigue, situation awareness and safety in offshore drilling crews. *Safety Science*, 44(9), 805–824. https://doi.org/10.1016/j.ssci.2012.05.027

Statistics Norway. (n.d.). 09170: Production account and income generation, by industry 1970 - 2024. Statbank Norway. SSB. Retrieved 6 January 2026, from https://www.ssb.no/en/statbank/table/09170

Wandahl, S., Neve, H. H. & Lerche, J. (2021). What a Waste of Time. *IGLC29*. https://doi.org/10.24928/2021/0115

Wandahl, S., Pérez, C. T., Salling, S., & Neve, H. H. (2023). Correlation of Construction Workers' Movement and Direct Work Rates. *Journal of Engineering, Project, and Production Management*, 13(2), 125–137. https://doi.org/10.32738/JEPPM-2023-0013