ADVANCING PRODUCTIVITY MEASUREMENT AND RESOURCE SCHEDULING THROUGH POSTURE-HOUR BASED CONSTRUCTION PLANNING

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Advancing productivity measurement and resource scheduling through posture-hour based construction planning

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CERTIFICATE OF ORIGINALITY

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Qi Kai

Abstract

The construction industry faces a persistent paradox: while technological advances have revolutionized how engineers design and build structures, the fundamental ways of understanding and managing human work on construction sites remain essentially unchanged, a disconnect that contributes directly to the industry's growing labor shortage. A worker spending an hour bent over tasks, such as rebar tying or concrete finishing, endures significantly higher physical strain than one performing standing tasks, like operating a concrete vibrator or pouring concrete. As construction sites become increasingly instrumented with sensors and cameras, and as computational methods grow more sophisticated, an opportunity emerges to fundamentally reimagine how we conceptualize, measure, and optimize human work in construction. This research develops a framework that transforms construction labor productivity and workforce management from time-based to posture-based planning, leveraging computer vision to quantify physical workload. It introduces scheduling methods that enable practitioners to explicitly consider ergonomic constraints alongside traditional project objectives in terms of time, cost, and quality.

To address this challenge, it is first essential to understand the current state of construction labor productivity (CLP) research and identify gaps in productivity measurement and workforce management knowledge. This comprehensive mapping exposes a critical gap:

the limited integration of worker occupational health and safety (OHS) considerations within the productivity framework.

Building on this identified gap, the second contribution of this research develops a novel labor productivity measurement framework that quantifies construction work through workers' physical postures, rather than relying solely on time. The proposed recognition algorithm, which integrates Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (Bi-LSTM), and Multi-Head Attention, achieves a posture classification accuracy of 85.3%. This performance was attained using YOLO-Pose to extract human body keypoints from laboratory-recorded videos and training the model on a dataset partitioned into training, testing, and validation sets. This posture-hour framework provides the granular, ergonomically-informed data necessary to bridge the gap between productivity assessment and worker OHS protection.

With posture-hour data quantifiable through computer vision, the final and most significant contribution of this research is the development of resource-constrained project scheduling methods that integrate these ergonomic insights into construction planning. This research introduces a posture-hour work scheduling framework that incorporates ergonomic constraints directly into construction planning, treating worker posture capacities as schedulable resources alongside traditional considerations, such as crew availability and task dependencies. Validation through real-world concrete-pouring cases demonstrates that while accounting for ergonomic constraints may impact project timelines, it provides policymakers with flexible options to proactively mitigate occupational health risks during the planning stage. Future research will focus on identifying the most reasonable task assignment schemes that can integrate ergonomic safety without increasing the total project duration. Rather than being a burden, this research offers a flexible solution for decision-makers by treating "posture-hours" as a schedulable resource. For instance, ergonomic constraints can be applied as optional parameters to non-critical activities with sufficient schedule slack, improving worker well-being without delaying the project's critical path.

This thesis demonstrates that the long-standing trade-off between productivity and worker occupational health and safety is not inevitable but rather a consequence of lacking adequate metrics and planning methods. Specifically, this research addresses key risk factors for work-related musculoskeletal disorders (WMSD) by quantifying overexertion from high-strain activities, the repetition of physical movement sequences, and the impact of awkward postures—such as bending, squatting, and prolonged arm-raising—that are often overlooked in traditional man-hour-based planning. By establishing posture hours as a measurable, plannable resource, this work provides both researchers and practitioners with a pathway toward truly sustainable construction practices, in which worker well-being becomes an integral part of project planning rather than an afterthought, making the industry more appealing and attractive to new generations. Moreover, by decomposing construction work into quantifiable posture sequences and durations, this research establishes a foundational framework for modeling and programming humanoid robots. Given that humanoid robotics involves high degrees of freedom requiring intricate posture programming and detailed task allocation, this study provides a crucial technical reference for optimizing task dispatching and operational procedures. Specifically, by identifying high-strain patterns and establishing 'posture-hour' thresholds, it offers a strategic pathway for managing the wear-and-tear of robotic joints and components by preventing mechanical overexertion.

Publications arising from the thesis

Journal Papers (Published)

1. **Kai Qi**, Owusu, E. K., Siu, M.-F. F., & Chan, P.-C. A. (2024). A systematic review of construction labor productivity studies: Clustering and analysis through hierarchical latent Dirichlet allocation. *Ain Shams Engineering Journal, 15*(9), 102896.

2. **Kai Qi**, & Ming Lu. (2025). Integrating posture-hour constraints into construction scheduling to enhance workforce wellbeing. Computer-Aided Civil and Infrastructure Engineering, 40, 6107–6126.

Journal Papers (In-Press)

3. **Kai Qi**, & Ming Lu.(2026) From labor-hours to posture-hours: A data-driven framework for construction worker workload estimation and activity sequence inference. Journal of Construction Engineering and Management. (In-Press).

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List of Abbreviations

OHS	Occupational health and safety
BIM	Building information modeling
CNC	Computer numerically controlled
MSDs	Musculoskeletal disorders
AI	Artificial intelligence
RULA	Rapid upper limb assessment
IMU	Inertial measurement unit
CPM	Critical path method
RACPM	Resource-activity critical-path method
IoT	Internet of Things
CNNs	Convolutional neural networks
LSTM	Long short-term memory
LOB	Line of balance
PPE	Personal protective equipment
HLDA	Hierarchical latent Dirichlet allocation
CLP	Construction labor productivity
NLTK	Natural language toolkit
nCRP	Nested Chinese restaurant process
KPIs	Key performance indicators
LDA	Latent Dirichlet allocation
COCO	Common objects in context
API	Application programming interface
ReLU	Rectified linear unit

HKCIC	Hong Kong Construction Industry Council
CP	Concrete pouring
IV	Internal vibration
CD	Consolidation
SC	Screeding
CI	Curing membrane installation
TR	Traveling
WT	Waiting
AON	Activity-on-node
JSON	JavaScript object notation

List of Symbols

$Z_{d,n}$	Hierarchical distribution variable for word *n*
$\boldsymbol{Z}_{-(d,n)}$	Level allocation and word allocation variables exclude $Z_{d,n}$
#[]	Number of instances that satisfy the condition
$\boldsymbol{P}_d$	Path selected by document *d*
d_i	The number of articles that have selected Topic *i*
$\Gamma(\,)$	Gamma function
a[i]	The output at frame *i*
X[i+m, n]	Input value at position *(i+m, n)*
W[m, n]	Kernel weight at position *(m, n)*
C^t	The state of the memory cell at the current time step
T_t	Newly added information in the current time step
h^t	Output of the current computation
$tanh(C^t)$	Information prepared for output after the memory cell update
b_t	The output of the self-attention layer at the current time step
$r'_{t,i}$	Attention value computed by applying the softmax function to the dot products of query q_t and keys k
v^i	V^i is the output value calculated by traversing all inputs through the weight matrix W^v.
l_{ipk}	The remaining capacity of worker *i* for maintaining posture *k*
A_{jp}	Proportional distribution of k posture requirements

P_r	The posture demand vector for the selected activity
AP_j	AP_j is given as the set of immediate predecessors of activity *j*
A_{jw}	$A_{jw} \in Z^+$ is a positive integer specifying the number of workers needed for activity *j*
A_{jt}	$A_{jt} \in R^+$ is a positive real number representing the required duration of activity *j*
A_{jf}	A_{jf} represents the end time of activity *j*
A_{js}	A_{js} represents the status of activity *j*
L_{ip}	$L_{ip} \in R^k$ is a vector representing the remaining work capacity of worker *i* for each posture
L_{irst}	$L_{irst} \in R^+$ is the earliest time at which worker *i* is released from previous activity and starts a new activity.

Chapter 1: Introduction

1.1 Worker shortage and worker OHS in construction

The unique project development needs and customized designs in the construction industry result in low-volume, high-variation manufacturing processes (Momeni *et al.*, 2022). Despite the widespread adoption of building information modeling (BIM), parametric product design, and computer numerically controlled (CNC) production equipment in modern fabrication facilities, such as structural steel shops (Aghajamali *et al.*, 2025), precast concrete plants, and modular construction facilities (Granello *et al.*, 2022; Yin *et al.*, 2019), the current state of prefabrication and offsite construction is still far from being fully automated. Construction remains a labor-intensive industry that heavily depends on skilled trade workers for tasks such as fitting and welding (Qi *et al.*, 2021). The scarcity of skilled construction workers is anticipated to worsen in technologically advanced economies like Canada and Hong Kong (Kumarage *et al.*, 2024; Sing *et al.*, 2017). At the same time, productivity improvement is increasingly recognized as a crucial factor in achieving sustainable economic growth (Rathnasinghe *et al.*, 2024). Reinforced concrete work in apartment buildings is particularly labor-intensive, with rebar workers, formwork workers, and concrete workers accounting for 63% of the total labor consumption (Mun *et al.*, 2023). In this context, the physical demands on workers have become a pressing issue that the construction industry needs to address.

Occupational health and safety (OHS) remains a significant challenge in construction, where musculoskeletal disorders (MSDs) account for over 20% of work-related injuries worldwide. These disorders—ranging from acute strains to chronic joint degeneration—mainly result from prolonged exposure to non-neutral postures such as bending, squatting, or overhead work. In addition to reducing awkward postures, balancing physical workload is a vital step in reducing OHS risks associated with MSDs. However, such OHS measures can conflict with productivity goals established during project planning. As suggested, companies must maximize "value-adding time" to stay competitive. In construction, increasing "direct work" time during the execution phase is considered a key approach for enhancing labor productivity. Therefore, finding an effective balance between workers' physical workload and project productivity is essential.

1.2 Research scope

This study aims to establish a mapping between work planning and workers' workload, with a focus on the concept of direct work in the construction industry. Direct work, or value-added work, actually refers to work that increases the value of a product (Starr, 1989). Work sampling is the process by which engineers record the work they observe workers doing in the workplace and categorize it according to its type. Liou and Borcherding believes that the proportion of direct work is related to efficiency, and to improve efficiency, the workflow should increase the proportion of direct work (Liou and Borcherding, 1986).

This study does not aim to increase the proportion of direct work. Based on the definition of direct work, this study aims to estimate workers' workload in connection with direct work through pre-construction data. In the construction industry, direct work is the basis for determining whether a task has been completed.

The corresponding direct work postures and durations are essential to complete the planned work. This is because, according to the definition of direct work, the product (i.e., the building in the construction industry) must undergo the necessary value-added processes (placing and connecting materials at specific locations as per design drawings and models). In contrast, indirect work, such as on-site material transportation and worker movement, does not directly contribute to the value of the product. Preparing and transporting materials, including handling at storage, and transferring materials from storage to the work area, is generally treated as semi-productive (supporting work) in work sampling. Non-productive time refers to periods when workers are not performing either direct work or supporting tasks, such as breaks, idle time, and waiting periods. It is a long-recognized challenge to distinguish between productive, semi-productive, and non-productive states of workers on-site in working sampling or productivity studies (Zahedi and Lu, 2022). This challenge presents a unique opportunity to develop more effective solutions utilizing vision computing and AI.

This study sets focus on tracking direct work for two reasons. First, the impact of indirect work on workers' physical workload is less and more controllable. Second, there is no strong correspondence between indirect work and the work plan. Note, in general, indirect work is considered waste by lean principles. Direct work constitutes the bulk of labor efforts that produce useful output. Hence, enhancing direct work planning and crew field performances would lead to overall productivity improvement. Therefore, the research scope of this study is limited to establishing a mapping and planning between the posture and duration of direct work performed by workers on the construction site.

1.3 Research problem statement

Occupational health and safety (OHS) remains a critical concern in labor-intensive industries, with musculoskeletal disorders (MSDs) representing one of its most significant contributors (Gallagher, 2005). These disorders result in multiple injuries, ranging from short-term muscle strains to chronic joint and skeletal pain, particularly in the back, waist, upper limbs, and lower limbs. The primary causes include prolonged exposure to awkward postures, which disrupt normal joint and spinal alignment (Potvin *et al.*, 1991), leading to uneven pressure distribution and muscle imbalances, where specific muscles become overactive while others weaken. Research has established a positive correlation between the duration of uncomfortable postures and the likelihood of MSD development.

To quantify this relationship, biomechanical modeling has been employed to predict OHS risks based on posture data. For instance, Palikhe et al., (2020) utilized skeletal tracking to derive a quantitative link between specific postures and MSD incidence. Another widely adopted approach is ergonomic risk assessment, exemplified by the Rapid Upper Limb Assessment (RULA) method developed by McAtamney and Nigel Corlett (1993), which evaluates posture risk based on joint angles. Beyond skeletal analysis, real-time monitoring technologies—including wearable sensors (Chen *et al.*, 2017), ambient sensor networks, and computer vision (Liu and Jebelli, 2024)—have significantly advanced posture detection in terms of both data accuracy and responsiveness.

Recent studies have explored various implementations of these technologies. For instance, Lee et al. (2023) utilized wearable IMUs to track full-body kinematics, demonstrating their capability for continuous posture monitoring in dynamic work environments. Computer vision approaches have also gained traction in ergonomic assessment. Chen et al. (2024) and Li and Lee (2011) implemented multi-camera systems with deep learning algorithms to automatically classify posture risks. Further improvements were achieved by Wang et al. (2022) by sensor fusion techniques that combine Inertial Measurement Unit (IMU) data with vision-based systems, thereby enhancing detection reliability even in visually complex settings.

The primary factor contributing to MSD risk among workers is the work itself. Recognizing this reality, many researchers have dedicated themselves to developing more precise and advanced methods for monitoring workers' physical conditions. However, monitoring alone does not equate to intervention or risk mitigation. Studies demonstrate that repetitive bending for just 30 minutes can induce back pain and muscle dysfunction that lasts up to 24 hours (Solomonow *et al.*, 1999). However, in practice, manual workers often endure task durations far exceeding this threshold to meet productivity demands. While advanced monitoring technologies provide valuable insights into posture-related risks, their true potential can only be realized when integrated with direct interventions at the task level.

This research focuses on integrating a novel resource constraint into task allocation by utilizing posture hours as a more granular measurement unit than traditional man-hours.; while labor pricing currently remains complex due to market influences and the difficulty of comprehensively capturing workload factors beyond posture, exploring the potential for labor pricing standards that incorporate posture-hours as a key factor represents a significant future research direction.

1.4 Research aim and objectives

1.4.1 Research aim

This research aims to redefine how construction workloads are measured and planned by integrating ergonomic posture analysis into labor productivity management systems. The approach shifts from traditional labor-hour metrics to AI-driven, posture-based analytics that enable accurate workload measurement and proactive prevention of musculoskeletal disorder (MSD) risks by integrating physical workload into project planning for data-driven worker allocation. By incorporating physiological limits, such as posture thresholds, into scheduling systems, this work connects productivity goals with worker well-being through data-driven task allocation and workflow design.

1.4.2 Research objectives

1. Computer Vision Framework Development

Develop a cost-effective computer vision system to quantify physical workload by classifying ergonomically significant postures, including walking, standing, bending, squatting, and arm-raising.

2. Objective Work Sampling Methodology

Replace subjective work sampling approaches with objective, granular posture tracking systems.

3. Posture-Hour Scheduling Framework

Propose and validate a novel posture-hour scheduling methodology that integrates posture-specific demands as constraints in labor allocation decisions.

4. Empirical Validation Studies

Conduct comprehensive validation through both controlled simulations (such as rebar-tying tasks) and real-world construction scenarios (including concrete pouring operations).

5. Systemic Occupational Health and Safety Advancement

Transform occupational health and safety management from reactive monitoring to proactive planning by establishing "posture-hours" as core measurement units.

1.5 Research significance

This research makes valuable contributions to construction management, occupational health and safety, and computational analytics by filling important gaps in current workload assessment methods. The study presents a transformative approach that replaces traditional labor-hour metrics with AI-driven posture-hour measurements, offering a more detailed and objective basis for workload measurement that directly considers biomechanical strain patterns often missed by conventional techniques.

The use of vision-based posture tracking with YOLO-Pose, a pretrained model to extract captured human joints for feeding data in proactive detection of musculoskeletal disorder risks (Maji *et al.*, 2022), as empirical data shows that 63% of rebar work involves high-risk bending and squatting positions. This development represents a paradigm shift in occupational safety, moving from reactive monitoring to proactive risk management during planning, thereby aligning with prevailing industry trends.

Methodologically, the research advances automated posture classification with 85.3% accuracy and presents a new multi-objective resource schedule optimization framework that balances minimizing posture deficits with project duration efficiency. This innovation pushes construction scheduling theory forward by incorporating human physiological factors into resource-limited planning models.

The practical implications offer actionable tools for ergonomic planning, productivity enhancement, and sustainable workforce management. By measuring physical strain buildup, the framework promotes long-term worker well-being while addressing industry challenges such as labor shortages and high turnover rates. This work provides a foundational infrastructure for future research in construction digitization, real-time monitoring systems, and human-centered project schedule optimization approaches.

1.6 Overview of the thesis

This research uses a three-phase process to develop and validate a framework for estimating and optimizing construction workload using posture-hour analysis. The approach combines literature review, data-driven framework creation, and real-world case studies. Phase one builds the theoretical base by examining current trends in construction labor productivity research with advanced topic modeling techniques. Phase two creates the core AI-powered system for automatic posture detection and workload measurement through computer vision and deep learning methods. Phase three applies the results to practical project scheduling and resource management models that balance productivity goals with ergonomic safety. This multi-phase method ensures rigorous theory, innovative methodology, and practical application, offering a complete solution to address key gaps in current construction workload assessment methods.

Chapter 4 explores research trends in construction labor productivity through a thorough systematic review and advanced analytical methods. The approach includes collecting literature from major academic databases, followed by careful data preprocessing to ensure the quality and relevance of selected publications. Hierarchical Latent Dirichlet Allocation (HLDA) is used to identify emerging research themes and patterns in the evolution of construction productivity studies. The analysis covers topic identification, trend analysis over time, and examination of current Construction Labor Productivity (CLP) modeling methods. Validation of the results ensures the trends and topics are reliable and accurate. This chapter lays the groundwork by highlighting research gaps and opportunities that emphasize the need for innovative approaches to workload assessment, especially pointing out limitations in current productivity measurement methods that neglect biomechanical and ergonomic factors critical for sustainable construction practices.

Chapter 5 presents the development and validation of a novel data-driven framework for estimating construction workloads and inferring activity sequences. The methodology centers on a framework that integrates computer vision technologies with ergonomic analysis to revolutionize workload quantification approaches. The framework incorporates a systematic classification of five ergonomically critical postures relevant to construction activities, followed by the development of a sophisticated recognition model structure utilizing the YOLO-Pose architecture and deep learning algorithms. Validation occurs through two distinct case studies: single-worker rebar tying operations and multi-worker concrete pouring activities. These applications demonstrate the framework's versatility across different construction scenarios and worker configurations. The methodology encompasses a detailed analysis of posture-hour patterns, an accuracy assessment of automated recognition systems, and validation of workload estimation algorithms. This chapter establishes the technical foundation for automated, objective workload assessment that forms the basis for subsequent scheduling optimization applications.

Chapter 6 operationalizes the developed framework through comprehensive project scheduling and resource allocation models that incorporate worker posture-hour thresholds as optimization constraints. The methodology develops an integrated application framework that balances traditional scheduling objectives with ergonomic safety considerations. Key components include posture demand and supply analysis, optimal worker allocation algorithms, and comprehensive preparation protocols for implementing posture-hour scheduling. The core innovation lies in the Algorithm for Posture-Hour Scheduling, which integrates multi-objective optimization problem formulations with practical heuristic rules to ensure feasible and efficient solutions. Validation occurs through detailed demonstration cases, including concrete pouring operations and alternative scheduling scenarios that compare traditional approaches with the proposed posture-hour methodology. The methodology examines trade-offs between project duration and worker ergonomic exposure, providing quantitative evidence for the benefits of human-centric scheduling approaches. This chapter culminates the research by demonstrating practical implementation pathways that enable industry adoption of the developed framework while maintaining productivity standards and enhancing worker OHS outcomes.

Chapter 2: Literature Review

2.1 Introduction

Labor productivity is a measure of labor efficiency, representing the ratio of output to input per unit of the workforce. Construction labor productivity (CLP) can be considered as an effective index to facilitate both building projects' profitability and industry economic growth (Allmon *et al.*, 2000; Rojas and Aramvareekul, 2003). The scholarly focus on labor productivity within the construction industry arises from a recognized need to bridge the gap between its modest improvements and the more pronounced advancements observed in other sectors, such as manufacturing (Durdyev and Ismail, 2019). The construction industry is characterized by its reliance on human labor and the unique, project-centric nature of its output, which introduces a level of variability and unpredictability not as prevalent in the highly standardized and automated realm of manufacturing. Recognizing the potential for significant economic gains through enhanced productivity in construction, academia, and industry, professionals have prioritized this area of study (Rathnayake and Middleton, 2023). Improving labor productivity in construction is not simply a theoretical concern but a practical imperative driven by the global imperative for efficient infrastructure development and the pressures of delivering projects within constrained budgets and schedules. Therefore, the emphasis on labor productivity within the construction industry has emerged from a combination of its current lag behind other industries and the pressing need to optimize performance in this critical sector (Adebowale and Agumba, 2023). Consequently, the volume of scholarly articles focusing on CLP has increased year over year.

The recurring topics, the concentrated efforts of numerous studies, and the introduction of varied new technologies signify a collective scholarly interest in addressing the same central issue of CLP. This convergence evidences a shared recognition of its importance. However, it concurrently presents a challenge in synthesizing a comprehensive understanding of the CLP literature. The presence of a dominant topic or topics, once identified and understood in their structural context, will be instrumental in painting a complete picture of the academic discourse surrounding CLP. By discerning the topic structure, researchers and practitioners can navigate the extensive body of CLP literature more effectively, identifying gaps, trends, and opportunities for future research and practical application. Previous studies have segmented CLP research into various thematic categories (Alaloul *et al.*, 2022). Nonetheless, such taxonomies often originate from subjective interpretations lacking in objectivity. This subjectivity can limit the comprehensiveness and neutrality of the classification.

To address the issue of subjectivity, bibliometric methods, such as keyword co-occurrence analysis, provide a relatively objective approach to clustering research topics by analyzing metadata, including keywords and author information. Keyword co-occurrence analysis can reveal keyword citation networks; however, the resulting clusters often lack a hierarchical structure and strong inter-cluster relationships. Moreover, keyword-based clustering fails to provide a meaningful description for each cluster, and author preferences heavily influence the selection of keywords.

To address the limitations of bibliometric methods, this study introduces a topic modeling approach using Hierarchical Latent Dirichlet Allocation (HLDA) for analyzing and delineating the topic structure within CLP-related literature (Al Refaie *et al.*, 2021). This method operates under the premise that a latent topic model exists, from which the corpus of selected documents emanates. The HLDA-generated topic model is anticipated to reflect the inherent topic structure of the analyzed documents, offering an objective representation of the thematic distribution. The input for the HLDA is a corpus summary of CLP-related literature, and its computational process is designed to minimize subjective bias. This study also quantifies the volume of published articles within each topic by year, tracing the evolution of CLP concepts since their inception. Furthermore, to facilitate a microscopic analysis, HLDA modeling is applied to articles from distinct periods, enabling the identification of pivotal moments when new technologies emerged in the CLP literature.

This study endeavors to systematically uncover and articulate the thematic landscape of CLP research spanning from 1973 to 2023. The objectives are multi-fold: first, to apply HLDA to model the corpus of CLP literature within scientific databases, thereby generating topic models and facilitating the clustering of articles; second, to chronologically organize the volume of publications within each identified topic and sub-topic, providing a temporal analysis of thematic evolution; third, to pinpoint historical trends in CLP research through time-sensitive analysis, capturing the advent and integration of new technologies within the field; and fourth, to distill the modeling methodologies of CLP studies based on the clustering outcomes. Utilizing the topic structure generated by the HLDA, this study has identified three principal themes within the CLP literature: project management optimization, data-driven modeling, and worker performance. Additionally, the study examines the evolution of research trends across different time frames, focusing on four key dimensions: the workers, construction management, macroeconomic factors, and environmental considerations. The contribution of this research is to crystallize the core themes and structural topic patterns within the CLP domain, providing scholars with a panoramic view of the scholarly landscape and enabling practitioners to discern emerging research hotspots. The HLDA model proposed by this study stands to serve as a predictive tool for categorizing the topics of future CLP-related literature.

This research unfolds in a systematic manner, commencing with an introduction that contextualizes the significance of CLP and the rationale for employing in its analysis. Following this, the literature review surveys existing literature and introduces HLDA, while the methodology delineates the approach for data collection and analysis. Results and discussion then elucidate the findings from the HLDA model, examining the implications for the field. The summary synthesizes these insights, reflecting on their theoretical and practical contributions, and suggests avenues for future research.

2.1.1 Workload assessment

Workload is a multifaceted concept in the construction industry that can be examined from various perspectives. At the project level, workload reflects the total amount of work required to complete a project or a specific phase (Jagars-Cohen *et al.*, 2009; Sing *et al.*, 2012). This macro-level workload is often measured in terms of time (Genaidy *et al.*, 1989), by recording the duration of each task and using the data for statistical analysis and optimization. The primary goal of such analysis is to improve labor productivity by identifying and reducing inefficiencies in workers' actions.

From the perspective of individual workers, workload refers to the physical and mental demands imposed upon them by a specific scope of work (Hashiguchi *et al.*, 2020; Kim *et al.*, 2022). While mental workload has been linked to construction safety (Kim *et al.*, 2022), its measurement is subjective mainly, and often involves uncertainties (Aktas Potur *et al.*, 2022). In contrast, physical workload, which is the focus of this study, can be objectively measured and is a primary contributor to worker fatigue, injuries, and musculoskeletal disorders. Excessive physical workload often results from maintaining ergonomically unfavorable postures for extended periods or continuously lifting and carrying heavy objects (Moon *et al.*, 2020). Physical workload can be further categorized into physiological workload, measured by heart rate and oxygen consumption, and biomechanical workload, assessed through posture, worker activity, and external load weight (Carvajal-Arango *et al.*, 2021; Van Der Molen *et al.*, 1998).

One of the key challenges in project-level workload assessment is capturing the complex interplay of factors that influence the duration and effort required for each task. These factors can include the complexity of the design, site conditions, weather, material and equipment availability, and the skills and experience of the workforce (Christian and Hachey, 1995; Guo *et al.*, 2017). To address this complexity, researchers have developed frameworks and models that incorporate multiple variables and their interactions, such as the expectancy model (Maloney and McFillen, 1985) and the action-response model (Halligan *et al.*, 1994).

In addition to considering the inherent characteristics of each task, project-level workload assessment must also account for the dependencies and constraints between tasks, including resource-constrained precedence relationships (Kim and Garza, 2005). Critical path analysis and network scheduling techniques have been widely used to identify the sequence of tasks that determine the overall project duration and to optimize resource allocation (Castro-Lacouture *et al.*, 2009; Sonmez and Rowings, 1998b). To cater to the practical needs of planning and scheduling construction activities under finite resources, the Critical Path Method (CPM) extends to the Resource-Activity CPM (RACPM), resulting in the project's critical path seamlessly linked with resource allocation and utilization in project planning (Lu and Li, 2003a); it is noteworthy that RACPM lends itself well to the detailed workload analysis in terms of labor-hours in workface planning. Recent advancements in digital technologies, such as Building Information Modeling (BIM) and Internet of Things (IoT) devices, have opened new possibilities for project-level workload assessment. BIM enables the creation of detailed 3D models of construction projects, which can be used to simulate and analyze the workload associated with various design options and construction sequences (Liu *et al.*, 2015; Zhang and Li, 2004). IoT devices, such as sensors and wearables, can collect real-time data on worker activities and site conditions by associating work activities with their corresponding locations, enabling more accurate and dynamic workload estimation in labour-hours (Aryal *et al.*, 2017; Soleimanifar *et al.*, 2014).

Integrating project-level and individual-level workload assessment is an emerging area of research that holds promise for optimizing construction processes and improving worker well-being. By combining macro-level workload models with micro-level data on worker posture, activity, and physiological responses, it may be possible to develop adaptive scheduling and resource allocation strategies that balance project efficiency with worker health and safety(Lee *et al.*, 2021). The present research extends this line of research by tracking a worker's workload in executing construction activities beyond the normal "labor-hours", proving the concept of tracking a worker's "posture-hours" by utilizing the latest computing algorithms (including vision computing, image processing, and AI training).

2.1.2 Workface Labor Productivity Assessment

Labor productivity is defined as "a measure of the overall effectiveness of an operating system in utilizing labor, equipment, and capital to convert labor efforts into useful output and is not a measure of the capabilities of labor alone" (Hendricson 2008). Evaluating labor productivity at the worksite involves the effective measurement of labor efforts and useful output, which is crucial for effective construction project management and control. Conventional methods for measuring labor efforts, such as time and motion studies, have been extensively employed to examine craft worker activities and identify opportunities for productivity enhancement (Josephson and Bjorkman, 2013; Thomas and Holland, 1980; Yates, 2014). These studies involve randomly observing and categorizing worker activities into predefined categories, including value-adding tasks, supporting activities, and delays (Dai *et al.*, 2009; Durdyev and Mbachu, 2011; Kumaraswamy and Chan, 1998; Lindhard and Wandahl, 2014; Thomas and Daily, 1983).

Although time and motion studies contributed to the understanding of labor productivity, they were also subject to criticism. Some researchers contended that these methods primarily indicated worker "busyness" rather than accurately predicting productivity or quantifying inefficient work hours (Logcher and Collins, 1978; Samelson and Borcherding, 1980; Thomas, 1991). The relationship between observed activity proportions and actual labor productivity remains an area of ongoing investigation (Neve *et al.*, 2020; Tsehayae and Fayek, 2012).

Notwithstanding their limitations, time and motion studies remain valuable tools for diagnosing and measuring project performance. They were successfully applied across various construction sectors to identify productivity improvements and inform management practices (Babalola *et al.*, 2019; Bakas *et al.*, 2020; Ghodrati *et al.*, 2018; Kükrer and Eskin, 2021). However, reported productivity rates exhibit considerable variability, ranging from 17.5% to 61.1% underscoring the need for more robust and comprehensive assessment methods to strike a balance between the application cost of productivity assessment methods and their effectiveness in accounting for sufficient details (Hajikazemi *et al.*, 2017; Strandberg and Josephson, 2005).

In conjunction with productivity modeling, workload estimation plays a crucial role in understanding labor productivity at a fundamental level. Visual recognition of worker postures and activities forms the foundation for collecting the raw data used in productivity assessment. Posture recognition is a critical component of workload estimation, as it provides valuable insights into the physical demands and ergonomic risks associated with various construction tasks. Accurate and efficient posture recognition, achieved through advanced techniques such as computer vision and machine learning, can significantly enhance the granularity and reliability of labor productivity data (Luo *et al.*, 2018; Yang *et al.*, 2016). By integrating posture-based workload estimation with productivity modeling, construction managers can gain a deeper understanding of labor performance factors and make informed, data-driven decisions to optimize resource allocation and project outcomes. This has motivated the present research to account for workers' postures during construction activities by leveraging advanced computing technologies.

2.1.3 Worker activity recognition

Human oversight in construction, including safety inspections, progress monitoring, and productivity assessments, relies heavily on visual checks. However, manual approaches face several limitations, including incomplete data, workflow disruptions, and high costs. Computer vision offers solutions to these issues. In recent years, the development of computer vision and machine learning techniques has made it possible and promising to automatically and continuously monitor worker activities using cameras (Jiang *et al.*, 2018; Luo *et al.*, 2018). Researchers have explored various machine learning algorithms, such as Convolutional Neural Networks, to classify worker motions and activities (Gong *et al.*, 2022; Kim *et al.*, 2019; Sanhudo *et al.*, 2021). Deep learning-based methods have achieved state-of-the-art performance in video-based action recognition tasks (Akinosho *et al.*, 2020; Luo *et al.*, 2019). Luo et al. proposed a hierarchical statistical method that leverages deep action recognition and Bayesian nonparametric learning to capture and understand workers' activities in far-field surveillance videos. Luo et al. (2018) also introduced a two-stream convolutional neural network model that encodes activities through spatial and temporal streams and designed a fusion strategy, producing promising results in activity recognition from construction site surveillance videos. Tao et al. (2020) developed a multi-modal approach for worker activity recognition, comprehensively utilizing inertial measurement unit signals and video data from a smart armband and a visual camera, showing high recognition accuracy on an assembly task dataset.

2.1.4 Worker-centric planning approaches

In addition to directly intervening in workers' actual movements, another direction for research on preventing OHS disorders among workers is to approach it from the perspective of work planning. Traditional construction planning methods have primarily focused on optimizing time and resource allocation, often overlooking the well-being of workers. The Critical Path Method (CPM) and its extensions, such as the Line of Balance (LOB) and the Resource-Activity Critical Path Method (RACPM) (Lu and Li, 2003b; Tang *et al.*, 2018), effectively integrate activity and resource planning. RACPM further enhances resource-constrained scheduling by incorporating resource-technology precedence relationships (Ju and Xie, 2009; Lu and Li, 2003b). However, there remains an opportunity to expand its application by incorporating ergonomic considerations, particularly in labor-intensive tasks where occupational health and safety (OHS) risks are likely to arise. (Karim and Adeli, 1999a) developed an object-oriented system for construction scheduling that encapsulates project activities (tasks/plans) and resources through dedicated classes. Their framework supports dynamic scheduling by allocating resources to activities and updating activity states through operations such as *"Schedule() and Update()"*.

Building on this object-based paradigm, our work extends the scheduling model by explicitly incorporating worker postures as a third critical object class, in addition to activities and resources.

In contrast, manufacturing sectors have pioneered worker-centric scheduling models to mitigate OHS disorders. Job rotation, for instance, has been systematically optimized to balance workload and reduce ergonomic risks. Studies by Botti et al. (2017) and Dinler and Işık (2020) developed mathematical frameworks to schedule rotations for aged workers and assembly-line operators, respectively, by alternating tasks to minimize repetitive strain. These models quantify ergonomic exposure using risk assessment tools, ensuring workload distribution aligns with workers' physical capacities (Botti *et al.*, 2017; Dinler and Işık, 2020). Similarly, Savino et al. (2020) empirically demonstrated that integrating ergonomic postures into workforce scheduling reduces production idle time while lowering biomechanical stress, highlighting a tangible trade-off between efficiency and worker health. Tao et al. (2025) incorporate OHS risk factors as scheduling constraints, where the OHS risk for a single task increases with the number of consecutive working days. However, even within the same job category, variations in task-specific postures create challenges in consistently and uniformly assessing workers' occupational health and safety (OHS) risks.

Safety integration in construction planning has seen incremental advances, such as the Safety Base & Safety Net system (Kartam, 1997), which embeds safety protocols into CPM schedules. However, this approach targets accident prevention rather than chronic OHS risks arising from prolonged awkward postures. Notably, while manufacturing research has quantified the impact of ergonomics on scheduling outcomes (Savino *et al.*, 2020); analogous studies in construction remain scarce. The absence of posture-aware planning frameworks for dynamic construction environments represents a critical gap, as site tasks often involve non-repetitive but high-risk movements (e.g., overhead lifting, bending).

Despite existing research on ergonomic interventions (such as tool modifications, Personal Protective Equipment (PPE), and training) and some efforts to incorporate fatigue factors into scheduling models, a significant research gap remains in directly integrating workers' physiological constraints, especially cumulative strain risks measured through "postures" as core objectives in construction planning. Work-related occupational health risks are not entirely unavoidable; they can be proactively managed by redefining planning units (from traditional "man-hours" to "posture-hours") and creating algorithms to systematically optimize work sequences and crew assignments during planning. This approach would simultaneously lessen cumulative exposure to hazardous postures while maintaining productivity. The current study addresses this gap by proposing and validating a posture-aware construction planning method that advances beyond reactive monitoring and localized interventions. By proactively managing posture exposure risks during the planning phase, this research presents a new comprehensive approach to reducing occupational health and safety (OHS) issues in construction, while also tackling workforce sustainability challenges in the industry.

2.2 Methodology

The development of PTM has enabled scholars to examine texts objectively. The HLDA approach produces more interpretable results than the LDA method (Blei *et al.*, 2007). Having control over the model's input data can improve the output's interpretability. Thus, filtering and cleaning the input data is required before deriving the topic model. The basic steps of this study are described as follows (Figure 2.1). First, pre-screening is used to exclude irrelevant items. Then, data cleansing is used to delete any content in the document that is unrelated to the document's subject. Finally, topic models is generated using HLDA algorithms.

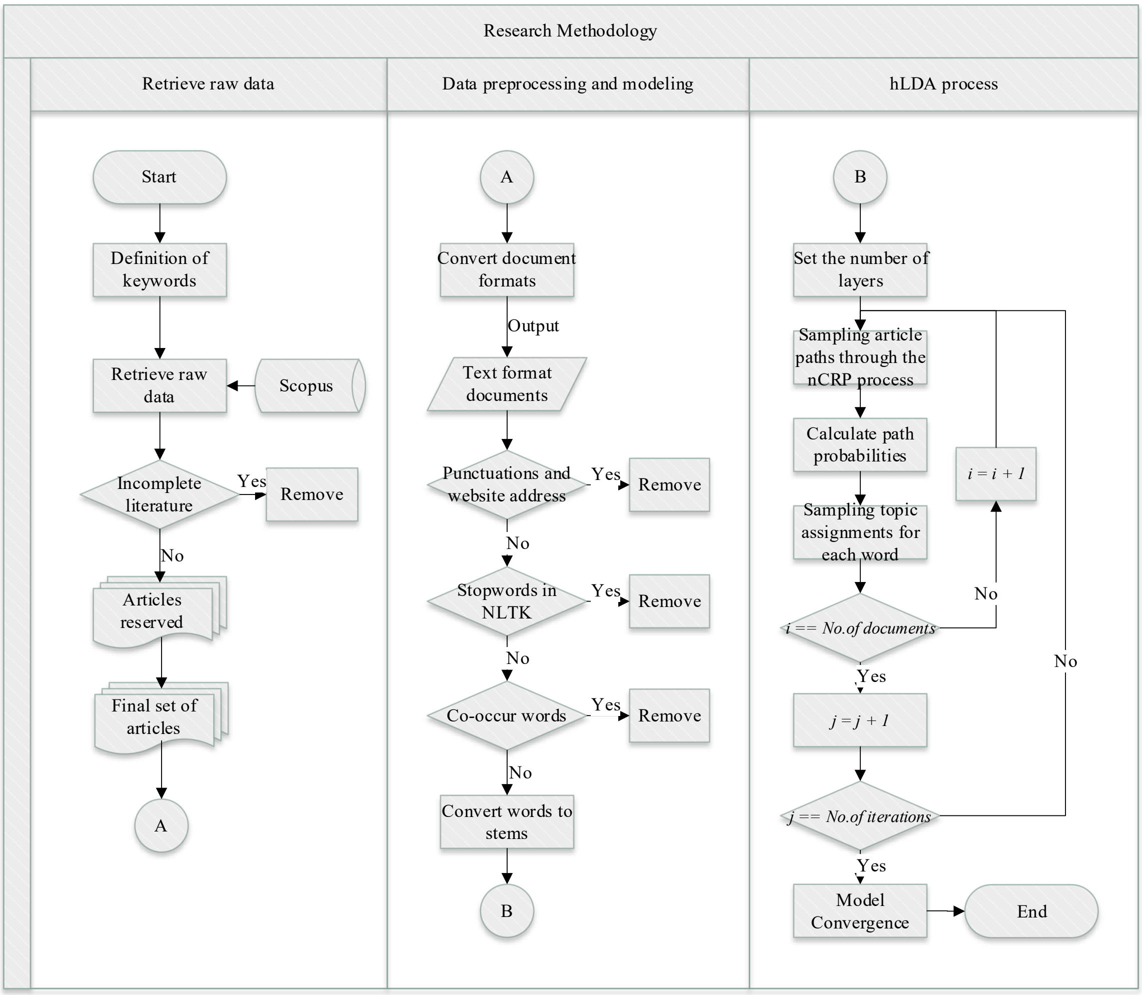

Figure 2.1 Flowchart of research methodology

Step 1: The literature collection process for researching construction labor productivity involved defining relevant keywords related to the topic, ensuring a focused search. The chosen keywords encompassed various aspects of labor productivity in the construction industry. The retrieval of raw data was conducted using Scopus search engine with comprehensive coverage of engineering-related articles. However, to ensure the quality and completeness of the literature, incomplete articles that lacked abstracts were removed as these articles could potentially be outdated or missed crucial information.

Step 2: In the data preprocessing phase for Hierarchical Latent Dirichlet Allocation

(HLDA), several steps are performed to ensure the quality and suitability of the input data. Firstly, the conversion of document formats enables uniformity in the data representation. Secondly, the removal of punctuation and website addresses eliminates irrelevant characters and links. Thirdly, the application of the Natural Language Toolkit (NLTK) aids in removing stopwords and common words that do not contribute significantly to the overall meaning. Furthermore, the elimination of co-occurring words further refines the dataset to reduce redundancy. Lastly, the conversion of words to their stems using techniques such as stemming and lemmatization simplifies the vocabulary by reducing words to their base or root forms.

Step 3: Initially, each word in the documents to a specific sub-topic and topic will be assigned. Then, the probability distributions of sub-topics and topics based on the assigned word-topic assignments will be updated. This iterative process continues until solution converged when achieving a stable and optimal representation of the hierarchical topic structure. By maximizing the likelihood of the observed data and utilizing the Dirichlet priors, HLDA learns the latent topic hierarchy and provides a robust framework for uncovering hierarchical topic and sub-topic relationships within the text corpus.

2.2.1 Literature collection

The literature collection process for researching construction labor productivity involved a careful selection of search strategy due to the potential for irrelevant articles from default fuzzy search methods. Using “construction labor productivity” as keywords, 2417 articles were searched, however, many of them were not directly related to the topic. To address this issue, a more precise search strategy was employed. The syntax "TITLE-ABS-KEY (construction W/10 labor W/0 productivity) OR TITLE-ABS-KEY (construction W/10 labour W/0 productivity) AND (LIMIT TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "re"))" was used to ensure that the keywords "construction" and "labor" (or "labour") appeared within a limited proximity to "productivity". The search results must include the keywords "construction" and "labor" within 10 words, and "productivity" with no intervening words. The search was narrowed by limiting the document type to research articles, review articles, and conference papers. As such, the number of searched articles was reduced to 591.

2.2.2 Data preprocessing

Since HLDA is a bag-of-words model, the sequence of input words has no impact on the output (Blei *et al.*, 2007). So only words that express actual meaning in the article can help the algorithm identify the topic of the article. The form of the output is a collection of hierarchical topics and corresponding topic terms. Therefore, to make only words that can reflect the meaning of the article appear in the output model, content that does not relate to the article will be excluded, such as function words, auxiliary words, punctuation, and website addresses. The 40 stopwords, such as "a, an, the" in English, provided by the Natural Language Toolkit (NLTK) were used to filter the content.

After training the topic model, the topic terms that have a high probability distribution will be identified to determine the meaning of each topic based on the topic terms. To easily distinguish the topics, the words that co-occur in CLP-related articles, such as "construction", "labor", and "productivity" were filtered. These frequently used words in corpus are shown in Table 2.1. The frequency is the proportion of the number of corresponding words among all words when preprocessing the data. After deleting the co-occurring words, specific study subjects can be detected by reviewing the high-frequency phrases, such as the CLP modeling techniques and worker productivity benchmarks. Finally, the words were restored to stems so as to unify the variations in different tenses and voices.

Table 2.1 Top 10 most frequent words in corpus

Including co-occurring words		Without co-occurring words	
Words	Frequency	Words	Frequency
Productivity	0.0453	Worker	0.0155
Construction	0.0336	Model	0.0116
Factor	0.0144	Effect	0.0113
Labor	0.0111	Site	0.0081
Industry	0.0068	Management	0.0080
Study	0.0066	Improve	0.0080
Result	0.0062	Affect	0.0080
Labour	0.0062	Development	0.0074
Paper	0.0056	Influence	0.0071

2.2.3 Hierarchical topic modeling

The HLDA assumes that each document in the corpus is generated based on a tree-like topic model. Each node in the model represents a topic. A topic is the probability distribution of words belonging to that topic. The HLDA method's document generating procedure requires each document to go through two steps. The first step is to produce topic words. The second step is to choose topic paths.

The path picked by each document and the topic assigned for each word (each word belongs to which topic) can be determined by sampling the corpus using an a posteriori inference approach.

The **<u>1st step</u>** is to assign the topic for word *n* in document *d*. The model training process is implemented by Gibbs sampling algorithm. By repeatedly sampling the path for each article and the topic assigned for each word, the final sample converges as a distribution which is stabilized. Initially, a topic should be randomly assigned to each word in the corpus, and randomly assign a topic path for each document as $\{P_{1:D}^{(t)}, Z_{1:D}^{(t)}\}$ .Then, randomly assign the level for each word *n* in document *d*, according to the posterior probability given by Eq. (1).

$$p(Z_{d,n} \mid \boldsymbol{Z}_{-(d,n)}, \boldsymbol{p}, \boldsymbol{w}, m, \sigma, \eta) \propto p(Z_{d,n} \mid Z_{d,-n}, m, \sigma) p(w_{d,n} \mid \boldsymbol{Z}, \boldsymbol{P}, \boldsymbol{W}_{-(d,n)}, \eta) \quad (1)$$

where $Z_{d,n}$ represents the hierarchical distribution variable for word *n* in document *d*. $p(Z_{d,n} \mid Z_{d,-n}, m, \sigma)$ represents the topic assignment probability for word *n*, and $p(w_{d,n} \mid \boldsymbol{Z}, \boldsymbol{P}, \boldsymbol{W}_{-(d,n)}, \eta)$ represents the topic word generation probability for word *n*. $\boldsymbol{Z}_{-(d,n)}$ and $\boldsymbol{W}_{-(d,n)}$ are the level allocation and word allocation variables exclude $Z_{d,n}$ and $W_{d,n}$.

The first segment of Eq. (1) $p(Z_{d,n} \mid Z_{d,-n}, m, \sigma)$ can be expanded as Eq. (2). The second segment of Eq. (1) $p(w_{d,n} \mid \boldsymbol{Z}, \boldsymbol{P}, \boldsymbol{W}_{-(d,n)}, \eta)$ can be expanded as Eq. (3).

$$p(Z_{d,n}=k \mid Z_{d,-n},m,\sigma)=\frac{m\sigma+\#[Z_{d,-n}=k]}{\sigma+\#[Z_{d,-n}\geq k]}\prod_{j=1}^{k-1}\frac{(1-m)\sigma+\#[Z_{d,-n}>j]}{\sigma+\#[Z_{d,-n}\geq j]} \tag{2}$$

$$p(w_{d,n} \mid \boldsymbol{Z},\boldsymbol{P},\boldsymbol{W}_{-(d,n)},\eta)\propto \#[\boldsymbol{Z}_{-(d,n)}=Z_{d,n},\boldsymbol{P}_{Z_{d,n}}=P_{d,Z_{d,n}},\boldsymbol{W}_{-(d,n)}=W_{d,n}]+\eta \tag{3}$$

Where #[] represents the number of instances that satisfy the condition. $\#[Z_{d,-n}=k]$ represents the number of words with the topic level *k* in document *d* except word *n*, and $\#[\boldsymbol{Z}_{-(d,n)}=Z_{d,n},\boldsymbol{P}_{Z_{d,n}}=P_{d,Z_{d,n}},\boldsymbol{W}_{-(d,n)}=W_{d,n}]$ represents the number of words $W_{d,n}$ in other documents assigned to path P_d and level $Z_{d,n}$.

The **<u>2nd step</u>** is to sample the path. For each document $d\in\{1,\ldots,D\}$, randomly select the topic paths according to the posterior probability given by Eq. (4).

$$p(P_d \mid W,C_{-d},Z,\eta,\gamma)\propto p(P_d \mid P_{-d},\gamma)p(W_d \mid P,W_{-d},Z,\eta) \tag{4}$$

where $\boldsymbol{P}_d$ is the path selected by document *d*. $p(\boldsymbol{W}_d \mid \boldsymbol{P},\boldsymbol{W}_{-d},\boldsymbol{Z},\eta)$ is the probability for the path chosen by document *d*, and $p(\boldsymbol{P}_d \mid \boldsymbol{P}_{-d},\gamma)$ is the prior probability for the paths based on nCRP.

The first segment of Eq. (4) $p(\boldsymbol{P}_d \mid \boldsymbol{P}_{-d},\gamma)$ is the prior of $\boldsymbol{P}_d$ which can be determined by nested Chinese restaurant process (nCRP) (Blei *et al.*, 2007) as Eq. (5) and Eq. (6). Each document selects the topic according to the conditional probability. As the number of sampled documents increases during the iterations, the probability of the selected topic being chosen again outnumbers the probability of generating a new topic. nCRP is the process of continuously repeating the nCRP in each topic and the documents belonging to that topic. Based on nCRP, the generation process of a document can be given.

$$p\left(\text{Topic } i \text{ which has been selected} \mid \text{previous documents}\right) = \frac{d_i}{\gamma + d - 1} \tag{5}$$

$$p\left(\text{Next topic which has not been selected} \mid \text{previous documents}\right) = \frac{\gamma}{\gamma + d - 1} \tag{6}$$

where d_i represents the number of articles that have selected Topic i, and γ is a parameter that controls whether the d^{th} document selects a new topic or a topic that has been selected by other documents.

The second segment of Eq. (4) $p(\boldsymbol{W}_d \mid \boldsymbol{P}, \boldsymbol{W}_{-d}, \boldsymbol{Z}, \eta)$ can be expanded as Eq. (7).

$$p(\boldsymbol{W}_d \mid \boldsymbol{P}, \boldsymbol{W}_{-d}, \boldsymbol{Z}, \eta) = \prod_{l=1}^{\max(Z_d)} \frac{\Gamma(\sum_w \#[Z_{-d} = l, P_{-d,l} = P_{d,l}, \boldsymbol{w}_{-d} = w] + V\eta)}{\prod_w \Gamma(\#[Z_{-d} = l, P_{-d,l} = P_{d,l}, \boldsymbol{w}_{-d} = w] + \eta)} \frac{\prod_w \Gamma(\#[Z = l, P_l = P_d, \boldsymbol{w} = w] + \eta)}{\Gamma(\sum_w \#[Z = l, P_l = P_d, \boldsymbol{w} = w] + V\eta)} \tag{7}$$

where, $\#[Z_{-d} = l, P_{-d,l} = P_{d,l}, \boldsymbol{w}_{-d} = w]$ represents the number of words w in other documents assigned to path P_d and level l, and $\#[Z = l, P_l = P_d, \boldsymbol{w} = w]$ represents the number of words w in all documents assigned to path P_d and level l, $\Gamma()$ represents the standard gamma function, V is the total vocabulary size.

After sampling converged, the path selected for each document in the corpus and the topic assigned for each word can be determined.

2.2.4 Example of HLDA process

To illustrate the HLDA training process, the three provided documents were used.

Document 1: “Construction labour productivity factors can be identified through careful analysis of project management practices, workforce skill levels, technological advancements, and resource allocation strategies.”

Document 2: “In construction project management, critical factors identified to influence productivity include skilled labour, technological integration, material availability, and effective scheduling, robust safety measures, and clear communication.”

Document 3: “Construction labour productivity modeling or measurement involves quantifying and analyzing the efficiency and output of the workforce to optimize construction processes and identify areas for improvement.”

Step 1: Data pre-processing.

The documents are tokenized and a vocabulary of unique words is created. The vocabulary size V is 43.

Vocabulary: [“Construction”, “labour”, “productivity”, “factors”, “identified”, “careful”, “analysis”, “project”, “management”, “practices”, “workforce”, “skill”, “levels”, “technological”, “advancements”, “resource”, “allocation”, “strategies”, “modeling”, “measurement”, “involves”, “quantifying”, “analyzing”, “efficiency”, “output”, “optimize”, “processes”, “identify”, “areas”, “improvement”, “critical”, “influence”, “include”, “technological”, “integration”, “material”, “effective”, “communication”, “scheduling”, “robust”, “safety”, “measures”, “clear”]

Step 2: Set initial topic assignments.

The topic labels are randomly assigned to each word in the documents. The number of topics can be predetermined based on prior knowledge or set arbitrarily. For simplicity, it is assumed that there are three levels.

Initial topic assignments for each document

Document 1: [Topic 0, Topic A, Topic a_1]

Document 2: [Topic 0, Topic B, Topic b_1]

Document 3: [Topic 0, Topic B, Topic b_2]

Step 3: Initialize topic counts and word assignments.

The number of words assigned to each topic is counted and the topic assigned to each word are tracked. Table 2.2 shows the initial topic assignment for each word.

Table 2.2 Initial topic assignment for each word

Document 1	Topic	Document 2	Topic	Document 3	Topic
construction	0	construction	B	construction	B
labour	A	project	0	labour	0
productivity	0	management	B	productivity	b_2
factors	0	critical	0	modeling	0
identified	A	factors	0	measurement	b_2
careful	a_1	identified	0	involves	0
analysis	0	influence	b_1	quantifying	B
project	a_1	productivity	0	analyzing	b_2
management	A	include	b_1	efficiency	0
practices	a_1	skilled	B	output	b_2
workforce	0	labour	B	workforce	0
skill	a_1	technological	b_1	optimize	B
levels	0	integration	B	construction	0
technological	A	material	0	processes	b_2
advancements	0	availability	B	identify	B
resource	a_1	effective	0	areas	B
allocation	A	scheduling	b_1	improvement	0
strategies	a_1	robust	B		
		safety	b_1		
		measures	b_1		
		clear	b_1		
		communication	b_1		

Step 4: Iterative Gibbs sampling.

Gibbs sampling is iteratively performed to update the topic assigned to each word in the documents. Gibbs sampling involves sampling a new topic assigned to each word based on the current state of the model. The Gibbs sampling process is repeated for a certain number of iterations until the model solution converges. In each iteration, the topic assignments should be updated based on topic-word distribution (Step 4.1) and document-path distribution (Step 4.2).

Step 4.1: Update topic-word distribution.

Topic-word distribution is calculated by counting the number of times each word is assigned to each topic. The probability of a word belonging to a particular topic can be estimated.

For example, to allocate the level of the word "productivity" in document 1, the probability that the word is associated with each level should be determined. There are 3 possible levels, which are "level 0, level A, and level a_1". The probability of each level can be calculated using Eq. (1) [by multiplying the results of Eq. (2) and Eq. (3)].

For the word "productivity" in document 1, if "productivity" is assigned to level 0, the value of $\#[Z_{d,-n}=k]$, and $\#[\boldsymbol{Z}_{-(d,n)}=Z_{d,n},\boldsymbol{P}_{Z_{d,n}}=P_{d,Z_{d,n}},\boldsymbol{W}_{-(d,n)}=W_{d,n}]$ is needed. The value $\#[Z_{\boldsymbol{d},-n}=0]$ represents the number of words with level 0 in document 1, except the word "productivity". The value $\#[\boldsymbol{Z}_{-(d,n)}=Z_{d,n},\boldsymbol{P}_{Z_{d,n}}=P_{d,Z_{d,n}},\boldsymbol{W}_{-(d,n)}=W_{d,n}]$ represents the number of words "productivity" assigned to the same path with the same level but in different documents; in this case, the value is 0.

For "productivity" in document 1, the probability of assigning "productivity" in Topic 0 is calculated by substituting the calculated input values into Eq. (2) and Eq. (3).

The inputs for Eq. (2) are $\#[Z_{d,-n}=0]=6$, $\#[Z_{d,-n}=1]=5$, and $\#[Z_{d,-n}=2]=6$. Then, Eq. (2) becomes [Eq. (8)].

$$p(Z_{d,n}=0 \mid Z_{d,-n},m,\sigma)=\frac{m\sigma+6}{\sigma+17} \tag{8}$$

The input for Eq. (3) is $\#[\boldsymbol{Z}_{-(d,n)}=Z_{d,n},\boldsymbol{P}_{Z_{d,n}}=P_{d,Z_{d,n}},\boldsymbol{W}_{-(d,n)}=W_{d,n}]=0$. Then, Eq. (3) becomes [Eq. (9)].

$$p(w_{d,n} \mid \boldsymbol{Z},\boldsymbol{P},\boldsymbol{W}_{-(d,n)},\eta) \propto \eta \tag{9}$$

The probability of reassigning "productivity" in Topic 0 can be calculated by Eq. (1) [as Eq. (10)] by multiplying the results of Eq. (8) and Eq. (9).

$$p(Z_{d,n} \mid \boldsymbol{Z}_{-(d,n)},\boldsymbol{p},\boldsymbol{w},m,\sigma,\eta) \propto \eta\frac{m\sigma+6}{\sigma+17} \tag{10}$$

The variable η, m, σ are hyperparameters that control the convergence speed of the solution model. The default values of hyperparameters η, m, σ are 0.1, 0.5, 0.2 respectively. Then, the probability of assigning "productivity" to Topic 0 is "$3.49e^{-2}$". The number "$3.49e^{-2}$" is utilized as a weight to decide the topic associated with the word "productivity".

In this case, the weight of reassigning "productivity" is $3.49e^{-2}$, $7.21e^{-5}$, and $2.89e^{-2}$ for Topic 0, Topic A, and Topic a_1, respectively. Random sampling is conducted based on the determined weights. The document can be assigned to Topic 0 with the weight of $3.49e^{-2}$. The allocation can be achieved by multinomial sampling. For other words in document 1, the allocation can be achieved through the same process.

$\boxed{\text{Step 4.2: Update document-path.}}$

For document 1, there are 5 possible paths which are "0-A-a_1, 0-A-a_2, 0-B-b_1, 0-B-b_2, 0-C-c_1". To allocate the path of document 1, the probability of each possible path is required. Path "0-A-a_1" can be separated to "0-A" and "A-a_1" steps. To calculate the first segment of Eq. (4), the nCRP result of each step should be multiplied. Because the path "0-A" has already existed, Eq. (5) is used for path "0-A" and the result is 1/(γ+3–1) =1/(γ+2). Similarly, Eq. (6) is used for path "A-a_1" and the result is γ/(γ+3–1) =γ/(γ+2). The first segment of Eq. (4) can be expanded as Eq. (11).

$$p(P_d \mid P_{-d}, \gamma) = \frac{\gamma}{(\gamma+2)^2} \tag{11}$$

Eq. (7) represent the second segment of Eq. (4), $\#[Z_{-d} = 0, P_{-d,l} = P_{d,l}, \boldsymbol{w}_{-d} = w]$ should be calculated.

For example, word "productivity" is allocated at level 0 along Path 0-A-a_1 as both Document 1 and Document 2. Thus, besides Document 1, the word "productivity" allocated as level 0 with Path 0-A-$a_1$in other documents (Document 2) is 1. So $\#[Z_{-d} = 0, P_{-d,l} = P_{d,l}, \boldsymbol{w}_{-d} = w]$ for word "productivity" is 1. In other words, the word "productivity" allocated as level 0 with Path 0-A-$a_1$in all documents

(Document 1 and Document 2) is 2. So $\#[Z=0,P_l=P_d,\boldsymbol{w}=w]$ for word "productivity" is 2. Counting the value of $\#[Z_{-d}=l,P_{-d,l}=P_{d,l},\boldsymbol{w}_{-d}=w]$ and $\#[Z=l,P_l=P_d,\boldsymbol{w}=w]$ of each word in Document 1, the value of Eq. (7) can be calculated. The input data for Eq. (7) are shown in Table 2.3.

Table 2.3 Input data for Eq. (7)

Words	$\#[Z_{-d}=0,$ $P_{-d,l}=P_{d,l},$ $\boldsymbol{w}_{-d}=w]$	$\#[Z_{-d}=1,$ $P_{-d,l}=P_{d,l},$ $\boldsymbol{w}_{-d}=w]$	$\#[Z_{-d}=2,$ $P_{-d,l}=P_{d,l},$ $\boldsymbol{w}_{-d}=w]$	$\#[Z=0,$ $P_l=P_d,$ $\boldsymbol{w}=w]$	$\#[Z=1,$ $P_l=P_d,$ $\boldsymbol{w}=w]$	$\#[Z=2,$ $P_l=P_d,$ $\boldsymbol{w}=w]$
construction	0	2	0	1	2	0
labor	1	1	0	1	2	0
productivity	1	0	1	2	0	1
factors	1	0	0	2	0	0
identified	1	0	0	1	1	0
careful	0	0	0	0	0	1
analysis	0	0	0	1	0	0
project	1	0	0	1	1	0
management	0	1	0	0	2	0
practices	0	0	0	0	0	1
workforce	1	0	0	1	0	0
skill	0	0	0	0	1	0
levels	0	0	0	1	0	0
technological	0	0	1	0	1	1
advancements	0	0	0	1	0	0
resource	0	0	0	0	0	1
allocation	0	0	0	0	1	0
strategies	0	0	0	0	0	1

The above input data is used to substitute Eq. (7) [as Eq. (12)].

$$
\begin{aligned}
&p(\boldsymbol{W}_d \mid \boldsymbol{P}, \boldsymbol{W}_{-d}, \boldsymbol{Z}, \eta) = \\
&\frac{\Gamma(\sum_w \#[Z_{-d}=0, P_{-d,l}=P_{d,l}, \boldsymbol{w}_{-d}=w]+V\eta)}{\prod_w \Gamma(\#[Z_{-d}=0, P_{-d,l}=P_{d,l}, \boldsymbol{w}_{-d}=w]+\eta)} \\
&\frac{\prod_w \Gamma(\#[Z=0, P_l=P_d, \boldsymbol{w}=w]+\eta)}{\Gamma(\sum_w \#[Z=0, P_l=P_d, \boldsymbol{w}=w]+V\eta)} \\
&\frac{\Gamma(\sum_w \#[Z_{-d}=1, P_{-d,l}=P_{d,l}, \boldsymbol{w}_{-d}=w]+V\eta)}{\prod_w \Gamma(\#[Z_{-d}=1, P_{-d,l}=P_{d,l}, \boldsymbol{w}_{-d}=w]+\eta)} \\
&\frac{\prod_w \Gamma(\#[Z=1, P_l=P_d, \boldsymbol{w}=w]+\eta)}{\Gamma(\sum_w \#[Z=1, P_l=P_d, \boldsymbol{w}=w]+V\eta)} \\
&\frac{\Gamma(\sum_w \#[Z_{-d}=2, P_{-d,l}=P_{d,l}, \boldsymbol{w}_{-d}=w]+V\eta)}{\prod_w \Gamma(\#[Z_{-d}=2, P_{-d,l}=P_{d,l}, \boldsymbol{w}_{-d}=w]+\eta)} \\
&\frac{\prod_w \Gamma(\#[Z=2, P_l=P_d, \boldsymbol{w}=w]+\eta)}{\Gamma(\sum_w \#[Z=2, P_l=P_d, \boldsymbol{w}=w]+V\eta)}
\end{aligned} \tag{12}
$$

Then, the result of Eq. (7) is given [as Eq. (13)].

$$
p(\boldsymbol{W}_d \mid \boldsymbol{P}, \boldsymbol{W}_{-d}, \boldsymbol{Z}, \eta) = \frac{\Gamma(1+\eta)^9 \Gamma(3+\eta)^3 \Gamma(2+43\eta)^2 \Gamma(7+43\eta)}{\Gamma(\eta)^{12} \Gamma(8+43\eta)^2 \Gamma(9+43\eta)} \tag{13}
$$

The probability of assigning document 1 to Topic path “0-A-a_1” can be calculated [as Eq. (14)].

$$
p(P_d \mid \boldsymbol{W}, \boldsymbol{C}_{-d}, \boldsymbol{Z}, \eta, \gamma) = \frac{\Gamma(1+\eta)^9 \Gamma(3+\eta)^3 \Gamma(2+43\eta)^2 \Gamma(7+43\eta)}{\Gamma(\eta)^{12} \Gamma(8+43\eta)^2 \Gamma(9+43\eta)} \frac{\gamma}{(\gamma+2)^2} \tag{14}
$$

The variables η, γ are hyperparameters. $\Gamma()$ represents the gamma function. The default values of hyperparameters η and γ ,are 0.1 or 1 respectively. Then, the probability of allocating document 1 to “0-A-a_1” is $5.77e^{-26}$.

The weights of assigning document 1 to Topic paths “0-A-a_1, 0-A-a_2, 0-B-b_1, 0-B-b_2, 0-C-c_1 are $5.77e^{-26}$, $3.47e^{-23}$, $4.67e^{-25}$, $9.53e^{-29}$, and $2.44e^{-18}$” respectively.

Whether the document is assigned to "0-A-a_1" is dependent on the random sampling result by multinomial sampling based on the determined weights. Figure 2.2 shows the iterative process of document-path selection.

Step 5: Repeat Steps 4.

If the number of iterations is limited to 100, this process will be repeated 100 times. Repeat steps 4 for enough iterations until the model converges to a stabilized result. The convergence can be determined by monitoring any changes of topic-word and document-path distributions across iterations. Table 2.4 represents the topic assignment for each word after the 1st iteration. The assigned topic of many words remains unchanged after this iteration, such as "productivity, construction, identified".

Table 2.4 1st iteration topic assigned for each word

Document 1	Topic	Document 2	Topic	Document 3	Topic
construction	0	construction	A	construction	0
labour	0	project	0	labour	0
productivity	0	management	A	productivity	b_2
factors	A	critical	0	modeling	0
identified	A	factors	A	measurement	b_2
careful	a_1	identified	0	involves	0
analysis	0	influence	a_1	quantifying	B
project	a_1	productivity	0	analyzing	b_2
management	A	include	a_1	efficiency	0
practices	a_1	skilled	A	output	b_2
workforce	0	labour	A	workforce	0
skill	a_1	technological	A	optimize	B
levels	0	integration	0	construction	0
technological	A	material	0	processes	b_2
advancements	0	availability	0	identify	B
resource	a_1	effective	0	areas	B
allocation	A	scheduling	A	improvement	0
strategies	a_1	robust	B		
		safety	a_1		
		measures	a_1		
		clear	A		
		communication	a_1		

After the 2nd iteration, document 1 is assigned to new Topic C (Table 2.5). It can be seen that words with higher co-occurrence frequency are more likely to be assigned to higher levels, such as “construction, labour”.

Table 2.5 2nd iteration topic assignment for each word

Document 1	Topic	Document 2	Topic	Document 3	Topic
construction	0	construction	A	construction	0
labour	0	project	0	labour	0
productivity	0	management	A	productivity	b_2
factors	0	critical	0	modeling	0
identified	C	factors	A	measurement	b_2
careful	c_1	identified	0	involves	0
analysis	0	influence	a_1	quantifying	B
project	c_1	productivity	0	analyzing	b_2
management	A	include	a_1	efficiency	0
practices	c_1	skilled	A	output	b_2
workforce	0	labour	0	workforce	0
skill	c_1	technological	A	optimize	B
levels	0	integration	0	construction	B
technological	C	material	0	processes	b_2
advancements	C	availability	0	identify	B
resource	c_1	effective	0	areas	B
allocation	C	scheduling	A	improvement	0
strategies	c_1	robust	B		
		safety	a_1		
		measures	a_1		
		clear	A		
		communication	a_1		

Step 6: Finalize topic structure.

After the 100th iteration, the assignment of topic for each word is stabilized (Table 2.6). Most of the co-occurring words are assigned to Topic 0, such as “construction, labor, productivity”. Document 1 and document 2 are also assigned to Topic A. The subject headings include “factors, identified, skill”. It can be seen that Topic A summarizes articles on the identification of influencing factors.

Table 2.6 100^{th} iteration topic assignment for each word

Document 1	Topic	Document 2	Topic	Document 3	Topic
construction	0	construction	0	construction	0
labour	0	project	0	labour	0
productivity	0	management	A	productivity	0
factors	A	critical	0	modeling	0
identified	A	factors	A	measurement	B
careful	a_1	identified	0	involves	0
analysis	a_1	influence	a_2	quantifying	B
project	0	productivity	0	analyzing	b_2
management	A	include	a_2	efficiency	0
practices	a_1	skilled	A	output	b_2
workforce	0	labour	0	workforce	0
skill	A	technological	A	optimize	B
levels	0	integration	0	construction	B
technological	A	material	0	processes	b_2
advancements	a_1	availability	0	identify	B
resource	a_1	effective	0	areas	B
allocation	a_1	scheduling	A	improvement	0
strategies	a_1	robust	B		
		safety	a_2		
		measures	a_2		
		clear	A		
		communication	a_2		

The topic structures are iterated as Figure 2.2. Initially "document 1" was assigned to the same topic path as "document 2", but as the number of iterations continued, the topic structure was finally fixed at two topics (Topics A, B) and three sub-topics (Topics a_1, a_2, b_1).

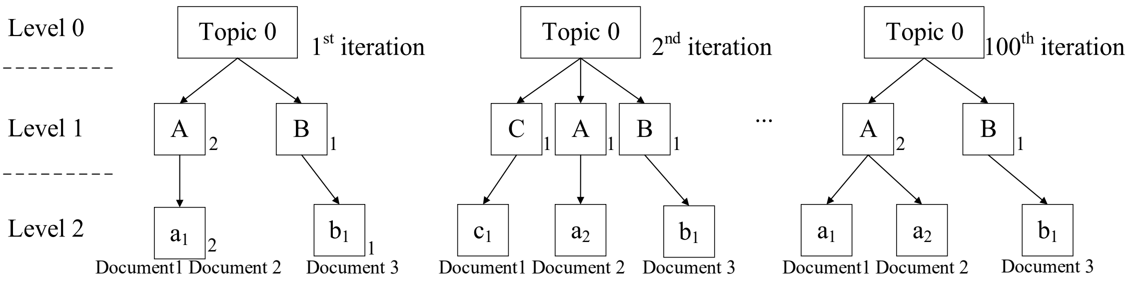

Figure 2.2 Topic structure of example documents

2.3 Results

The HLDA model faces the challenge of determining the appropriate number of topic layers, as different numbers of layers can affect the model's accuracy. An insufficient number of layers may not adequately capture the information contained within the document collection, while an overly granular layering may generate unnecessary topics. In this study, HLDA models with two, three, and four layers were applied to investigate the impact of layer depth on the model's performance and to identify the optimal number of layers for representing the latent topic structure within the construction labor productivity literature.

A two-layer HLDA model only generated two topics even after 5,000 iterations. Table 2.7 illustrates the results of the two-layer model. In fact, a two-layer model does not possess a true hierarchical structure because the first layer, Topic 0, is fixed and contains only one topic. Furthermore, the stem words in the table include many general terms, such as “industri, use, project, build”, making it difficult to discern specific thematic information. The two-layer HLDA model's lack of granularity and genuine hierarchical structure suggests that it would not adequately capture the latent topic structure of the CLP literature.

The three-layer, four-layer topic model’s structure is shown in Figure 2.3 and Figure

2.4. When the number of layers in the HLDA model is increased to four, the total number of topics within the model reaches 54. The distribution of articles under the fourth-layer topics tends to be more uniform, with the most populous second-layer topic, topic a2, associated with 220 articles, accounting for more than one-third of the total corpus. Compared to the three-layer HLDA, the four-layer model exhibits a significant increase in the total number of topics, from 30 to 54. It is also noteworthy that topics b1 and c3 do not branch out into further subtopics, indicating that the classification of articles under these two topics has reached its limit. Overall, the four-layer model provides a more fine-grained classification of article topics.

Table 2.8 presents the high-frequency topic stems for each topic in the four-layer HLDA model. The fourth-layer topics can clearly distinguish the meaning represented by each topic. For instance, topic a21 contains stems such as “carbon, emiss, environment”, indicating that a21 is related to carbon emissions and environmental issues. However, the differences between the second-layer topics are not as apparent, with many repeated topic words. For example, the stem “identify” appears in every second-layer topic, and “impact” appears in topics A, B, and C. This issue persists in the third-layer topics, with the stem “determin” appearing in both topics a1 and a2. This problem may arise from over-classification in the four-layer model, where increasing the depth of classification results in articles previously belonging to the same category being assigned to different topics. For example, topics b23 and a21 related to environmental issues are allocated to different topics. This excessive granularity may lead to a loss of coherence and interpretability in the topic structure.

Table 2.7 high-frequency stems of two-layer HLDA model

Topics	High-frequency stems
0	factor, labour, industri, work, project, improv, worker, affect, research, studi, identifi, site, manag, result, import, thi, influenc, perform, time, signific, also, develop, materi, effect, measur, indic, base,
A	model, use, project, labor, data, method, thi, activ, build, studi, develop, manag, practic, impact, result, research, system, provid, predict, effect, approach, plan, perform, effici, chang, propos, present, schedul,
B	develop, use, increas, labor, cost, industri, build, growth, method, technolog, econom, product, region, system, economi, new, chang, process, equip, sector, per, provid, china, structur, energi, model, agricultur, number, condit,

Table 2.8 High-frequency stems of four-layer model

Topics	High-frequency stems
0	method, result, measur, cost, time, system, provid, increas, process, activ
A	thi, site, identifi, impact, influenc, worker, collect, materi, signific, import
a1	floor, build, learn, determin, activ, cycl, plan, rate, simul, repetit
a11	vacuum, central, commut, may, pattern, shirk, cleaner, dustcont, behaviour, particular
a12	approach, estim, optim, oper, frontier, task, durat, paramet, effici, framework
a13	facil, equip, machin, modular, pipe, instal, temporari, layout, scaffold, mechan
a14	buildabl, formwork, design, concret, reinforc, effici, activ, investig, beam, object
a15	lean, renov, cultur, zombi, cle, stakehold, organis, vaw, practis, nvaw
a2	rate, analysi, result, base, differ, show, also, variabl, determin, method
a21	carbon, emiss, environment, energi, prefabr, china, shift, build, peak, provinc
a22	metric, program, temperatur, vulner, fiveminut, locat, per, benchmark, rate, percent
a23	growth, sector, wage, countri, popul, econom, economi, capit, neg, employ
a24	clp, predict, network, neural, fuzzi, formwork, context, ann, propos, select
a25	simul, logist, crew, congest, approach, learn, dynam, fuzzi, agentbas, space
a26	motiv, theori, compani, employe, percept, divers, organ, environ, remuner, worker
a27	survey, questionnair, import, rank, identifi, rework, delay, overrun, rel, caus
a28	chang, loss, order, claim, impact, quantifi, contract, contractor, track, lost
a3	design, three, neg, strategi, best, adopt, predict, smp, preconstruct, novel
a31	practic, build, safeti, implement, phase, tool, contractor, materi, dure, enhanc
a32	osc, skill, fca, execut, deriv, bridg, requir, paint, end, word
a33	sleep, health, mental, qualiti, psycholog, stress, preval, advers, anxieti, demograph
a34	wall, masonri, slag, strength, erect, insul, wast, ash, adhes, raw
B	impact, worker, site, collect, rate, thi, identifi, environ, signific, aim
b1	materi, appropri, hierarch, approach, hong, link, influenc, window, stand, without
b11	activ, recognit, action, interact, object, locat, acceleromet, classif, worker, algorithm
b2	region, review, influenc, global, area, import, countri, clp, time, literatur

b21	bim, inform, autom, build, design, adopt, integr, order, steel, organ
b22	china, hous, econom, chongq, chines, resourc, market, residenti, enterpris, urban
b23	weather, safeti, climat, hot, schedul, heat, wbgt, stress, temperatur, health
b24	framework, loyalti, manageri, driver, satisfact, mfb, second, mediat, indian, path
b25	commun, handsfre, hand, path, walkietalki, radio, match, prior, author, convers
C	thi, impact, identifi, contractor, signific, collect, site, relat, influenc, import
c1	strategi, index, craft, foreign, safeti, object, introduc, employ, skill, especi
c11	benchmark, matur, framework, procedur, baselin, kpi, disrupt, cim, databas, thermal
c12	worker, human, skill, commun, group, interview, paramet, enhanc, step, aptitud
c13	organ, plan, wage, budget, analyt, deriv, number, account, expand, simul
c2	growth, intens, enterpris, equip, grow, organiz, mushroom, platform, deliveri, three
c21	agricultur, technolog, engin, integr, innov, rural, promot, new, green, environment
c22	firm, intern, french, contractor, probabl, einvoic, oper, concret, distribut, ciw
c23	flow, copq, artisan, claim, output, percent, profit, load, empir, expend
c3	overman, acceler, quantifi, often, sheet, question, weekend, multipl, begin, taiwan
c31	overtim, schedul, impact, shift, compress, analysi, sourc, quantit, per, number
D	identifi, thi, site, worker, signific, import, result, influenc, investig, low
d1	form, invest, print, lop, printer, camcord, high, commun, reli, entail
d11	state, financi, australian, crisi, frontier, appear, chang, capit, tempor, australia
d12	concret, scc, dprint, girder, purlin, hang, bridg, slab, convent, maximum
d2	rate, determin, countri, conduct, growth, contribut, review, economi, focus, impact
d21	region, per, employ, sector, inequ, capita, dispar, incom, consumpt, coeffici
d22	cost, plant, mainten, power, program, petrochem, nuclear, solar, contain
d23	clp, review, train, motiv, articl, sector, apprenticeship, journal, gap, databas
d24	mine, vietnam, coal, equip, relev, underground, strength, excav, technolog, vietnames
d25	decis, welfar, analyt, ahp, among, drive, make, remuner, consider, criteria
d26	weld, rebar, tie, reinforc, cage, reduc, joint, manhour, train, strength
d27	pandem, covid, dure, overrun, offshor, delay, rail, era, wind, takt
d28	learn, build, prefabr, curv, wast, floor, lift, cycl, hous, theori

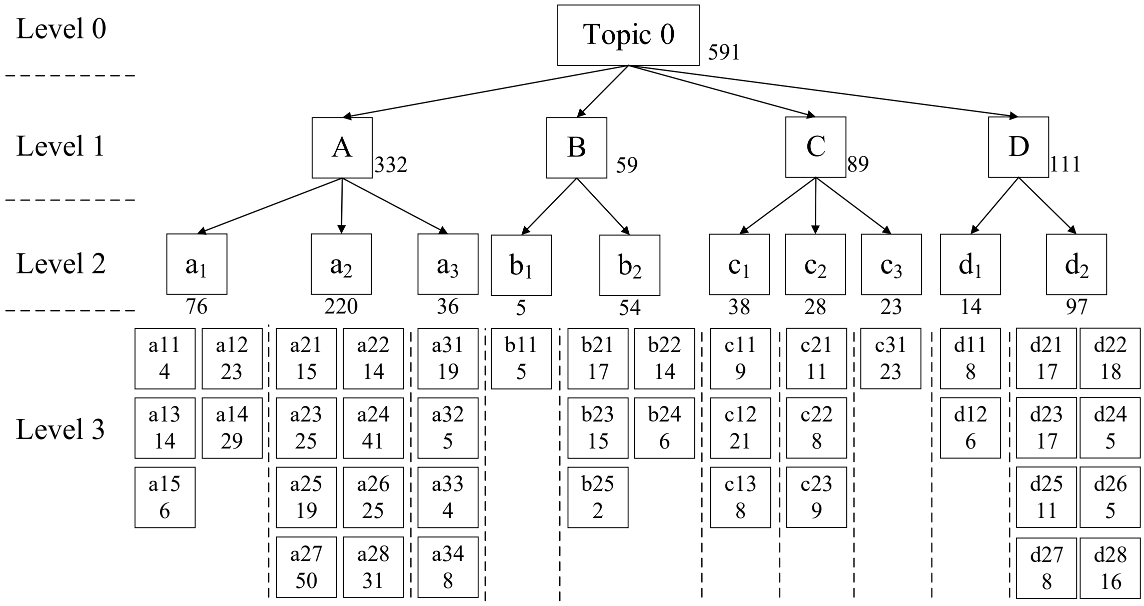

Figure 2.3 Structure of four-layer topic model

Considering the balance between granularity and interpretability as per the two-layer, three-layer, and four-layer HLDA model structures, the three-layer model was selected. The two-layer model suffered from a lack of genuine hierarchical structure and granularity. It generated only two topics with general stem words, making it challenging to identify specific thematic information. On the other hand, the four-layer model resulted in over-classification, with the total number of topics exceeding double that of the three-layer model. This excessive granularity led to a loss of coherence and interpretability in the topic structure, as evidenced by repeated topic words across different layers and the assignment of articles with similar themes to different topics. In summary, the HLDA model with three layers strikes a balance between capturing the latent topic structure of the CLP literature while maintaining a coherent and interpretable representation of the identified topics.

In the three-layer topic model, there are 591 articles grouped into 3 topics and 26 sub-topics, as can be seen. In summary, the percentages of papers assigned with Topic A to Topic C are 47.72%, 42.64%, and 9.64% respectively. It can be indicated that the number of papers related to Topic A is the highest, accounting for 282 out of 591. The high-frequency stems of each topic are shown in Table 2.9.

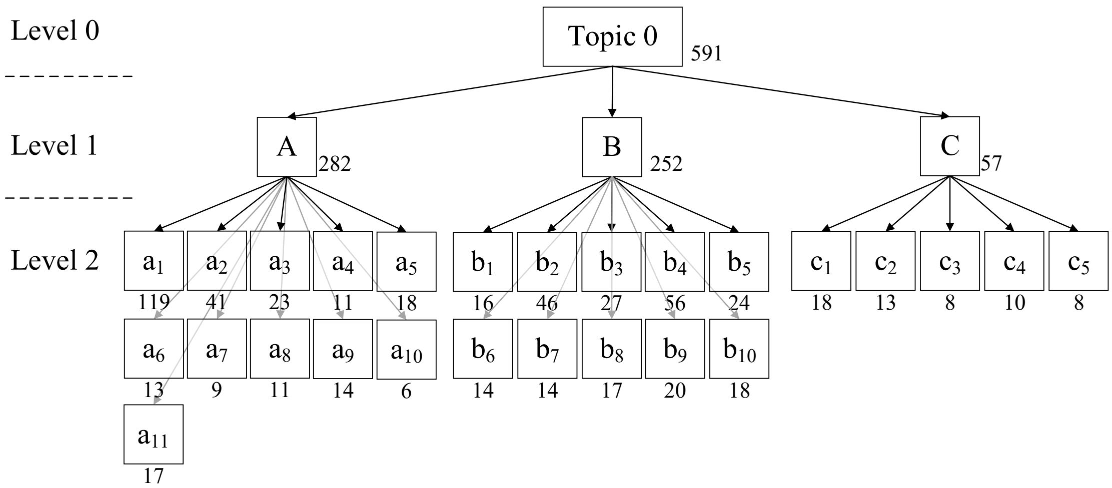

Figure 2.4 Structure of three-layer topic model

Table 2.9 Top 10 high-frequency stems of each topic

Topic	High-frequency stems
0	industri , work , improv , perform , factor , thi , develop , effect , research , increas ,
A	manag , model , data , base , collect , result , oper , propos , build , thi ,
a_1	factor , affect , identifi , worker , survey , questionnaire , influenc , project , rank , motiv ,
a_2	buildabl , formwork , learn , factor , floor , concret , influenc , effect , build , activ ,
a_3	cost , program , metric , plant , mainten , rework , petrochem , mechan , nuclear , improv ,
a_4	technolog , mine , coal , method , excav , lean , equip , residenti , underground , work ,
a_5	materi , logist , wast , prefabr , deliveri , onsit , kanban , control , electr , panel ,
a_6	facil , equip , machin , instal , pipe , modular , temporari , layout , produc , budget ,
a_7	learn , tool , tie , rebar , curv , save , student , task , game , vari ,
a_8	system , method , vacuum , cycl , worker , task , manual , central , fragment , accur ,
a_9	optim , estim , effici , oper , frontier , approach , congest , thi , framework , lift ,
a_{10}	weld , strength , paramet , joint , age , distribut , masonri , influenc , cage , human ,
a_{11}	perform , matur , index , benchmark , variabl , best , manhour , indic , procedur , overrun ,
B	model , data , develop , analysi , base , manag , activ , system , present , result ,
b_1	weather , worker , temperatur , condit , climat , health , stress , hot , area , high ,
b_2	model , clp , factor , predict , fuzzi , network , neural , formwork , context , expert ,
b_3	region , growth , sector , per , level , employ , economi , rate , econom , energi ,
b_4	chang , schedul , loss , overtim , impact , project , contractor , work , shift , order
b_5	growth , hous , popul , economi , clp , china , sector , wage , market , countri ,
b_6	concret , process , wall , cost , form , print , structur , unit , technolog , brick ,
b_7	agricultur , integr , econom , technolog , plan , engin , structur , new , promot , innov ,
b_8	research , clp , review , framework , articl , literatur , futur , previou , studi , train ,
b_9	inform , autom , bim , design , track , technolog , challeng , benefit , build , decis ,
b_{10}	practic , manag , build , project , safeti , implement , phase , materi , tool , data ,
C	data , base , system , model , activ , worker , valu , two , present , propos ,
c_1	industri , carbon , emiss , build , china , environment , prefabr , provinc , energi , peak ,
c_2	manag , motiv , osc , theori , skill , theoret , remuner , personnel , format , busi ,
c_3	action , recognit , worker , activ , object , monitor , locat , accuraci , interact , copq ,
c_4	relationship , wage , loyalti , job , aptitud , test , variabl , gross , rate , fiveminut ,
c_5	sleep , plan , probabl , firm , einvoic , associ , ciw , invoic , otr , softwar ,

Table 2.10 presents a partial depiction of the time-dependent results obtained from the HLDA model. To analyze the trends of topics over time, the HLDA model generates the topic, topic layer, and stems of each topic for different time periods. The length of each period in the HLDA model varies, as the number of CLP-related literature from distant years is limited and the research focus and theories differ significantly from older literature. Consequently, earlier literature exhibits higher generality, and the time intervals for analysis are set at 10-year intervals before 2000, 5-year intervals before 2010, and yearly intervals after 2010. Other years' data are presented in Table 2.11.

Table 2.10 Top 10 high-frequency stems of time dependent result

2021	
TP 0_LV 0 (doc 38)*	project , develop , factor , use , industri , affect , model , improv , research ,
TP 1_LV 1 (doc 7)	million , tool , fall , correl , ncd , techniqu , process , protect , accid , number ,
TP 2_LV 2 (doc 3)	renov , thi , lean , research , emiss , cle , equip , reduc , four , energi ,
TP 12_LV 2 (doc 4)	practic , safeti , hrm , smp , provid , ten , enhanc , death , thousand , show ,
TP 4_LV 1 (doc 19)	worker , base , studi , skill , statist , analysi , thi , review , data , commun ,
TP 5_LV 2 (doc 7)	factor , pandem , bim , particip , firm , specif , indic , identifi , within , previou ,
TP 8_LV 2 (doc 4)	clp , select , strategi , sme , predict , four , enhanc , limit , address , support ,
TP 11_LV 2 (doc 2)	durat , area , countri , floor , unit , influenc , compar , weather , state , topic ,
TP 16_LV 2 (doc 3)	industri , job , gross , variabl , clp , new , workplac , ict , applic , workforc ,
TP 17_LV 2 (doc 3)	rework , method , cost , flowlin , process , residenti , problem , work , decreas ,
TP 9_LV 1 (doc 12)	environment , polici , case , approach , base , higher , quantifi , impact , emiss ,
TP 10_LV 2 (doc 4)	worker , health , motiv , issu , mental , work , caus , lead , percept , order ,
TP 15_LV 2 (doc 2)	estim , budget , oper , propos , simul , reliabl , cost , analyt , cumul , point ,
TP 20_LV 2 (doc 4)	learn , mushroom , hous , grow , tallwood , enterpris , analysi , prefabr , innov ,
TP 21_LV 2 (doc 2)	slag , wast , buildabl , provid , ash , power , experi , composit , slab , plant ,
2022	
TP 0_LV 0 (doc 59)	factor , use , project , studi , model , work , develop , method , data , result ,
TP 1_LV 1 (doc 8)	promot , support , mfb , requir , examin , genet , resourc , type , demotiv ,
TP 2_LV 2 (doc 4)	motiv , clp , satisfact , effect , autonom , related , compet , worker , leadership ,
TP 18_LV 2 (doc 4)	valu , output , region , base , kmdayperson , algorithm , correspond , softwar ,
TP 3_LV 1 (doc 17)	manag , review , knowledg , research , analys , time , variou , limit , paper ,
TP 4_LV 2 (doc 3)	osc , skill , manag , requir , system , renov , nvaw , deriv , futur , autom ,
TP 5_LV 2 (doc 3)	pandem , covid , overrun , rail , may , cost , loss , employ , era , dure ,
TP 6_LV 2 (doc 6)	subject , propos , case , framework , offshor , expert , increas , modular , takt ,
TP 20_LV 2 (doc 5)	clp , industri , import , rii , questionnair , articl , analysi , masonri , consist ,
TP 12_LV 1 (doc 22)	industri , safeti , manag , region , show , improv , provid , indic , high ,
TP 13_LV 2 (doc 6)	model , predict , activ , machin , formwork , clp , learn , algorithm , accuraci ,

TP 14_LV 2 (doc 4)	develop , economi , growth , sec , realiti , market , electr , new , chang , see ,
TP 19_LV 2 (doc 6)	carbon , emiss , industri , predict , provinc , network , total , jiangsu , accid ,
TP 21_LV 2 (doc 6)	strategi , framework , improv , adopt , pcc , technolog , motiv , propos , design ,
TP 16_LV 1 (doc 12)	variou , claim , mani , poor , geospati , reliabl , context , static , investig ,
TP 17_LV 2 (doc 8)	chang , order , loss , impact , quantifi , contractor , project , delay , parti ,
TP 22_LV 2 (doc 4)	monitor , technolog , design , autom , inform , erect , wall , lidar , brick ,
2023	
TP 0_LV 0 (doc 31)	factor , model , use , project , studi , research , develop , predict , build , data ,
TP 1_LV 1 (doc 21)	industri , thi , materi , activ , improv , schedul , indic , increas , challeng ,
TP 2_LV 2 (doc 3)	bim , adopt , system , kanban , logist , manag , mmc , plan , design , demand ,
TP 4_LV 2 (doc 4)	activ , clp , research , articl , formwork , review , previou , techniqu , method ,
TP 9_LV 2 (doc 3)	cost , group , clp , project , skill , worker , way , lower , individu , investig ,
TP 10_LV 2 (doc 5)	growth , sector , technolog , regul , one , competit , micro , field , countri ,
TP 16_LV 2 (doc 3)	pcmp , develop , requir , multistori , printer , print , concret , cpm , addit ,
TP 19_LV 2 (doc 3)	analysi , impact , result , congest , daubert , due , loss , uncertainti , method ,
TP 7_LV 1 (doc 10)	data , improv , wast , case , among , task , contribut , measur , gener , implic ,
TP 8_LV 2 (doc 5)	worker , risk , sleep , qualiti , industri , offsit , poor , strategi , advers , foreign ,
TP 12_LV 2 (doc 5)	weather , impact , tropic , cost , type , rate , climat , variabl , main , two ,

Table 2.11 10 high-frequency stems of time dependent result from 1973 to 2020

1973_1990		
TP=0 LV=0 (doc=27)		factor , work , rate , develop , method , measur , increas , project , improv ,
TP=1	LV=1	plan , index , rise , base , gener , fund , analysi , measur , statist , major ,
TP=2	LV=2	energi , price , model , new , organ , effect , suppli , aggreg , countri , evalu ,
TP=3	LV=1	model , work , possibl , worker , describ , oper , affect , improv , well , camcord ,
TP=4	LV=2	manag , sampl , techniqu , studi , data , work , use , fiveminut , present , crew ,
TP=11	LV=2	excav , profit , make , hous , earthrock , system , qualiti , britain , hydraul ,
TP=7	LV=1	contract , index , manhour , condit , necessari , discuss , given , engin , indic ,
TP=8	LV=2	site , concret , equip , instal , weather , type , plant , materi , contractor , cost ,
TP=15	LV=2	popul , resourc , need , strategi , plan , economi , activ , growth , balanc , effort ,
1991~2000		
TP=0 LV=0 (doc=32)		cost , use , data , chang , studi , perform , present , industri , improv , factor ,
TP=3	LV=1	work , project , analysi , impact , industri , develop , materi , examin , reduc ,
TP=4	LV=2	trend , task , approach , increas , technolog , indic , valu , subsequ , differ , direct ,
TP=5	LV=2	effici , loss , studi , three , day , number , deliveri , hour , per , percentag ,
TP=46	LV=2	system , weather , activ , estim , schedul , mode , approach , price , provid ,
TP=70	LV=2	vacuum , system , site , buildabl , central , result , build , model , score , dustcont ,
TP=7	LV=1	project , develop , manag , work , thi , indic , equip , level , two , major ,
TP=8	LV=2	contractor , oper , french , firm , concret , level , least , german , build , countri ,
TP=68	LV=2	program , drawbench , size , number , oper , draw , combust , flow , esp , pipe ,
TP=79	LV=2	region , databas , distribut , employ , variabl , measur , motiv , compar , incom ,
TP=82	LV=2	wage , rural , urban , bangkok , mine , area , growth , chines , high , opencast ,
2001~2005		
TP=0 LV=0 (doc=33)		project , chang , impact , factor , time , result , studi , contractor , data , research ,
TP=1	LV=1	use , work , present , thi , loss , schedul , develop , identifi , problem , cost ,
TP=3	LV=2	model , thermal , predict , fuzzi , environ , network , expert , estim , illustr ,
TP=7	LV=2	overtim , mechan , overman , analysi , compress , improv , quantit , locat , shift ,

TP=8	LV=2	measur , claim , method , mile , approach , baselin , object , period , way , avail ,
TP=9	LV=2	site , import , consult , late , earli , deliveri , time , supplier , overrun , five ,
TP=12	LV=2	estim , process , must , bridg , four , condit , actual , unit , case , workforc ,
TP=14	LV=2	theori , manag , motiv , decis , higher , factor , hierarchi , process , make , thi ,
TP=15	LV=2	contract , design , buildabl , build , score , adjust , cumul , alter , potenti , electron ,
TP=4	LV=1	posit , formwork , signific , correl , reveal , mtf , compon , use , manufactur ,
TP=5	LV=2	technolog , improv , varianc , equip , understood , measur , comparison , thi ,
TP=17	LV=2	wage , rate , public , new , invest , cyclic , capit , vessel , real , growth ,
2006~2010		
TP=0 LV=0 (doc=66)		project , use , research , method , manag , thi , industri , effect , improv , studi ,
TP=3	LV=1	qualiti , congest , system , result , flow , effici , theori , often , reveal , machineri ,
TP=4	LV=2	space , approach , crew , organ , interact , individu , emerg , shown , higher ,
TP=25	LV=2	weld , fix , joint , learn , rebar , cage , cycl , floor , assembl , reinforc ,
TP=26	LV=2	equip , produc , facil , sector , per , economi , employ , incom , period , experienc ,
TP=27	LV=2	commun , human , issu , handsfre , need , field , hand , walkietalki , test , worker ,
TP=5	LV=1	project , use , data , model , practic , result , analysi , present , cost , base ,
TP=6	LV=2	buildabl , effect , factor , formwork , design , thi , effici , influenc , activ , reinforc ,
TP=9	LV=2	build , track , system , autom , design , technolog , indic , convent , comparison ,
TP=10	LV=2	perform , benchmark , measur , improv , indic , standard , index , activ , nation ,
TP=13	LV=2	schedul , overtim , shift , impact , compress , quantit , contractor , occasion ,
TP=23	LV=2	methodolog , disrupt , parti , claim , chang , caus , lost , lack , paper , countri ,
TP=15	LV=1	survey , rel , questionnair , perspect , throughout , work , physic , investig , engin ,
TP=16	LV=2	factor , worker , craft , impact , affect , differ , effort , group , report , compar ,
TP=17	LV=1	develop , demand , make , wage , manpow , relationship , save , possibl ,
TP=18	LV=2	industri , china , factor , data , level , resourc , countri , chines , human , firm ,
TP=19	LV=1	condit , qualiti , major , complet , although , flow , load , ten , valu , rate ,
TP=20	LV=2	hous , econom , chongq , industri , develop , citi , transform , china , dual , market ,
TP=21	LV=2	work , data , analysi , loss , wast , limit , basi , methodolog , decis , finnish ,
2011		
TP=0 LV=0 (doc=22)		factor , project , work , perform , research , data , thi , model , improv , affect ,
TP=1	LV=1	industri , time , major , analys , program , formwork , main , manag , effect ,
TP=2	LV=2	studi , key , period , method , constraint , similar , level , survey , dure ,
TP=9	LV=2	learn , collect , input , buildabl , import , floor , design , influenc , literatur , base ,
TP=3	LV=1	influenc , predict , ann , error , factor , reliabl , result , rate , model , condit ,
TP=4	LV=2	rate , estim , site , develop , fragment , network , weather , neural , record , reliabl ,
TP=5	LV=1	chines , compar , standard , clp , countri , evalu , contribut , inform , level , cross ,
TP=6	LV=2	activ , locat , acceleromet , recognit , use , select , framework , bodi , perform ,
TP=10	LV=2	growth , industri , factor , norm , countri , provid , poor , sector , figur , across ,
TP=7	LV=1	process , valu , flow , one , base , manag , qualiti , complet , level , total ,
TP=8	LV=2	manag , lift , plan , site , work , effici , oper , consid , studi , qualit ,
2012		
TP=0 LV=0 (doc=16)		thi , use , research , data , method , present , improv , provid , paramet , result ,
TP=5	LV=1	system , expert , daili , oper , base , import , factor , affect , develop , inform ,
TP=7	LV=2	fuzzi , model , perform , industri , estim , variabl , chang , network , address ,
TP=8	LV=2	factor , concret , buildabl , influenc , effici , reinforc , instal , effect , cost , oper ,
TP=10	LV=1	project , perform , plan , worker , program , cost , use , sustain , workfac , studi ,
TP=12	LV=2	industri , perform , matur , practic , measur , key , develop , cim , model ,

TP=71	LV=2	floor , activ , learn , first , model , steel , formwork , rate , bim , connect ,
TP=72	LV=2	sector , spain , growth , contribut , econom , global , neg , migrant , whilst , effect ,
2013		
TP=0 LV=0 (doc=17)		project , use , develop , manag , practic , improv , effect , perform , impact ,
TP=1	LV=1	factor , improv , industri , affect , survey , research , studi , materi , thi ,
TP=2	LV=2	among , zombi , issu , india , poor , research , group , organis , need , tradit ,
TP=4	LV=2	model , propos , system , measur , approach , dynam , influenc , differ , egypt ,
TP=5	LV=2	object , worker , action , recognit , interact , site , human , schedul , optim , work ,
TP=8	LV=2	build , floor , activ , learn , first , percent , econom , structur , financi , organ ,
TP=22	LV=2	modular , facil , best , process , index , equip , complet , pharmaceut , design ,
TP=24	LV=2	order , chang , bayesian , network , build , bimipd , model , caus , design , reduc ,
2014		
TP=0 LV=0 (doc=23)		project , factor , develop , identifi , level , model , provid , data , critic , present ,
TP=3	LV=1	industri , manag , research , studi , use , work , effect , improv , result , signific ,
TP=4	LV=2	affect , categori , primari , depend , rank , overal , compris , follow , among ,
TP=5	LV=2	shift , sewer , night , pile , day , oper , result , activ , traffic , instal ,
TP=6	LV=2	clp , framework , implement , paper , propos , benchmark , activ , tmiblp ,
TP=7	LV=2	estim , optim , frontier , approach , oper , thi , actual , ineffici , determin , effici ,
TP=8	LV=2	effect , paramet , financi , crisi , direct , state , influenc , indirect , perspect ,
TP=9	LV=2	level , metric , mean , growth , canada , differ , output , estim , cost , data ,
TP=17	LV=2	solar , schedul , system , apbsa , time , environ , plant , air , durat , eor ,
2015		
TP=0 LV=0 (doc=24)		factor , project , manag , use , develop , thi , work , studi , perform , result ,
TP=1	LV=1	use , industri , rang , project , data , research , benchmark , perform , simul , initi ,
TP=2	LV=2	year , achiev , temperatur , experi , optim , analysi , total , plot , box , respond ,
TP=16	LV=2	procedur , bim , model , impact , kpi , best , must , multipl , question , rfi ,
TP=17	LV=2	ceo , studi , copq , compani , percept , first , perceiv , iran , highlight , reduc ,
TP=3	LV=1	process , formwork , simul , game , plan , highris , student , suggest , propos ,
TP=4	LV=2	learn , curv , build , work , research , specif , theori , applic , evalu , case ,
TP=5	LV=1	industri , delay , project , signific , design , low , countri , contractor , effici ,
TP=6	LV=2	lack , affect , score , object , skill , rel , follow , thailand , chang , index ,
TP=9	LV=1	region , countri , climat , craft , present , time , health , turkey , worker , perspect ,
TP=11	LV=2	coal , equip , vietnam , industri , mine , develop , manual , modern , occup ,
TP=13	LV=2	model , predict , network , neural , factor , input , better , influenti , laborforc ,
2016		
TP=0 LV=0 (doc=30)		project , use , research , model , time , manag , method , result , thi , studi ,
TP=1	LV=1	factor , site , use , technolog , survey , develop , increas , activ , simul , explor ,
TP=2	LV=2	learn , floor , build , buildabl , number , curv , theori , cycl , determin , techniqu ,
TP=7	LV=2	region , level , dispar , converg , monthli , per , frontier , territori , rate , employe ,
TP=3	LV=1	manual , propos , purpos , estim , simul , cycl , site , task , oper , system ,
TP=4	LV=2	logist , materi , path , empir , comput , match , global , prior , posit , improv ,
TP=6	LV=2	model , clp , use , activ , context , wsp , contextspecif , approach , predict , factor ,
TP=8	LV=1	factor , worker , increas , level , affect , motiv , impact , overrun , data , low ,
TP=9	LV=2	build , industri , inform , metric , statist , index , sourc , mean , reveal , usag ,
TP=10	LV=2	overtim , crew , schedul , effect , variabl , perform , object , consid , three , incent ,
TP=11	LV=1	time , result , increas , year , decreas , data , train , work , hazard , direct ,
TP=12	LV=2	rebar , growth , prefabr , reduc , tie , electr , contractor , gun , experi , worker ,

2017	
TP=0 LV=0 (doc=26)	project , use , data , industri , improv , studi , research , perform , contractor , thi ,
TP=1 LV=1	activ , factor , collect , sustain , influenc , support , analysi , base , wide , measur ,
TP=2 LV=2	practic , implement , equip , model , develop , manag , overtim , multistori ,
TP=7 LV=2	estim , framework , measur , valu , formwork , frontier , floor , effici , approach ,
TP=3 LV=1	model , propos , heat , type , result , environ , job , path , explor , hot ,
TP=4 LV=2	worker , condit , work , stress , psycholog , differ , caus , experi , schedul , show ,
TP=11 LV=2	loyalti , bim , adopt , scc , cost , concret , throughout , relationship , convent ,
TP=5 LV=1	valu , structur , base , analysi , affect , technolog , mcp , activ , discuss , analys ,
TP=6 LV=2	factor , collect , identifi , fca , trade , done , thi , major , relat , declin ,
TP=8 LV=2	model , differ , factor , dynam , approach , propos , simul , fuzzi , effect , context ,
TP=9 LV=2	inequ , normal , correl , excess , real , invest , level , develop , gini , coeffici ,
2018	
TP=0 LV=0 (doc=41)	project , factor , use , studi , research , industri , thi , manag , improv , work ,
TP=1 LV=1	procur , equip , control , loss , cost , ahp , prioriti , done , along , issu ,
TP=5 LV=2	structur , plan , facil , intens , layout , temporari , account , unit , sem , otr ,
TP=9 LV=2	concret , dprint , case , lost , term , present , consider , quantif , difficult ,
TP=3 LV=1	develop , system , motiv , base , indic , remuner , busi , methodolog , compani ,
TP=4 LV=2	clp , economi , real , intern , nomin , alway , statist , differ , ppp , organ ,
TP=12 LV=2	model , context , tool , clp , predict , chang , adapt , exist , dynam , estim ,
TP=19 LV=2	cost , overrun , risk , respond , valu , road , west , simul , bank , particip ,
TP=7 LV=1	time , dure , identifi , execut , understand , number , particularli , research , base ,
TP=8 LV=2	work , worker , affect , machin , valu , experi , stressor , ani , essenti , site ,
TP=10 LV=1	oper , logist , control , optim , complex , twoprong , action , task , estim , evalu ,
TP=11 LV=2	manag , strategi , safeti , result , gener , relationship , relat , includ , address ,
TP=14 LV=1	welfar , site , qualiti , amen , cent , artisan , flow , address , deliveri , priorit ,
TP=15 LV=2	identifi , build , multistorey , step , context , phase , health , could , equip , four ,
TP=16 LV=1	assess , industri , lean , across , schedul , petrochem , barrier , challeng , approach ,
TP=17 LV=2	chang , framework , tempor , investig , evalu , structur , method , effici , causal ,
2019	
TP=0 LV=0 (doc=51)	project , work , factor , use , industri , research , studi , worker , site , thi ,
TP=3 LV=1	process , improv , learn , prefabr , new , chang , estim , compar , inform , vietnam ,
TP=4 LV=2	agricultur , technolog , rural , integr , develop , engin , promot , revit , main ,
TP=18 LV=2	growth , transform , employ , per , structur , decomposit , paper , effect , aggreg ,
TP=19 LV=2	caus , oper , contribut , variabl , model , approach , sign , nation , earli , frontier ,
TP=5 LV=1	machin , ensur , congest , account , direct , cost , implement , instal , complex ,
TP=6 LV=2	build , green , crew , environment , mechan , increas , innov , invest , industri ,
TP=21 LV=2	human , paramet , strength , work , mine , assess , technolog , mass , categori ,
TP=8 LV=1	relev , method , manag , factor , predict , propos , inform , current , monitor ,
TP=9 LV=2	practic , materi , safeti , health , build , phase , implement , data , dure , tool ,
TP=12 LV=2	model , techniqu , network , use , neural , oper , outperform , worker , regress ,
TP=10 LV=1	inform , manag , interview , group , igcw , curv , client , perform , projectspecif ,
TP=11 LV=2	data , approach , behavior , theori , support , fusion , sourc , type , monitor , queri ,
TP=13 LV=1	factor , group , manag , caus , top , rank , survey , countri , technic , categori ,
TP=14 LV=2	among , affect , motiv , influenc , employe , distribut , factor , challeng , manag ,
TP=15 LV=1	wage , state , survey , especi , reason , attribut , characterist , success , employ ,
TP=17 LV=2	form , variou , system , hang , complet , purlin , bridg , girder , loss , slab ,

2020		
TP=0 LV=0 (doc=55)		use , project , model , thi , result , industri , develop , data , factor , work ,
TP=1	LV=1	factor , studi , research , survey , affect , identifi , critic , improv , rate , site ,
TP=2	LV=2	durat , estim , simul , propos , valu , worker , activ , formwork , determin , due ,
TP=3	LV=2	worker , influenc , divers , motiv , clp , among , workforc , commut , employe ,
TP=9	LV=2	techniqu , predict , network , neural , regress , grnn , domain , petrochem ,
TP=12	LV=2	project , build , manag , practic , rework , materi , import , frequenc , questionnair ,
TP=33	LV=2	region , individu , posit , effect , dynam , enterpris , extern , recommend , bim ,
TP=37	LV=2	process , tunnel , determin , analys , statist , requir , print , structur , worksampl ,
TP=4	LV=1	build , prefabr , environment , factor , polici , econom , show , sector , provinc ,
TP=5	LV=2	carbon , industri , energi , emiss , peak , china , consumpt , rate , scenario , intens ,
TP=14	LV=2	temperatur , vulner , masonri , weather , area , adhes , condit , influenc , hot ,
TP=34	LV=2	cost , plant , firm , sleep , einvoic , nuclear , expect , invoic , associ , weekend ,
TP=6	LV=1	statist , scaffold , crew , thi , pipe , term , trade , teamwork , often , could ,
TP=7	LV=2	clp , improv , framework , predict , select , featur , strategi , propos , factor ,

* TP represents topics, LV represents layers, and doc refers to the number of documents.

2.4 Discussion

2.4.1 Topic analysis

The stems of the main topics in the CLP literature reveal key themes and focus areas within the field. The analysis shows that industrial aspects, work-related factors, and performance improvement are the most frequently discussed topics, with the stems “industri,” “work,” and “improv” having the highest occurrence frequencies, respectively. This suggests that researchers and practitioners in the construction industry are highly concerned with enhancing productivity and efficiency. Other significant themes include factors influencing productivity, such as development, effects, and research findings, as indicated by the stems “factor,” “develop,” and “effect”. Additionally, the analysis highlights the importance of measuring and analyzing performance, cost, and efficiency, as evidenced by the stems “perform,” “cost,” and “effici.” By summarizing the stems in the model, specific descriptions of each topic could be identified.

Topic A (Optimizing construction management and scheduling): This topic focuses on various aspects of management, including data modeling, collection, and analysis, proposing practical approaches to determine and compare project activities, evaluating the impact of systems and practices, and presenting results to optimize construction operations and scheduling with a focus on efficiency and value.

Topic a_1 (Worker performance and motivation in construction): This topic examines factors influencing worker performance and motivation in construction, focusing on project management, skill analysis, workforce participation, and the impact of delays on labor productivity.

Topic a_2 (Efficiency in design and construction processes): This topic explores buildability, formwork, concrete design efficiency, and reinforcement’s impact on construction activities, including floor levels, beam objects, and curved structures’ influence on overall efficiency.

Topic a_3 (Operational resilience in heavy industries): This topic explores cost containment, program metrics, plant maintenance, and process improvements, with a focus on petrochemical, nuclear, and mechanized industries. The goal is to identify trends, improve operational resilience, and manage outages efficiently.

Topic a_4 (Technological advancements in mining operations): This topic delves into technological advancements in mining methods, equipment, and systems, focusing on underground coal mining in and efforts to streamline operations, reduce energy consumption, and optimize resource utilization.

Topic a_5 (Sustainable practices in construction materials and logistics): This topic investigates construction materials, logistics, waste management, and sustainable energy solutions like solar and wind to improve efficiency and reduce transportation-related inefficiencies.

Topic a_6 (Efficiency in pharmaceutical manufacturing and construction): This topic focuses on the installation, layout, and control of facilities, equipment, and machinery, including modular and temporary structures, to optimize production processes and ensure efficient pharmaceutical manufacturing and construction operations.

Topic a_7 (Enhancing construction education through simulation): This topic involves the use of learning tools and simulations to enhance rebar tying skills, save time and costs, improve student training, and simulate real-world scenarios for dynamic and repetitive tasks in construction and education.

Topic a_8 (Vacuum cyclone technology in construction): This topic explores a system and method for vacuum cyclone technology to enhance worker tasks through automated and hands-free operations, improving efficiency and ergonomics on the job site.

Topic a_9 (Frontier approaches to construction efficiency): This topic focuses on optimizing efficiency in operations through a frontier approach, utilizing a framework for task estimation and strategies, exploring pilot studies and algorithms to achieve efficiency improvements in labor-intensive tasks.

Topic a_{10} (Assessing masonry performance under various conditions): This topic examines the influence of various parameters, such as weld strength, joint age, and temperature, on the performance of masonry structures, including factors like reinforcement, adhesives, and failure conditions.

Topic a_{11} (Performance assessment in construction post-COVID-19): This topic focuses on performance assessment using various indices, including benchmarks, manhours, and key performance indicators (KPIs), to analyze factors like thermal effects, lean principles, and trade predictions, even considering the impact of external events like COVID-19.

Topic B (Data-driven models and systems in construction): This topic encompasses research related to the development, management, and analysis of data-driven models and systems, with a focus on identifying and evaluating various approaches and methodologies to predict and measure the impact of different variables on the research outcomes.

Topic b_1 (Impact of weather and climate on construction workers): This topic focuses on the impact of weather and climatic conditions, such as high temperatures, heat stress, and humidity, on workers' health, mental state, and productivity in outdoor construction environments.

Topic b_2 (Predictive modeling in construction labor productivity): This topic explores predictive modeling in CLP, using techniques like neural networks, fuzzy networks, and artificial intelligence, with a focus on formwork and expert knowledge integration for accurate predictions.

Topic b_3 (Regional economic growth and construction): This topic investigates regional economic growth, including factors such as employment rates, energy consumption, income disparities, and financial structures, with a focus on analyzing the effects of economic changes and crises.

Topic b_4 (Schedule changes and impact analysis): This topic explores schedule changes, overtime impact, project disruptions, and quantification of losses in terms of time, work shifts, contract claims, and accelerated durations.

Topic b_5 (Labor productivity in China): This topic examines economic growth, housing, population, and CLP in China, focusing on wage trends, market dynamics, urbanization, and regional exchange.

Topic b_6 (Concrete construction aspects): This topic explores various aspects of concrete construction, including processes, costs, formwork, printing technology, structural units, bricks, and materials such as slag and composite.

Topic b_7 (Agricultural economics, and technology integration for rural development): Integrating agriculture, economics, and technology for rural development, promoting green practices, and implementing innovative solutions.

Topic b_8 (Reviewing construction labor productivity research): CLP research review framework analyzing literature, previous studies, and key articles to reveal perspectives on regional scopes and professions.

Topic b_9 (Technological innovations in construction process optimization): This topic examines the benefits and challenges of using information automation, BIM, and design technologies for process optimization, client orders, and cost-effective decision-making, incorporating fusion, lidar, geospatial data.

Topic b_{10} (Practical aspects of construction project management): Practical construction project management involving safety, materials, tools, data, strategies, contractors, health, and logistics to enhance performance and achieve quantifiable improvements in multi-story projects.

Topic C (Data-driven worker performance management): This topic involves the use of data, system, and model to assess and manage worker performance, collecting and measuring various characteristics, and proposing and implementing practices based on the evaluation and analysis of correlations.

Topic c_1 (Carbon emission reduction in Chinese industry): Carbon Emission Reduction in Chinese Industry) This topic analyzes industrial carbon emissions in China, focusing on energy-saving policies and techniques, to reduce pollution.

Topic c_2 (Management theories and business practices): This topic explores management theories, personnel motivation, and business practices, including discussions on the social and economic aspects in Ukraine and Indonesia, and the concept of compensating skilled workers.

Topic c_3 (Worker activity recognition for performance improvement): This topic delves into worker activity recognition, utilizing accelerometer-based sensors and algorithms to monitor and analyze human interactions with objects for improved accuracy in workplace performance.

Topic c_4 (Analyzing wage and job loyalty relationships): This topic focuses on the relationship between wages, job loyalty, and variables such as aptitude tests, gross rate, and workforce demand, employing empirical analysis and various statistical techniques for investigation.

Topic c_5 (Linking sleep, work planning, and health in construction firms): This topic examines the relationship between sleep, work planning, invoicing, software, client patterns, and health intensity in firms, including radwaste and external sector impacts.

The analysis of main topics in the CLP literature reveals key themes, with a strong focus on industrial aspects, work-related factors, and performance improvement. Researchers and practitioners are particularly concerned with productivity enhancement and efficiency, while other significant themes include factors influencing productivity, cost measurement, and performance analysis (Li *et al.*, 2016). Additionally, various specific topics were identified, such as management practices, worker performance and motivation (Jarkas, 2012), construction materials (Hamza *et al.*, 2022), technological advancements, and performance assessment. Topics also explored economic growth, predictive modeling, and data-driven approaches, as well as worker health and activity recognition (Shehata and El-Gohary, 2011). The literature also highlights efforts to reduce carbon emissions, promote green practices in agriculture, and optimize worker management and performance through data analysis and system implementation.

2.4.2 Topic trend analysis

Figure 2.5 shows the number of CLP articles published from 1973 to 2023 to highlight the research trend. The vertical axis reflects the number of publications, while the horizontal axis represents the year in which the paper was published. The earliest paper related to CLP was published in 1973, which proposed an approach to estimate the CLP of hydro-technical construction and emphasized the positive effect of worker's education (Levit, 1973). Since 1985, researchers' primary concerns diversified. Instead of using methods borrowed from industrial engineering, several models have been developed to specialize in estimating CLP such as the factors-based model (Thomas and Sakarcan, 1994). Although, In the year 2021, there was a noticeable decline in the quantity of articles across various subjects. The number of publications has increased significantly since 2003 and peaked in 2022. During this period, the number of papers related to data driven model reached its peak in 2020.

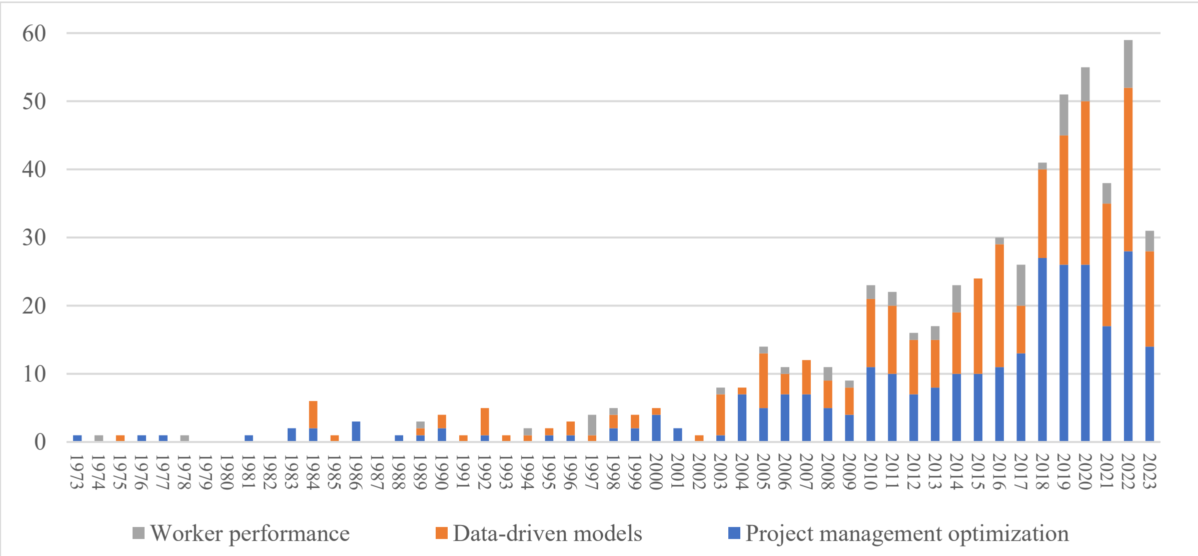

Figure 2.5 Number of articles published from 1973 to 2023

The research trend of subtopics does not necessarily follow the major topic to which it belongs, as seen by the distribution of the number of publications belonging to various subtopics over time. This article ranks subtopics by the number of papers published to examine research trends. Although the trend in sub-topic research from 1973 to 2023 is not immediately apparent, several sub-topics have seen an increase in recent years. The number of papers published under each topic from 2010 to 2023 is indicated in Table 2.12.

Table 2.12 Sub-topics ranked by the number of articles published from 2010 to 2023.

Topic	Rank	Number of papers
Performance factors affecting CLP	1	92
CLP prediction and modeling	2	37
Design factors affecting CLP	3	36
The impact of scheduling on CLP	4	36
Economic factors affecting CLP	5	23
Operational Resilience factors affecting CLP	6	17
Technological innovations on optimizing CLP	7	16
CLP in China	8	15
Reviewing CLP papers	9	15
The impact of sustainable practices on CLP	10	14

The number of articles published under the Sub-topic a_1 is 92. This is the same as in Figure 2.4, with the biggest number of published studies in the last 14 years concentrating on CLP factors identification. Although the number of articles related to management optimization has been the highest since 2010, articles related to models exhibits a greater variety of subtopics, potentially due to the diverse language used in articles focusing on CLP modeling and prediction, allowing for more distinct secondary themes. It contains articles on typical prediction and optimization of CLP. For example, (Ebrahimi *et al.*, 2021) used machine learning, hybrid feature selection, and particle swarm optimization to model CLP. There are also articles focusing on the quantification of cost risk (Hasan *et al.*, 2021) and the prediction of the impact of congestion on CLP (Dabirian *et al.*, 2021). When it comes to CLP modeling and prediction, researchers are more likely to employ a variety of modeling methodologies or to begin focusing on more specific study objectives. There have been 36 publications focused on the scheduling changes, demonstrating that more scholars are becoming interested in the influence of management practices or strategies on CLP. Under this theme, the improvement of CLP by human resource management (Gurmu and Ongkowijoyo, 2020) and safety management (Gurmu, 2021) is getting the attention of researchers. Papers related to sustainability has 14 articles published from 2010 to 2023. Articles under this theme mainly focuses on the impact of environment factors on CLP, including energy consumption (Johari and Jha, 2020).

The preceding analysis has categorized articles from 1973 to 2023 into three distinct topics**:** Topic A, which identifies factors influencing CLP; Topic B, which encompasses CLP prediction and modeling; and Topic C, focusing on data-driven methods to enhance on-site construction management practices. While this classification scheme emphasizes the form and methodology of research, it may not adequately address the purpose and subjects of the studies. Addressing this limitation, a time-dependent HLDA model was applied to segment articles across time periods from 1973 to 2023. This study has identified a total of 55 primary topics and 140 subtopics. Among these, 55 primary topics were filtered out as they represented research forms and methods, which were found to exhibit higher co-occurrence rates and were thus allocated to higher-level topics. The remaining 140 subtopics were more adept at capturing research objectives and subjects.

The subtopics were further classified into four categories based on their thematic relevance: those pertaining to workers, construction management, the environment, and macroeconomic factors. The worker-related themes encompass various aspects, including worker scheduling, overtime, team interactions, learning curves, wages, performance, incentive measures, and the influence of construction environments on workers. Themes related to construction management include scheduling, bidding, constructability, repetitive construction, building information modeling, and prefabricated construction. While there is significant overlap between worker-related and construction management themes (for instance, worker performance and wage management are integral components of on-site human resource management) separating worker-related aspects is justified by the substantial number of articles in this domain. Such separation aids in analyzing trends in worker-related literature. Environmental themes focus on energy consumption and carbon emissions. The distinction between environmental factors within worker-related themes and the environmental category lies in the former relating to the impact of construction environments on workers, while the latter pertains to the influence of human activities on the environment. Lastly, the macroeconomic category examines articles that primarily compare CLP across one or more countries or regions, emphasizing trends and statistical analyses.

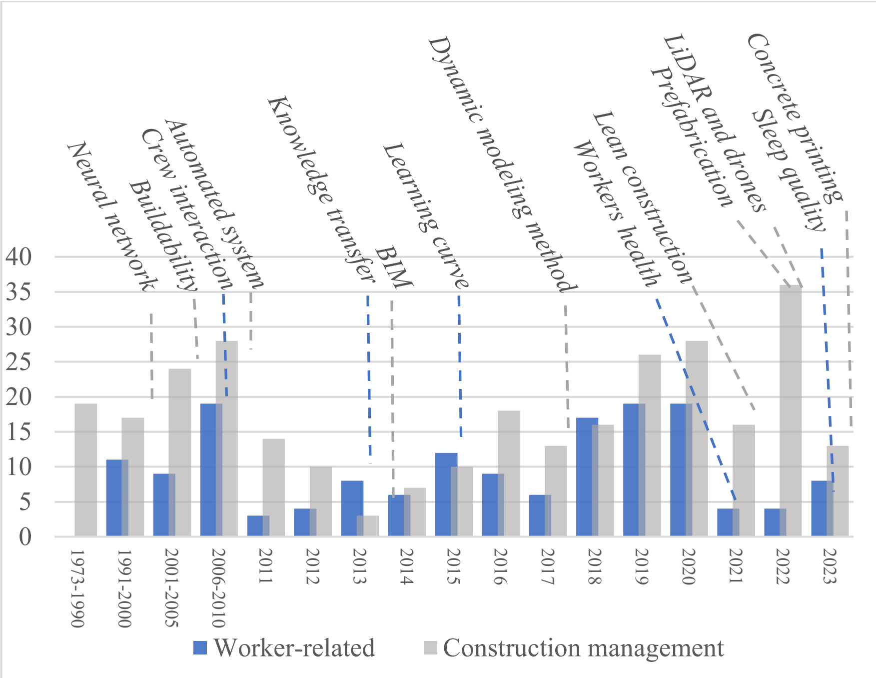

Figure 2.6 Trend of worker-related and construction management topics

As depicted in Figure 2.6, the horizontal axis represents 17 distinct time periods, while the vertical axis corresponds to the number of articles published on the respective topics. Additionally, the figure highlights temporal milestones denoting the initial emergence of key keywords. In the realm of construction management, the adoption of neural network analysis methods commenced relatively early, notably during the 1991-2000 timeframe. Subsequently, attention gravitated towards the investigatory pursuit of constructability factors within architectural design. Around 2013, the emergence of Building Information Modeling (BIM) technology became conspicuous, subsequently giving rise to a plethora of research focal points such as collaborative work processes and information-integrated delivery. In recent years, a flurry of fresh research trajectories has surfaced within the domain of construction management, encompassing lean construction principles, applications of LiDAR and drones, and advancements in concrete printing technologies. Concerning worker-related factors, notable emphasis has been directed toward scrutinizing labor conditions, efficiency, and the holistic well-being of workers. In terms of work efficiency, the year 2013 marked the application of knowledge transfer theories within CLP studies, subsequently catalyzing the enduring investigation into learning curves as an analytical methodology for discerning crew and worker learning mechanisms.

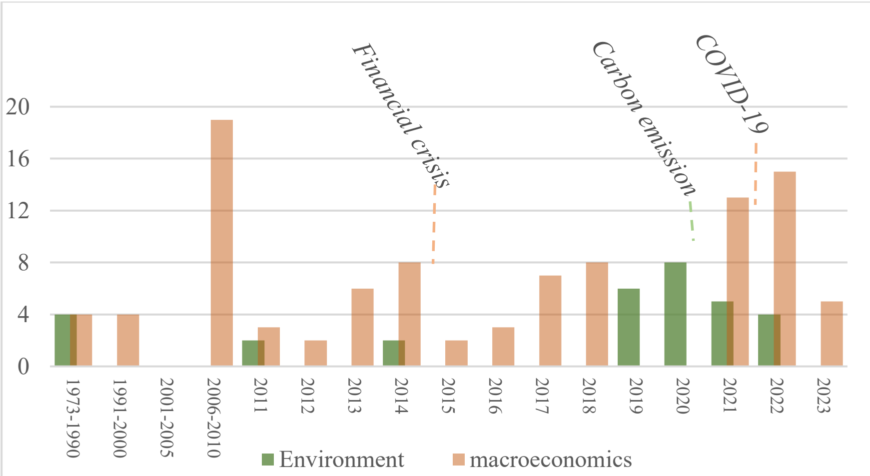

Figure 2.7 Trend of environment and macroeconomic topic

Illustrated in Figure 2.7, there is a discernible scarcity of articles within the Construction Labor Productivity (CLP) domain pertaining to macroeconomic and environmental factors. Notably, the category of macroeconomic studies demonstrates heightened global event awareness, with a notable surge observed in 2014 with articles addressing the repercussions of the financial crisis, as well as in 2021, whereby articles underscored the impact of the COVID-19 pandemic on CLP. In contrast, the domain of environmental-related studies exhibits relatively sparse overlap with CLP, with only a limited number of articles encompassed within this category. Among these, the year 2020 stands out, marked by the highest count of environmental-related articles (eight in total), predominantly focusing on themes surrounding carbon emissions.

2.4.3 Analysis of CLP modeling method

Table 2.13 Summary of research methods

Method	Number of papers	Publication and year
Machine learning	23	(Ebrahimi *et al.*, 2021; El-Gohary *et al.*, 2017; Faris Khamidi and Ahmad, 2011; Gerek *et al.*, 2015; Golnaraghi *et al.*, 2019; Heravi *et al.*, 2015; Momade *et al.*, 2020; Nasirzadeh *et al.*, 2020; Sonmez and Rowings, 1998a)
Fuzzy theory	16	(Assefa Tsehayae and Robinson Fayek, 2016; Fayek and Oduba, 2005; Kazerooni *et al.*, 2021; Nelsia *et al.*, 2020; Sarihi *et al.*, 2021; Shoar and Banaitis, 2018)
Agent-base modeling	7	(Dabirian *et al.*, 2021; Khanzadi *et al.*, 2018; Watkins *et al.*, 2009)
System dynamic modeling	4	(Al-Kofahi *et al.*, 2020; Khanzadi *et al.*, 2017; Nasirzadeh and Nojedehi, 2013a; Palikhe *et al.*, 2019)
Learning curve theory	5	(Jarkas and Horner, 2011; Jarkas, 2010)

Since 1990, researchers have begun to focus on modeling and predicting CLP. Many algorithms have also been adopted by researchers from 1990 to 2023. To examine the trend of methods adopted by researchers, this chapter summarizes articles related to models and extracts the research methods used in these articles for analysis. Table 2.13 presents the research methods employed in the articles on CLP modeling and prediction, ranked by the number of articles that utilize each method.

By categorizing and ranking articles, the top five research methods were identified. As indicated in Table 2.13, the number of researchers employing machine learning is the highest, with 23 publications (machine learning methods include artificial neural networks, support vector machines, and random forests). The artificial neural network technique was employed in 18 of the 23 papers, which is still statistically superior to the second-placed fuzzy theory approach. As shown in Table 2.13, five articles employ the learning curve theory as their research method. As can be seen, these five approaches are widely used in CLP research.

5.4 Analysis of keywords clustering

Bibliometric analysis methods, such as keyword clustering, have been widely used in literature analysis (Akinlolu *et al.*, 2022; Ezugwu *et al.*, 2021). Keyword clustering in bibliometrics organizes articles based on the frequency of co-occurrence of keywords. Figure 2.8 presents the results of a keyword clustering analysis performed using the VOSviewer software (van Eck and Waltman, 2009) on the literature covered in this study. In the figure, nodes represent keywords, and edges indicate the co-occurrence of two keywords within the same article. Due to the exclusion of standard co-occurring terms such as "construction," "labor," and "productivity," isolated nodes may appear in the visualization. The colors of the nodes and edges represent the clustering results, revealing distinct thematic groups within the CLP literature.

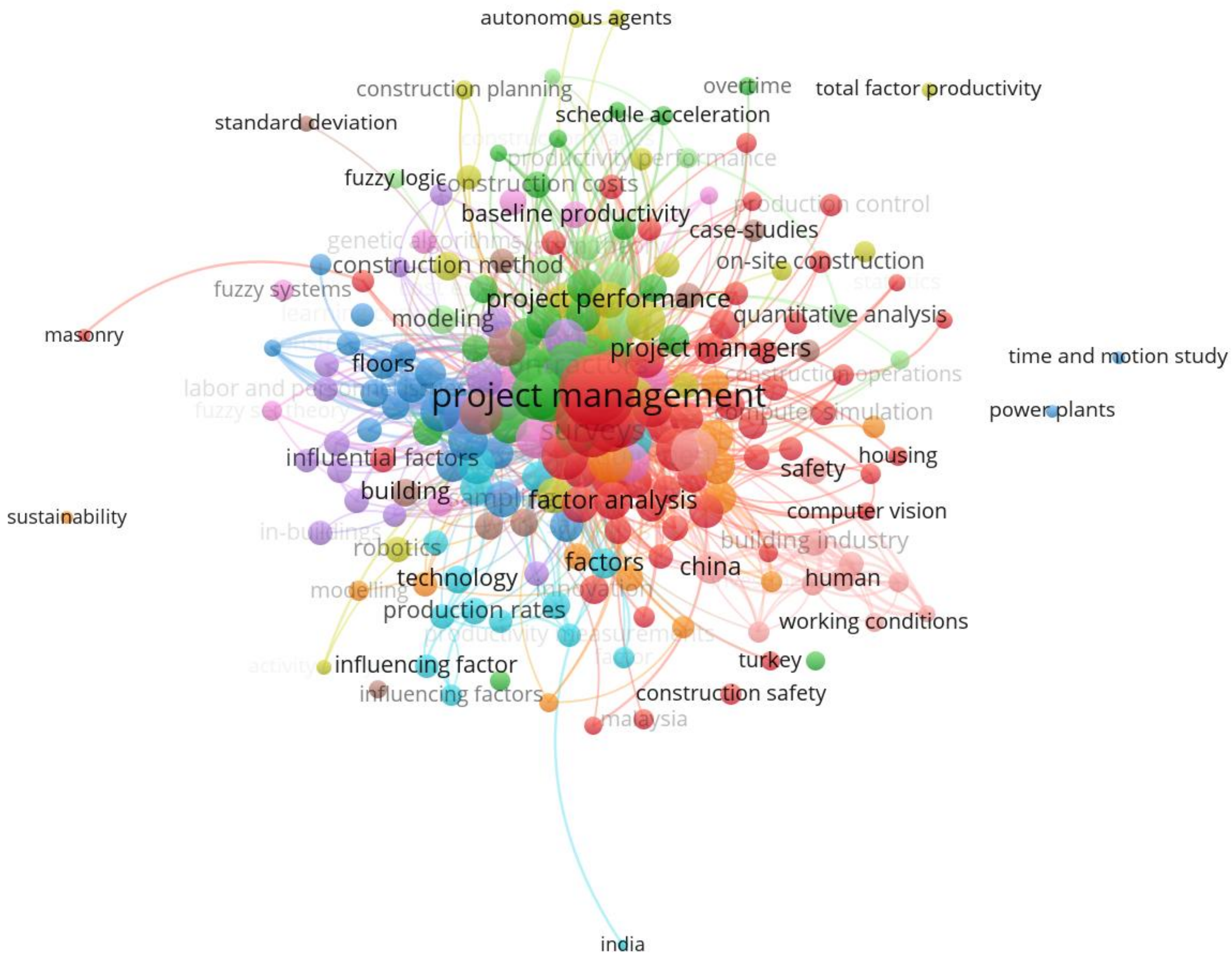

Figure 2.8 VOSviewer visualization of keyword co-occurrence network in CLP literature

It is worth noting that keyword clustering can also identify temporal trend information associated with keywords. Figures 2.9 to 2.12 present the co-occurrence networks of five keywords that have the most recent average publication years among the articles in which they appear. Figure 2.8 focuses on "COVID-19," while Figure 2.10 showcases "accident prevention" and "computer vision." Figure 2.11 highlights "lean production," and Figure 2.12 illustrates the network for "life cycle."

The analysis of the keyword-specific co-occurrence networks reveals that, apart from the highly time-sensitive topic of "COVID-19" (which was also identified by the HLDA approach), several other prominent themes have emerged in recent years within the CLP research domain. These include topics related to worker safety, artificial intelligence, construction management, and environmental concerns.

Figure 2.9 Co-occurrence network of the keyword "COVID-19"

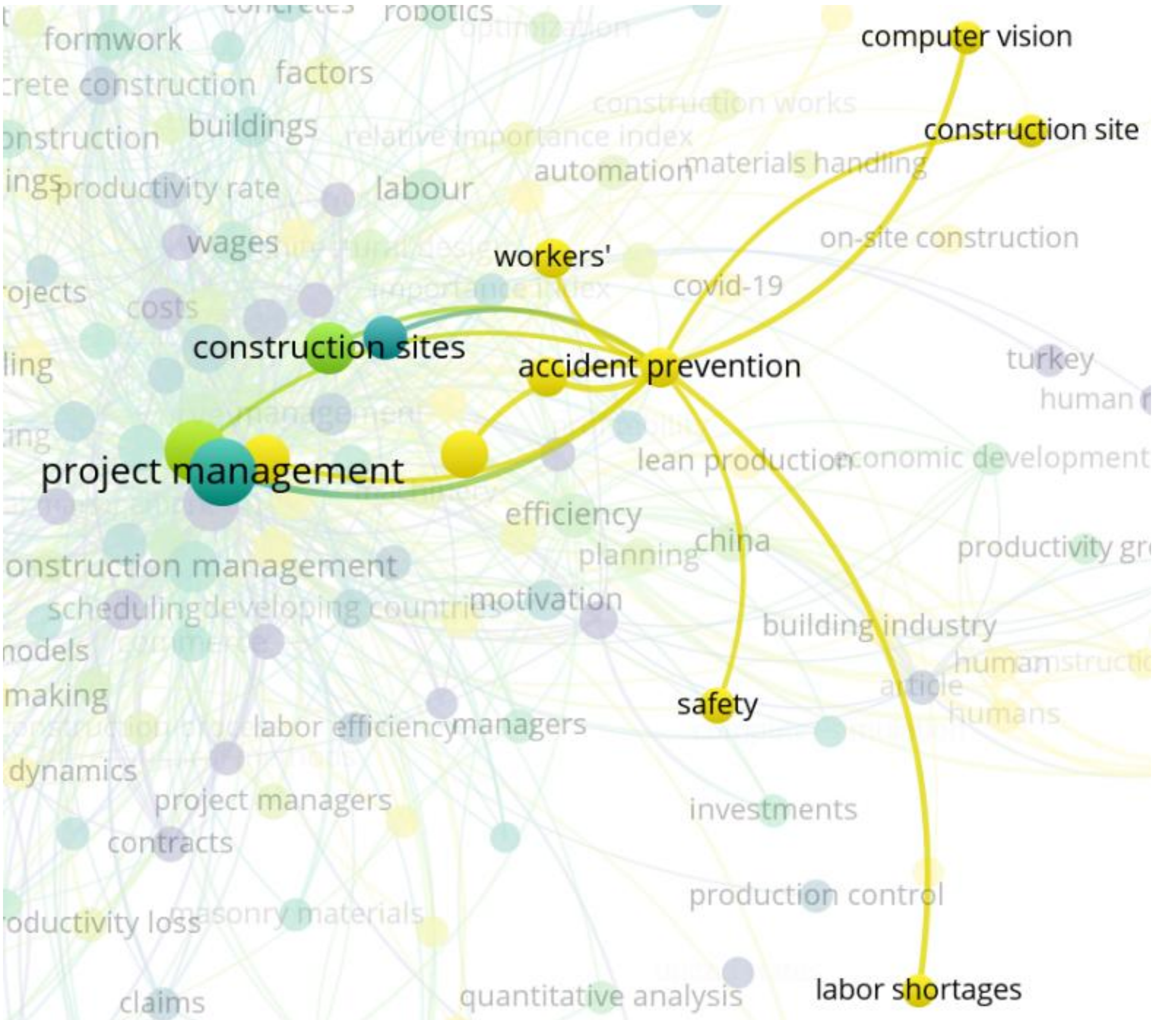

Figure 2.10 Co-occurrence network of "accident prevention" and "computer vision"

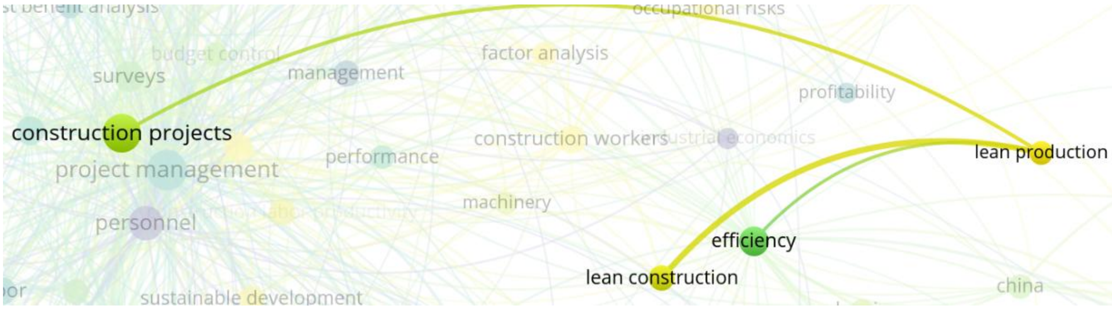

Figure 2.11 Co-occurrence network of "lean production"

Figure 2.12 Co-occurrence network of "life cycle"

Table 2.14 presents the results of keyword clustering, which categorized the keywords into 11 distinct clusters. Cluster 1 contains keywords such as "accident prevention," "construction safety," and "construction workers," indicating that this cluster is primarily related to workers and their safety. Additionally, the presence of keywords like "construction operation" and "construction works" in Cluster 1 suggests that the articles in this cluster tend to focus on the operational level of worker activities. Similarly, Cluster 2 frequently mentions terms related to "cost," such as "construction cost" and "labor cost," implying that this cluster is more concerned with construction cost issues.

However, this clustering approach also reveals some limitations. One notable issue is the lack of a hierarchical structure within the clusters. For example, Cluster 1 includes keywords related to construction safety and worker activities, as well as terms such as "human resource management" and "construction management," which fall under a broader category of construction management. This indicates that keywords with different semantic levels have been assigned to the same cluster. This discrepancy may be attributed to the author's tendency to manually categorize their articles using keywords that provide a general overview of the content. Moreover, different authors may have preferences when selecting keywords, which can lead to biases in the clustering of articles and subsequently affect further analysis.

Table 2.14 Keyword clusters in the CLP literature

Cluster	Keywords
1	accident prevention, budget control, computer simulation, computer vision, construction companies, construction environment, construction equipment, construction labour productivity, construction labours, construction management, construction operations, construction projects, construction safety, construction site, construction sites, construction workers, construction works, cost-effectiveness, covid-19, critical factors, developing countries, employee productivity, engineering research, factor analysis, housing, human resource management, importance index, improvement, influential factors, innovation, labor shortages, labor-intensive construction, lean construction, lean production, literature reviews, machinery, Malaysia, management, management strategies, managers, masonry, masonry materials, materials handling, occupational risks, on-site construction, performance, personnel, production control, productivity factors, productivity loss, project management, project managers, questionnaire surveys, relative importance index, statistics, surveys, turkey, variability, work hours, workers,
2	building materials, commerce, concrete, construction contractors, construction costs, construction trades, contractors, contracts, cost accounting, cost-benefit analysis, cost estimating, employment, human resources, labor costs, learning systems, mathematical models, overtime, prefabrication, productivity rate, quality control, regression analysis, schedule acceleration, schedule compression, scheduling, statistical methods, structural design, wages,
3	buildability, building construction, concrete buildings, concrete construction, constructability, construction manager, design, floors, formwork, labor-intensive, learning algorithms, learning curve theory, learning curves, power plants, rationalization, reinforced concrete, sampling, standardization, time and motion study, work sampling,
4	activity analysis, autonomous agents, benchmarking, Canada, civil engineering, computational methods, construction method, construction performance, construction planning, construction process, industrial construction, labor efficiency, labor, productivity improvements, productivity performance, project performance, robotics, total factor productivity, united states,
5	building construction projects, construction activities, construction firms, construction professionals, construction projects, costs, high-rise buildings, high-rise building constructions, in-buildings, labor and personnel issues, personnel issues, probability, productivity data, research, research studies, risk assessment, tall buildings,
6	artificial neural network, data acquisition, data collection, estimation, factor, factors, India, industrial management, influencing factor, influencing factors, measurement, neural networks, office buildings, production rates, productivity measurements, technology,
7	analytical hierarchy process, Australia, construction sectors, economics, industrial economics, investments, job satisfaction, modeling, motivation, personnel training, planning, productivity growth, sustainability, sustainable development,
8	architectural design, automation, building, building information modeling, buildings, case studies, modular construction, optimization, performance assessment, profitability, standard deviation,
9	artificial intelligence, baseline productivity, building projects, construction labor productivity, decision making, forecasting, fuzzy set theory, fuzzy systems, genetic algorithms, life cycle, Monte Carlo methods,
10	article, building industry, China, construction worker, economic development, efficiency, human, humans, male, safety, working conditions,
11	change orders, claims, discrete event simulation, fuzzy logic, modeling, quantitative analysis, sensitivity analysis, simulation, system dynamics, system theory,

The clustering approach used in VOSviewer is a community detection algorithm that is influenced by two parameters: the minimum cluster size and the resolution parameter. These parameters allow for manual control over the minimum number of keywords in each cluster and the average degree of clustering (higher resolution values result in more evenly distributed keywords across clusters). Table 2.15 presents the results obtained when both parameters are set to their default value of 1, revealing that the number of clusters reaches 86, with a significant portion of these clusters containing only a single keyword.

Table 2.15 Keyword clusters obtained from VOSviewer using default parameter settings (minimum cluster size = 1, resolution = 1)

Cluster	Keywords
1	budget control, commerce, construction activities, construction equipment, construction labor productivity, construction management, construction projects, construction sites, construction workers, contractors, cost accounting, cost-benefit analysis, cost-effectiveness, costs, developing countries, employment, human resource management, importance index, industrial management, labor, labor costs, personnel, productivity improvements, productivity rate, project management, questionnaire surveys, regression analysis, research, scheduling, surveys, tall buildings, tall buildings, wages,
2	architectural design, buildability, building, buildings, concrete buildings, concrete construction, concrete, constructability, design, design/methodology/approach, floors, formwork, labor-intensive, rationalization, reinforced concrete, standardization,
3	article, building industry, China, construction worker, economic development, efficiency, human, humans, male, working conditions,
4	artificial neural network, forecasting, influencing factor, influencing factors, neural networks, production rates, sampling, work sampling,
5	accident prevention, computer vision, construction site, literature reviews, occupational risks, performance, workers',
6	benchmarking, civil engineering, construction performance, data acquisition, data collection, productivity measurements, project performance,
7	construction sectors, economics, investments, motivation, planning, productivity growth, sustainable development,
8	building construction, building construction projects, construction projects, high-rise buildings, high-rise building constructions, in-buildings,
9	automation, building information modeling, profitability, quality control,
10	artificial intelligence, fuzzy logic, fuzzy set theory, industrial construction,
11	construction operations, labor-intensive construction, management, managers,
12	lean construction, lean production, materials handling, production control,
13	learning algorithms, learning curve theory, learning curves, learning systems,
14	modeling, simulation, system dynamics, system theory,
15	engineering research, innovation, machinery,
16	construction manager, factor analysis, influential factors,

17	labor efficiency, optimization, robotics,
18	construction contractors, construction trades, structural design,
19	factor, factors, India,
20	change orders, claims, quantitative analysis,
21	productivity loss, project managers, work hours,
22	mathematical models, schedule acceleration, schedule compression,
23	analytical hierarchy process, job satisfaction,
24	autonomous agents, computational methods,
25	baseline productivity, building projects,
26	construction professionals, research studies,
27	construction labor productivity, Malaysia,
28	decision-making, life cycle,
29	labor and personnel issues, personnel issues,
30	masonry, masonry materials,
31	measurement, office buildings,
32	labor, turkey,
33	contracts, statistical methods,
34	construction firms, productivity data,
35	labor shortages,
36	activity analysis,
37	case-studies,
38	risk assessment,
39	sensitivity analysis,
40	computer simulation,
41	covid-19,
42	construction planning,
43	construction process,
44	variability,
45	construction safety,
46	modeling,
47	Australia,
48	employee productivity,
49	genetic algorithms,
50	fuzzy systems,
51	housing,
52	human resources,
53	safety,
54	construction companies,

55	improvement,
56	relative importance index,
57	management strategies,
58	Canada,
59	construction environment,
60	Monte Carlo methods,
61	on-site construction,
62	cost estimating,
63	performance assessment,
64	modular construction,
65	personnel training,
66	probability,
67	productivity factors,
68	overtime,
69	construction method,
70	productivity performance,
71	building materials,
72	construction costs,
73	standard deviation,
74	statistics,
75	prefabrication,
76	critical factors,
77	sustainability,
78	industrial economics,
79	discrete event simulation,
80	technology,
81	time and motion study,
82	total factor productivity,
83	United States,
84	power plants,
85	construction works,
86	estimation,

The Hierarchical Latent Dirichlet Allocation (HLDA) method, which operates on the content of articles, can extract a richer set of information compared to keyword-based clustering approaches.

The content of a document inherently contains a higher volume and variety of semantic information extracted by the proposed HLDA technique, compared to the information extracted by a limited set of keywords provided by researchers. Notably, the keyword selection is subject to the preferences and biases of researchers, leading to inconsistencies and limitations in representing the actual thematic structure of the literature.

The fundamental difference between these two approaches lies in their ability to uncover the latent semantic structure of the literature. HLDA, by analyzing the full text of the articles, can identify the underlying topics and their hierarchical relationships, providing a rich and interpretable representation of the research landscape. This approach is not limited by the sparsity or inconsistency of keyword assignments, as it considers the entire semantic content of the articles.

2.4.4 Result validation

To validate the findings of this study, a comparison is made between the results obtained using the proposed HLDA model and those derived from the Latent Dirichlet Allocation (LDA) technique. By comparing the topics and their associated stem words identified by both methods, the robustness and validity of the findings can be demonstrated. LDA is a generative probabilistic model for discovering latent topics in a collection of documents. LDA has been applied across various domains, including natural language processing, information retrieval, and text mining, due to its ability to uncover hidden semantic structures within large corpora.

The LDA model was applied based on the same CLP dataset. However, due to the lack of hierarchical relationships in the LDA model, high-frequency co-occurring words may cluster within the same topic, leading to a skewed distribution of articles towards the most frequent topics. Thus, high-frequency words were filtered out during the data preprocessing stage when the LDA model was applied. Furthermore, the LDA model requires specifying the number of topics in advance, which can directly influence the resulting distribution of topic words. To determine the optimal number of topics, the topic coherence metric, which measures the semantic similarity between the top words in each topic, was employed.

Figure 2.13 illustrates the topic coherence scores for LDA models with the number of topics ranging from 1 to 20. As the number of specified topics increases, the topic coherence score generally exhibits an upward trend, reaching its maximum value when the number of topics equals 13. This indicates that the topic words are most strongly related to each other when the model has 13 topics. Consequently, the 13-topic LDA model was adopted for subsequent analysis in this study.

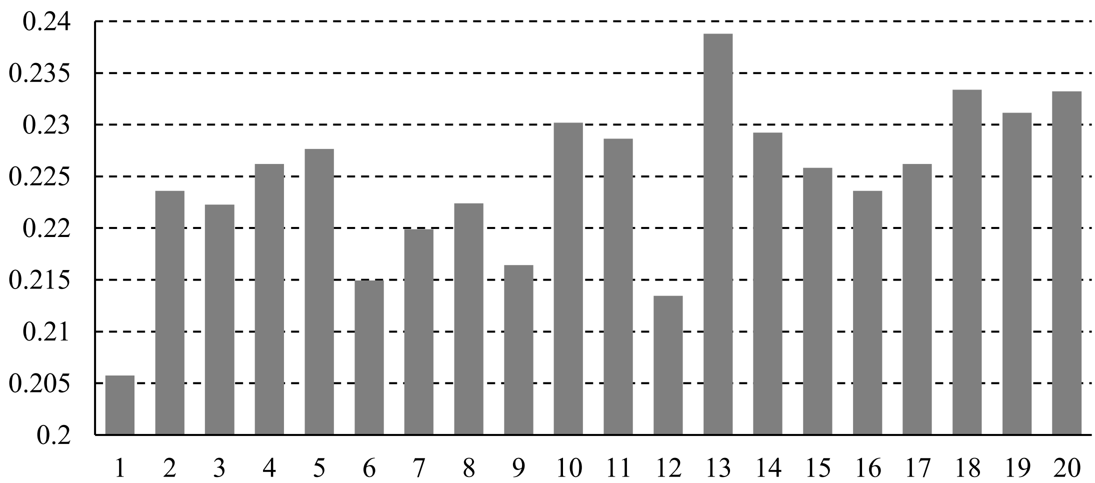

Figure 2.13 Topic coherence in LDA models across different numbers of topics

Table 2.16 presents the high-frequency topic words and the number of articles assigned to each topic for the 13-topic LDA model. It is worth noting that the LDA model does not assign a unique topic to each article; instead, it generates a distribution of topics for each article. In comparison with the findings of this study, the topic with the highest probability in each article's topic distribution was considered its assigned topic.

Upon examination, it is evident that many topics in the LDA model exhibit a high degree of similarity with the topics identified by the HLDA model. For instance, Topic 1 in Table 2.16 and Topic a1 in the three-layer HLDA model both contain the stems “factor, affect, identifi, worker.” However, Topic a1 comprises 119 articles, while Topic 1 in the LDA model contains 219 articles. This discrepancy may be attributed to the inclusion of co-occurring words that were not removed, as well as the assignment of articles with more evenly distributed topics to Topic 1. Other topics that demonstrate a high level of similarity include Topic a2 (HLDA) and Topic 3 (LDA), Topic a6 (HLDA) and Topic 12 (LDA), and Topic c1 (HLDA) and Topic 10 (LDA).

Table 2.16 High-frequency stems of the LDA model

Topics	Number of articles	High-frequency stems
1	219	factor, affect, identifi, worker, manag, survey, studi, influenc, clp, site
2	39	cost, estim, oper, time, frontier, task, optim, plant, worker, weather
3	38	buildabl, formwork, factor, learn, effect, design, influenc, effici, concret, reinforc
4	47	growth, product, sector, region, floor, rate, per, employ, countri, chang
5	17	concret, technolog, method, mine, coal, process, form, materi, strength, equip
6	32	materi, logist, bim, inform, design, plan, deliveri, system, compani, reduc
7	33	develop, china, industri, agricultur, econom, hous, popul, rural, energi, economi
8	57	chang, product, impact, schedul, loss, overtim, contractor, work, result, order
9	34	model, predict, clp, fuzzi, network, context, propos, learn, activ, factor
10	14	carbon, emiss, energi, shift, peak, pile, predict, provinc, safeti, china
11	21	manag, osc, skill, lean, best, deriv, review, must, crew, evalu
12	24	facil, equip, machin, modular, instal, design, compani, mechan, gross, motiv
13	16	matur, weld, vacuum, central, temperatur, distribut, vulner, joint, commun, reinforc

In summary, the LDA model application driven by the same CLP dataset provides a means of validating the findings generated using the proposed HLDA model. Despite the differences in the hierarchical structure and the number of articles assigned to each topic, the LDA model identified several topics with high similarity to those found in HLDA model, as evidenced by the presence of common high-frequency topic words. This similarity suggests that the HLDA model's results are robust and consistent with other widely used topic modeling techniques. However, the LDA model's lack of hierarchical relationships and the potential inclusion of co-occurring words may lead to a more even distribution of articles across topics, resulting in a higher number of articles assigned to specific topics compared to the HLDA model. The overall consistency between the two models supports the findings. It demonstrates the capability of using the proposed HLDA model in uncovering the latent topic structure, as supported by the CLP literature.

2.5 Summary

This systematic review has presented a comprehensive analysis of CLP research through the innovative application of HLDA. This study spans half a century of scholarly work, from 1973 to 2023, with the extensive body of literature being segmented into manageable clusters that represent the evolving trends and focal points within the domain of CLP. The employment of HLDA has demonstrated substantial methodological progress in overcoming the limitations of traditional review methods, which are often qualitative and subject to the biases inherent in manual classification. By leveraging the hierarchical topic modeling capabilities of HLDA, a structured, multi-layered landscape of CLP research has been uncovered, revealing the intricate interconnections between topics and subtopics. Unlike earlier reviews of CLP literature (Greenhalgh and Peacock, 2005; Hamza *et al.*, 2022; Yi and Chan, 2014), this article has pioneered the application of objective analytical methods for examining the literature. This approach enables the assessment and categorization of topics according to academic interests with greater precision. In fact, the literature processing method proposed in this article can help scholars understand the macro trend of a topic in today's era of increasingly abundant academic outputs.

A significant finding of this research is the identification and clustering of CLP research into a hierarchical structure, which illuminates the complex relationships and thematic progressions within the field. Utilizing the HLDA algorithm, the study categorized 591 scholarly articles into three primary topics and 26 sub-topics, offering a three-layer, tree-like topic model. Notably, the study revealed that computational methods, especially artificial neural networks (ANN), have gained significant traction in estimating and enhancing CLP, marking a transformative integration of data analytics into construction management practices. This marks an improvement in the reliability of data-driven recognition models. At the same time, topics related to worker Occupational Health and Safety (OHS), as discussed in sections Topic b1, b10, and c5 of this chapter, have also entered an accelerated phase of development. Some studies focusing on recognizing worker activities have already emerged, but the connection between such research and construction management, as well as worker health, remains unclear. Research that links data-driven AI models with worker health has the potential to create significant value in the future.

Chapter 3: A Data-Driven Framework for Construction Workload Estimation and Activity Sequence Inference

3.1 Introduction

The unique project development needs and customized designs in the construction industry result in low-volume, high-variation manufacturing processes (Momeni et al. 2022). Despite the widespread adoption of building information modeling (BIM), parametric product design, and computer numerically controlled (CNC) production equipment in modern fabrication facilities, such as structural steel shops (Aghajamali et al. 2025), precast concrete plants, and modular construction facilities (Granello et al. 2022; Yin et al. 2019), the current state of prefabrication and offsite construction is still far from being fully automated. Construction remains a labor-intensive industry that heavily depends on skilled trade workers for tasks such as fitting and welding (Qi et al. 2021). The scarcity of skilled construction workers is anticipated to worsen in technologically advanced economies like Canada and Hong Kong (Kumarage et al. 2024; Sing et al. 2017). At the same time, productivity improvement is increasingly recognized as a crucial factor in achieving sustainable economic growth (Rathnasinghe et al. 2024). Reinforced concrete work in apartment buildings is particularly labor-intensive, with rebar workers, formwork workers, and concrete workers accounting for 63% of the total labor consumption (Mun et al. 2023).

Construction workers are subjected to more physically demanding tasks compared to those in manufacturing industries, and high workloads are often unavoidable. However, there is a discrepancy between the methods used to assess workload, such as the volume of reinforced concrete (Yang et al. 2022) or the weight of the rebar (Yang et al. 2020), and the actual physical conditions of the workers. These methods do not capture detailed information about workers' postures and movements, which are essential factors in determining their physical workload and the risk of developing work-related musculoskeletal disorders and injuries. This discrepancy highlights a fundamental knowledge gap: current productivity metrics, centered on labor-hours, primarily capture time-on-task efficiency but ignore the intensity of physical exertion associated with different postures. Consequently, there is an absence of an equitable assessment of labor input that balances productivity with ergonomic risks, limiting the ability to consider workers' occupational health in construction planning.

Current workload estimation methods in the construction industry often rely on predefined labor hour constants and historical project data (Goulding et al. 2012; Nasirzadeh and Nojedehi 2013). These approaches, while useful for high-level planning and budgeting, lack the granularity needed to accurately assess the physical demands placed on individual workers. Moreover, these methods are often based on subjective judgments and may not reflect the actual work conditions on-site (Loosemore 2014). In addition to labor constants, work sampling techniques have been widely used to assess construction productivity (Tsehayae and Fayek 2016). These methods involve randomly observing and categorizing worker activities into predefined categories, such as direct work, supportive work, and idle time. However, work sampling studies have been criticized for relying on human observers, their subjectivity, and potential inaccuracies in representing actual productivity levels (Josephson and Bjorkman 2013). Collectively, these limitations underscore a broader knowledge gap in linking physically demanding work characteristics—such as posture duration and ergonomic strain—to workload estimation. Recent advances in AI-based posture recognition (Akinosho et al. 2020; Luo et al. 2019) and ergonomic risk modeling offer new opportunities to address this gap (Anwer et al., 2021), while established ergonomic risk assessment methods like REBA and RULA represent the gold standard for precision in individual risk diagnosis (McAtamney and Nigel Corlett 1993). This study introduces a posture-hour based framework tailored for productivity study and work planning, aimed to bridge the gap between ergonomic science and construction management.

To address these limitations and fill the identified knowledge gap, this study proposes a novel approach to estimating construction workers' workload using computer vision techniques. By leveraging posture estimation algorithms and deep learning models, this research aims to quantify workers' postures and their duration, introducing the concept of "posture-hours" from traditional labor-hours. This posture-based approach enables a more accurate and detailed assessment of physical workload by directly linking workers' actions to their contribution to project progress, while also accounting for ergonomic risks. The shift to posture-hours represents a distinct advancement by providing a granular, human-centric metric that can inform data-driven work planning in construction in terms of optimizing both productivity and worker wellbeing. The proposed methodology involves collecting video data from simulated and real tasks (e.g., rebar-tying and concrete pouring), applying state-of-the-art posture estimation models (e.g., YOLO-Pose), and training deep-learning models for posture classification. To facilitate both research verification and practical adoption, the framework is intentionally built using well-proven, open-source, and cost-efficient machine learning algorithms.

By providing a more granular and accurate assessment of construction workers' physical workload, this study contributes to the development of data-driven strategies for optimizing labor productivity, reducing the risk of work-related injuries, and ultimately improving the sustainability of the construction industry. The insights gained from this research can inform the design of ergonomic interventions, task allocation, work plan and scheduling practices, as well as support the development of advanced technologies for construction automation and human-robot collaboration down the path.

3.2 Methodology

3.2.1 Proposed framework

Advancements in computer vision have enabled improved workload estimation in construction settings. This research focuses on posture tracking for construction workers through video analysis of worksite operations. As illustrated in Figure 3.1, surveillance footage from active construction sites serves as input to the proposed posture-hour extraction method, while the output provides temporal distributions of worker postures.

The methodology employs the YOLO-Pose pre-trained model for data preprocessing, extracting body key-point coordinates for each worker across video frames. Temporal patterns in these coordinates contain implicit data about postural dynamics. Manual annotation defines mappings between coordinate sequences and predefined posture classifications, enabling subsequent training of deep learning models. The implementation combines multiple open-source algorithms, achieving a model accuracy of 85.33%. Details on the algorithms, training parameters, and validation using the rebar installation case study.

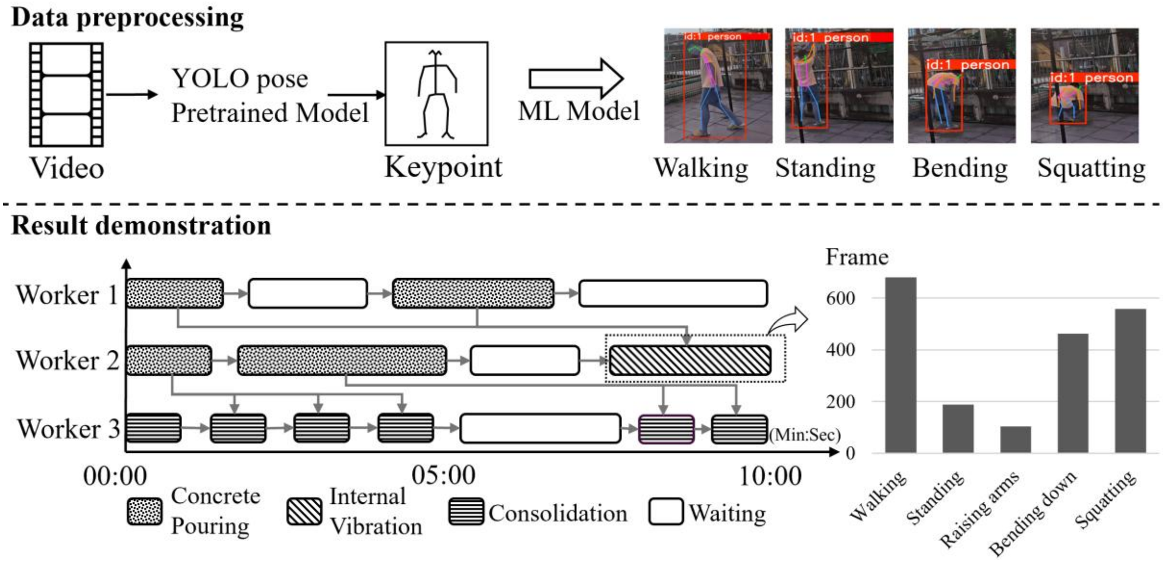

Figure 3.1 Proposed framework to turn site video into worker posture hours during direct work.

3.2.2 Classification of postures

Existing studies on construction labor productivity, particularly work-sampling methods, relied on manual on-site observations to capture instantaneous worker statuses through periodic visual inspections. Workers are classified as "productive time" or "direct work" when they display explicit working postures or engage in tool handling. Researchers have established diverse criteria for determining direct work, employing approaches ranging from tool possession checks to posture analysis. For instance, the posture classification framework proposed by Buchholz assessed four anatomical dimensions: upper limbs, lower limbs, neck position, and torso orientation(Buchholz et al. 1996). However, this multidimensional assessment introduces redundancy in construction contexts, as worker postures are not mutually exclusive permutations of these body segments; certain combinations occur more frequently in construction operations. To simplify posture classification for construction planning(Zhou et al. 2024), Zhou streamlined these postures into categories such as “shouldering materials,” “carrying materials,” “sitting-rest,” “standing-rest,” “squatting-rest,” “squatting-operation,” “standing-operation,” “moving,” and “other.” In this study, construction worker postures are categorized into five distinct classes (Table 3.1): walking, standing, bending, squatting, and raising arms.

The selection of the five postures—walking, standing, bending, squatting, and arms-raising—was guided by their high frequency in labor-intensive construction tasks and their significant ergonomic implications. This taxonomy is inspired by simplified frameworks common in construction ergonomics and productivity research (Zhou et al., 2024) to balance analytical accuracy with practical applicability. Specifically, postures such as bending and squatting are strongly correlated with lower back disorders, while arm-raising is associated with shoulder strain from overhead work. The strategic simplification to critical postures allows the model to maintain operational relevance by depicting value-adding activities, while ensuring analytical tractability within the scope of this research.

Table 3.17. Description of activities

Activities	Description	Abbr.
Concrete Pouring	Transferring freshly mixed concrete into formwork using pumps, buckets, or direct chutes ensures continuous material flow.	CP
Internal Vibration	Densification of concrete using immersed poker vibrators to eliminate entrapped air and achieve specified compaction standards.	IV
Consolidation	Manual elimination of voids in vertical elements using shovels or tampers prior to mechanical vibration, critical for narrow formwork applications.	CD
Screeding	Precision leveling of concrete surfaces with straightedges or laser-guided screeds to establish elevation control.	SC
Curing Membrane Installation	Deployment of moisture-retaining polyethylene sheets or spray-applied compounds to maintain hydration conditions.	CI

Traveling	Worker relocation between task zones within the worksite, including material fetching and equipment repositioning.	TR
Waiting	Non-value-adding intervals caused by workflow interruptions, material shortages, or crew coordination delays.	WT

This study proposes a low-cost automated approach to monitor construction site productivity by leveraging widely available video surveillance data. The method employs computer vision techniques to model and analyze worker activities in real-time, enabling workload estimation, productivity assessment, and task-specific performance tracking. For individual workers, posture keypoint detection is used to identify and track activity patterns; details are shown based on the first case in the appendix. In multi-worker collaborative scenarios, the system integrates two critical dimensions: spatial positioning and task recognition. As illustrated in the ensuing case study, a manually collected multi-worker concrete pouring dataset could be automatically extracted by existing open-source algorithms. Worker coordinates could be tracked using the DeepSORT algorithm(Wojke et al. 2017), which associates movement trajectories with individual identities, while the Slowfast algorithm analyzes temporal and spatial features in video data to classify specific tasks being performed (Feichtenhofer et al. 2018). It is important to note that every video frame analyzed in this study, including those capturing transitional or ambiguous postures between defined categories, was systematically assigned to one of the five posture classes based on the spatial thresholds defined in Table 3.1. No frames were excluded from the analysis. This approach ensured that the total recorded working time was fully accounted for in the subsequent posture-hour calculations, preventing any underestimation of task duration.

3.2.3 Recognition model structure

Advancements in deep learning models for time-series data analysis have led to the development of sophisticated, open-source algorithms that can be readily implemented in various applications. However, low-cost and high-performance solutions are paramount for practical deployment in construction sites. This study proposes a novel approach that leverages video footage alone to estimate the details and durations of rebar workers' actions, thereby providing a cost-effective solution for workload estimation.

Posture keypoints are detected using the YOLO-Pose pre-trained model, which extracts 17 body keypoint coordinates per frame following the COCO 2017 format to track activity patterns. The captured data, segmented into one-second clips, is divided into training and validation (testing) subsets, with oversampling and undersampling techniques applied to ensure balanced representation across the five posture classes. The rebar-tying task is simulated by a trained researcher following standard HKCIC training procedures on a BIM-designed shear wall testbed featuring a 200 mm-thick wall and 150 mm-thick slab. This simulation occurs in a controlled laboratory setting, using 30 fps surveillance footage, with the experimental area configured to include a rebar storage site located 1 meter from a tying structure spanning a 2-meter vertical range. The source code is provided in Table A in the appendix.

The proposed framework consists of data preparation, preprocessing, feature extraction, model architecture design, training, and evaluation. Surveillance videos were collected in a controlled laboratory setting, with subjects simulating rebar-tying poses to facilitate precise annotation. The videos were segmented into one-second clips, each containing 30 frames. The YOLO-Pose model was utilized to extract 2D human keypoints from each frame, following the COCO 2017 keypoint annotation format (Maji *et al.*, 2022). The resulting sequences of keypoint coordinates serve as the input data for the pose recognition model. Class imbalance was addressed through the use of oversampling and undersampling techniques. The model architecture incorporates convolutional layers to capture spatial patterns, bidirectional LSTMs to model temporal dependencies, and multi-head attention layers to capture the global context. The model was trained using the Adam optimizer, sparse categorical cross-entropy loss, and accuracy metrics, with callbacks employed to prevent overfitting and save the best weights.

3.2.3.1 Dataset preparation

The data source consists of surveillance footage captured in a controlled environment to ensure the optimal extraction of features from the input data. The experimental subjects, who were previously trained, simulated the process of rebar tying to facilitate accurate pose annotation. Although the video recording conditions in actual construction sites may vary (e.g., occlusion, insufficient lighting), the data collected during the construction process is sufficient to address these issues, as most construction sites deploy surveillance cameras from various angles for safety or other considerations. The recorded videos underwent preprocessing, including zooming in, flipping, and reversing, and were captured from different angles to gather more comprehensive information. All recorded videos were divided into one-second clips, each containing 30 frames. Table 3.2 presents the number of clips in each posture. Squatting and bending down clips are the most numerous in the dataset, reflecting their prevalence in rebar work. This leads to class imbalance, addressed by oversampling minority classes and undersampling majority classes to obtain a maximum of 180 samples per class.

Table 3.18 Number of clips in each posture

Posture	Number of Clips
Bending down	173
Squatting	254
Standing	123
Raising arms	65
Walking	152

5.2.3.2 Data Preprocessing for Input

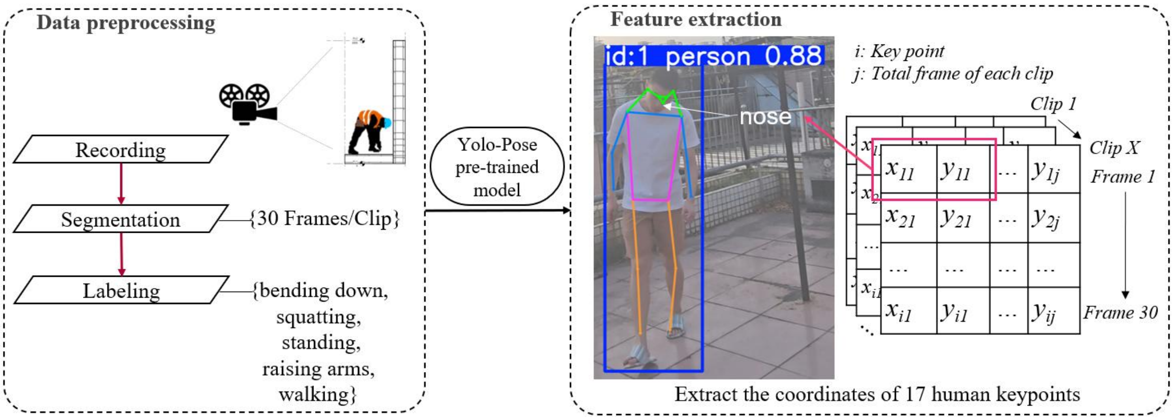

Figure 3.2 Data preprocessing and feature extraction

The dynamics of workers' poses contain multidimensional information. The spatial dimension is crucial, as the worker's position in the video recording varies. More importantly, the relative positions of the worker's key points also serve as essential features for estimating behavior. For instance, the angles between the shoulder, hip, and knee joints show distinct differences between standing and squatting poses. Generally, this angle is greater than 90 degrees when standing, while it is less than

90 degrees during squatting. In addition to static spatial information, the temporal dimension plays a vital role. The worker's position changes between frames, and capturing motion is often necessary for recognizing poses or actions. Dynamic time-series information contains more information than static information in a single image. To more accurately estimate the worker's pose, this study uses the dynamics of the worker's key points within a one-second interval as the input data for the behavior recognition model (Figure 3.2). All recorded videos were divided into one-second clips, each containing 30 frames. For each frame of the loaded videos, 2D human keypoints were extracted using the YOLO-Pose model for keypoint detection. The data annotation format follows the COCO 2017 keypoint annotation format, which includes 17 human skeleton key points(Singh *et al.*, n.d.). This study extracted the horizontal and vertical coordinates of the 17 key points in each frame to extract human pose features. The coordinates of key points not only imply the overall spatial position of the human body but also the relative positional relationships among key points. The keypoint sequences were padded to a fixed length of 30 frames to create uniform input lengths. The videos and their extracted keypoint sequences were processed to generate the final dataset, which was used to train and evaluate the model. This resulted in a dataset where each sample contained the 2D coordinates of the detected key points across the 30-frame sequence. The dataset was split into training and testing subsets to enable model training and performance assessment. The combination of laboratory environment-based data collection, YOLO-Pose-based key point extraction, and dataset preparation techniques yields a pipeline that converts video footage into structured pose data suitable for input into the proposed sequence modeling approach.

5.2.3.3 Model Architecture

The proposed pose recognition model architecture was designed using the Keras functional API (Douglass, 2020). The input layer accepts sequences with a shape of (*max_frames, num_keypoints * 2*), where *max_frames* represents the fixed length of the pose sequences and *num_keypoints * 2* corresponds to the flattened array of 2D coordinates obtained by concatenating the x and y values for each extracted keypoint (Figure 3.2).

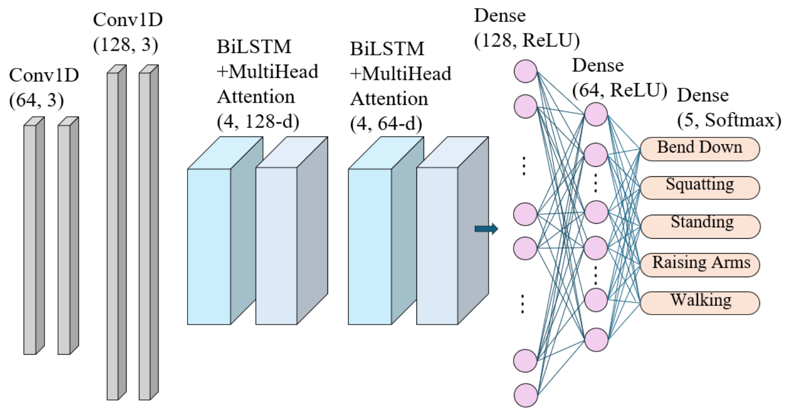

Figure 3.3 Posture Recognition Model Structure

As shown in Figure 3.3, the input sequences are first processed by two convolutional blocks, each consisting of two 1D convolutional layers with Rectified Linear Unit (ReLU) activation functions, followed by max pooling layers to downsample the feature maps and capture local patterns in the pose sequences.

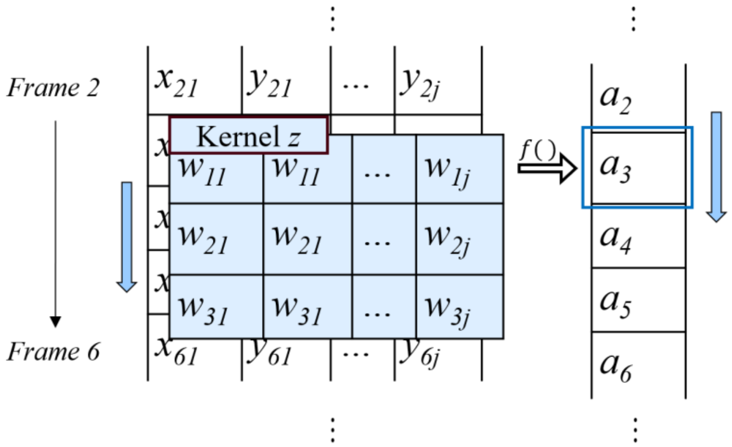

Figure 3.4 Structure of single Conv1D kernel

$$a[i] = ReLU(\sum_{m=0}^{k-1}\sum_{n=0}^{j-1} X[i+m,n] \cdot W[m,n] + b) \qquad \text{Equation (1)}$$

a[i] = The output at frame *i*

ReLU = Rectified Linear Unit activation function

X[i+m, n] = Input value at position *(i+m, n)*

W[m, n] = Kernel weight at position *(m, n)*

b = Bias

k, j = Kernel size and input depth

Figure 3.4 illustrates the computation of a single kernel with an input data of $i=4$. As shown, a single kernel extracts the pose space information from three frames, with the kernel dimension being $(k \times j)$, where $k=3$ m represents the position of the parameters within the convolutional kernel, and in this study, its values are *0, 1,* and *2*. The term $i+m$ represents the sliding of the convolutional kernel over the input data. Each time the kernel slides, the value of i increases by one, resulting in different input data being multiplied element-wise with the numbers inside the convolutional kernel. in this study. Therefore, the vector *a[i]* extracted by kernel *z* from 30 frames represents the directly extracted spatio-temporal features from adjacent time steps. The first Conv1D layer has 64 convolutional kernels. Each kernel extracts a unique feature vector that captures both spatial and temporal information from the input data. As a result, the first layer's output is a set of 64 different feature vectors, Eq.1 describes this process, which includes not only the weights contained in the kernel but also a bias *b* that outputs the next value through an activation function. This study comprises four Conv1D layers, enabling the extraction of deeper-level implicit relationships. While the Conv1D block excels at capturing spatial interrelationships within the input data and the temporal information of adjacent time steps, additional modeling techniques are required to effectively address more complex temporal patterns.

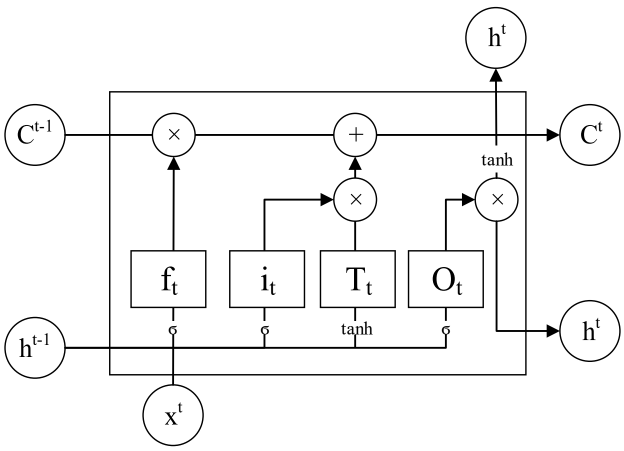

Figure 3.5 Structure of LSTM

In addition to the information from temporally adjacent positions, long-distance dependencies also need to be captured, as many actions often require sustained observation to determine the current action's classification. To accurately classify actions, the model should be able to make decisions based on the contextual information within the input data. This requires the model's internal structure to identify and understand the long-distance relationships between input vectors, even when they are not adjacent in time. Long Short-Term Memory (LSTM) layers are designed to tackle this challenge effectively. As illustrated in Figure 3.5, LSTM layers contain an internal memory cell C that can store the contextual relationships during the current inference process, and this cell undergoes forgetting and memorization as the inference progresses. Eq. 2 describes the formula for updating this memory cell.

$$C^t = f_t \times C^{t-1} + i_t \times T_t \qquad \text{Equation (2)}$$

In the equation, C^t represents the state of the memory cell at the current time step, which consists of two parts. The first part, $f_t \times C^{t-1}$, is the forgetting mechanism, where f_t contains a parameter matrix with the same dimension as the previous memory cell, controlling the information to be forgotten from the previous state through the SoftMax function (which outputs values between 0 and 1). T_t represents the newly added information in the current time step, which is a *tanh* function (outputting values between -1 and 1). Similarly, it is also a Softmax function controlling the amount of new information memorization. The output of the memory cell is represented by Eq. 3 below.

$$h^t = O_t \times \tanh(C^t) \qquad \text{Equation (3)}$$

In the equation, h^t represents the output of the current computation, where $tanh(C^t)$ is the information prepared for output after the memory cell update. O_t is another gate controlling the output. The LSTM mechanism internally contains four parameter matrices: three control gates that manage the forgetting, memorization, and output of information from the memory cell, while the fourth parameter matrix is responsible for understanding the input information of the current computation. LSTM can pass the memory cell to the next stage of computation, and due to the existence of the forgetting mechanism, it can process sequential information beyond adjacent time steps.

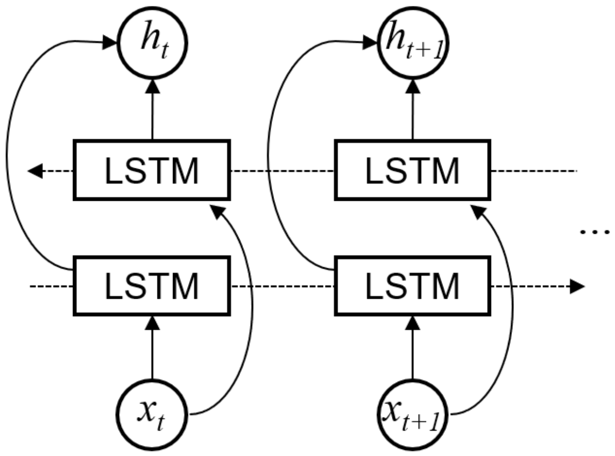

Figure 3.6 BiLSTM structure

When classifying poses, recognition is feasible regardless of whether the pose dynamics are forward or backward. Moreover, many actions are reversible; for instance, the "bend down" action can be identified during both standing up and bending over. Therefore, both forward and backward input data contain the necessary information for pose recognition. To handle these dependencies, bidirectional LSTM is required (Figure 3.6). In this research, the convolutional blocks' output is fed into two bidirectional LSTM layers, capable of learning long-term dependencies and temporal patterns in both forward and backward directions. Layer normalization is applied to the LSTM outputs to improve training stability and convergence.

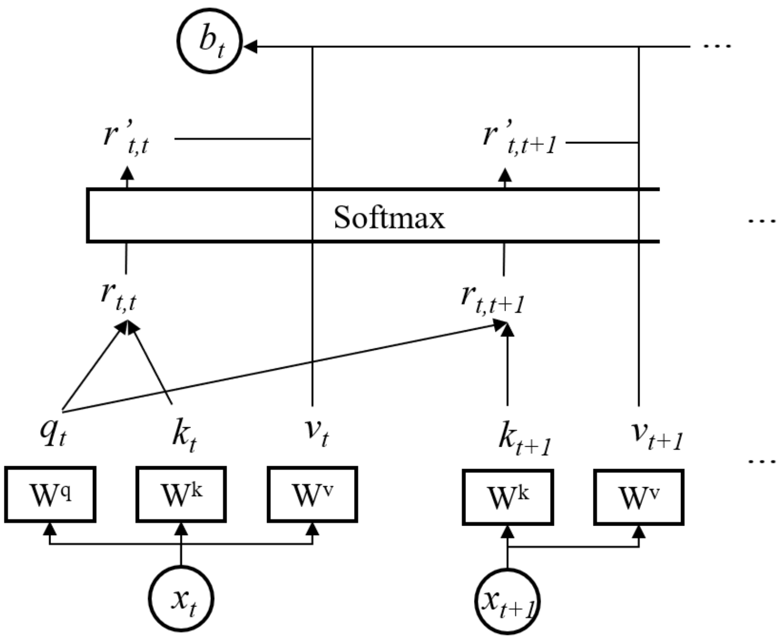

Figure 3.7 The self-attention mechanism

In addition to sequential dependencies, time series data processing also involves handling unordered dependencies, which is addressed by the attention mechanism in this study. As shown in Figure 3.7, the self-attention mechanism contains three parameter matrices. The query value q_t is obtained by multiplying the input vector of the current time step with W^q, while the key values k are computed by multiplying the input vectors of all time steps with the parameter matrix W^k. By calculating the dot product between q_t and each k, the relevance r of the current time step to every other time step is obtained, commonly referred to as attention. This step demonstrates that the self-attention layer completes the computation of the entire input sequence within a single output time step, effectively reading the entire input data for each output. The output of the self-attention mechanism is represented by **Eq. 4**.

$$b_t = \sum_{i=1}^{n} r'_{t,i} \times v^i \qquad \text{Equation (4)}$$

Eq. 4 shows that b_t is the output of the self-attention layer at the current time step. $r'_{t,i}$ is the attention value computed by applying the SoftMax function to the dot products of query q_t qt and keys k. Instead of assigning weights to input data based on sequential information, r' assigns weights based on relevance. Similarly, v^i is the output value calculated by traversing all inputs through the weight matrix W^v. Multi-head attention involves multiple sets of W^q, W^k, and W^v matrices, allowing the model to jointly attend to information from different representation subspaces at different positions. The outputs from each attention head are concatenated and linearly transformed to obtain the final self-attention output. This mechanism enables the model to capture complex dependencies and relationships within the input sequence, facilitating more accurate pose recognition.

To obtain a fixed-length representation of the pose sequences, global average pooling is applied to the output of the LSTM and attention layers. Two dense layers with ReLU activation and dropout regularization follow this, which learn high-level features and representations. Finally, a dense layer with Softmax activation outputs the predicted probabilities for each pose class, enabling multi-class classification of the rebar worker poses. The combination of convolutional NN, LSTM, attention, and dense layers allows the model to effectively capture spatial and temporal dependencies in the pose sequences and learn discriminative features for accurate pose recognition.

5.2.3.4 Model Training and Evaluation

The model was trained using the Adam optimizer (Kingma and Ba, 2015) with exponential learning rate decay and compiled with a sparse categorical crossentropy loss function and accuracy metric. Model checkpoints and early stopping callbacks were employed to save the best model weights and prevent overfitting. The model was trained using the specified hyperparameters, and the training and validation accuracy curves were plotted to visualize the model's performance.

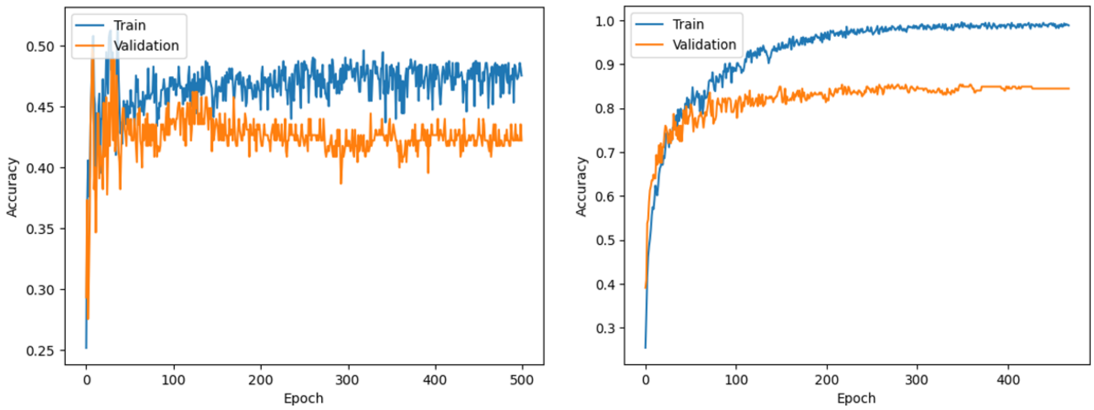

Figure 3.8 Model Accuracy

The choice of learning rate significantly affects the model's training accuracy. As shown in Figure 3.8 (left), with a fixed learning rate of 0.001, the accuracy experiences a steep drop around epoch 40, resulting in a final model accuracy below 50%. This indicates that the parameter adjustment in this instance had overshot the optimal value, preventing subsequent training from moving toward the minimum error. To address this issue, the current study employed an exponential learning rate decay strategy. By utilizing the Exponential Decay learning rate scheduler from Keras (Douglass, 2020), the learning rate gradually decreases throughout training. The initial learning rate was set to 0.0001, and every 20 epochs (decay_steps), the learning rate was multiplied by a decay_rate of 0.96. This approach allowed the model to make larger adjustments in the early stages of training when the loss was high and fine-tuned the parameters as it approached the optimal solution. As illustrated in Figure 3.8 (right), the application of exponential learning rate decay results in a more stable training process. The trained model achieved an accuracy of

85.33% on the validation set (unseen data reserved from training), demonstrating its ability to effectively recognize and classify rebar worker poses.

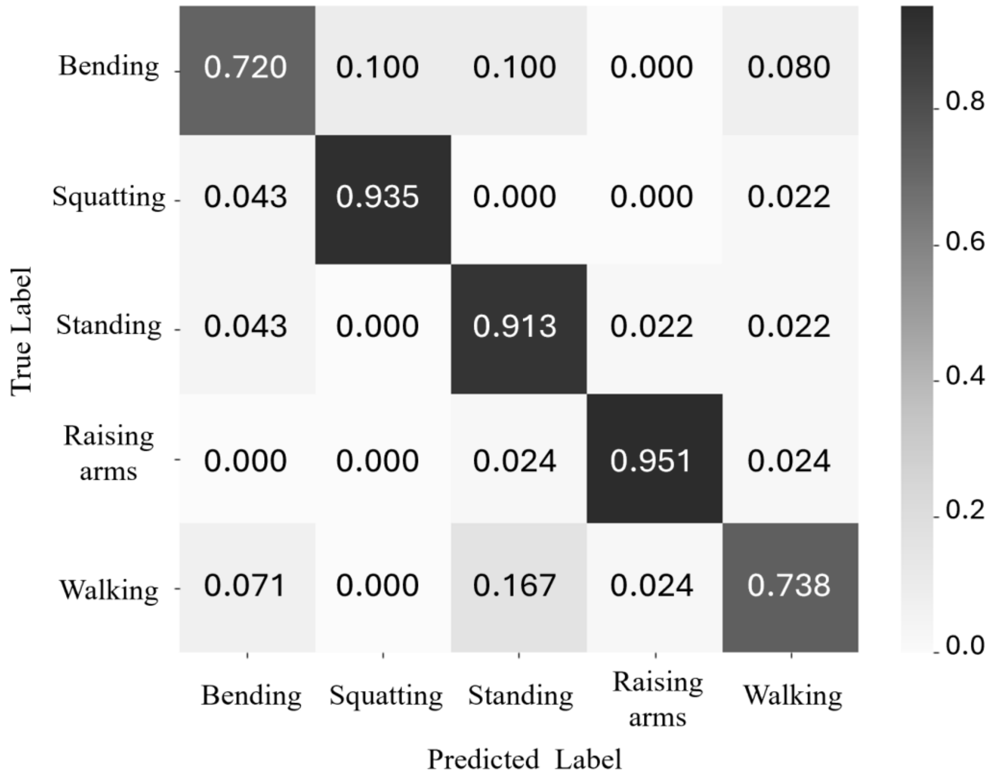

Figure 3.9 Confusion matrix for the posture recognition model

A detailed per-class performance analysis was conducted, which provides a more nuanced understanding of the model's capabilities. The macro-average F1-score was 0.849, indicating robust overall performance across all posture classes. Notably, the model achieved exceptional performance in identifying “Raising Arms” (F1-score: 0.95) and “Squatting” (F1-score: 0.91). The confusion matrix revealed that the primary source of error was the misclassification of “Bending” and “Walking” (with misclassification rates of 28.0% and 26.2%, respectively), which were often confused with “Squatting” and “Standing”. This suggests that these posture pairs exhibit greater visual similarity from the viewpoint of the site monitoring camera.

Table 3.19 Number of parameters in each layer

Layer	Output Shape	Number of Parameters
Conv1D (64, 3)	(30, 64)	(3 * 34 + 1) * 64 = 6,592
Conv1D (64, 3)	(30, 64)	(3 * 64 + 1) * 64 = 12,352
Conv1D (128, 3)	(15, 128)	(3 * 64 + 1) * 128 = 24,704
Conv1D (128, 3)	(15, 128)	(3 * 128 + 1) * 128 = 49,280
Bidirectional (LSTM (128))	(7, 256)	4 * (128 * 128 + 128 * 128 + 128) = 131,584
MultiHeadAttention (4, 128)	(7, 256)	4 * (128 * 128 * 3 + 128) = 196,608
Bidirectional (LSTM (64))	(7, 128)	4 * (256 * 64 + 64 * 64 + 64) = 66,048
MultiHeadAttention (4, 64)	(7, 128)	4 * (64 * 64 * 3 + 64) = 49,152
Dense (128)	(128)	128 * 128 + 128 = 16,512
Dense (64)	(64)	128 * 64 + 64 = 8,256
Dense (5)	(5)	64 * 5 + 5 = 325
Total		561,413

As shown in Table 3.3, the proposed model leverages Conv1D layers (6,592 and 12,352 parameters) to capture spatial patterns, bidirectional LSTMs (131,584 and 66,048 parameters) to model temporal dependencies, and multi-head attention layers (196,608 and 49,152 parameters) to capture global context. The dense layers encode model parameters to (16,512, 8,256, and 325 parameters) interpret these features for pose classification. Table 3.3 shows that the majority of the model's 561,413 parameters are allocated to the recurrent and attention layers, aligning with their significance in learning complex spatio-temporal representations for worker pose recognition. The progressive dimensionality reduction demonstrates a hierarchical feature extraction process. His synergistic architecture and efficient parameter allocation contribute to the model's strong performance in analyzing human pose sequences.

In short, this model leveraged state-of-the-art pose estimation and deep learning techniques to classify human poses into five action categories in connection with rebar installation work. The combination of convolutional layers, bidirectional LSTMs, and attention mechanisms enabled the model to capture spatial and temporal dependencies in the pose sequences effectively. The use of oversampling ensures balanced class representation, while the mechanisms of dropout regularization and early stopping prevented overfitting.

3.3 Case study

3.3.1 Method application: Single-worker rebar tying

3.3.1.1 BIM model information

Figure 3.10 illustrates a rebar structure design developed using a BIM model inspired by the practical exam for the rebar worker trade test administered by the Hong Kong Construction Industry Council (HKCIC: Trade test). The model aimed to replicate real-world construction scenarios while maintaining a controlled environment for simulating and recording rebar-tying activities. To balance realism and simplicity, the BIM model streamlined components from the HKCIC trade test, retaining only elements critical to evaluating the behavior recognition model's effectiveness in workload estimation. The structure depicts a corner section of a shear wall, incorporating standard wall panel components typical of rebar workers' daily tasks. Key specifications include a 200 mm-thick wall and a 150 mm-thick slab. To enhance realism, the design integrated an embedded concealed column reinforced with horizontal stirrups. Seismic considerations were addressed by tightening stirrup spacing in the lower portion of the structure, creating a dense reinforcement zone. These features collectively captured diverse rebar-tying scenarios encountered on actual sites, while omitting irregular elements from the original HKCIC model. By focusing on standard wall panels, this simplified case study enabled a targeted assessment of the behavior recognition model's performance in estimating workload for common structural configurations.

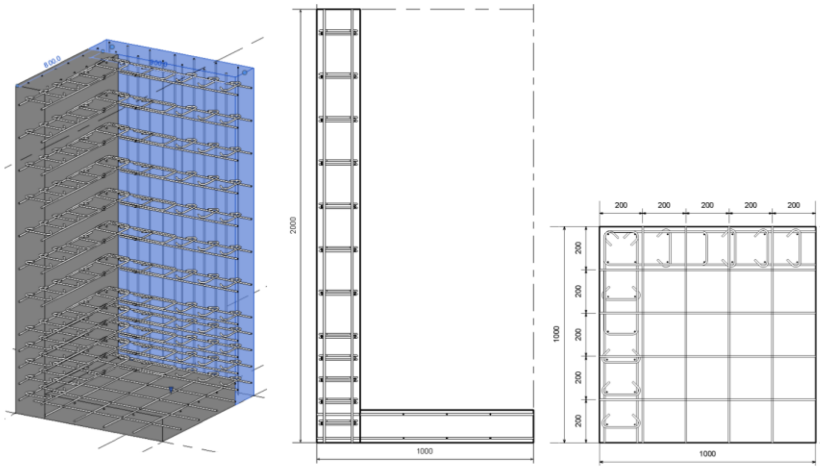

Figure 3.10 BIM-based rebar structure design: testbed for case study

The rebar specification table (Table 3.4) in the case study section provides an overview of the reinforcement components used in the BIM model. While this research focuses on workload estimation based on rebar-tying postures, it is important to note that rebar handling and transportation also significantly contribute to the overall workload in real construction scenarios. In the simulated task, the rebar storage area was located within one meter of the tying location; however, in actual projects, this distance can vary considerably. Current industry practices often rely on the total weight of rebar to determine task duration for rebar workers. Table 3.4 reveals that lighter components, such as horizontal stirrups and tie bars, constitute a substantial portion of the total rebar quantity. This discrepancy could introduce inaccuracies in posture-based workload estimation, as the effort required to handle and transport these components is not accounted for. Nevertheless, the case study's simplified setup remains sufficient and realistic for validating the proposed concept.

Table 3.20. Rebar types and quantities in the BIM model

Rebar type	Diameter	Number
Wall transverse reinforcement	8 mm	48
Wall longitudinal reinforcement	10 mm	24
Slab reinforcement	8 mm	16
Horizontal stirrup	8 mm	24
Tie bar	8 mm	64

Table 3.5 presents the number of tying nodes across different height ranges, emphasizing the importance of evaluating tying-point locations in relation to workers' postures. Unlike standardized manufacturing processes, construction work, particularly rebar tying, lacks fixed workstations, necessitating constant postural adjustments to access dispersed tying nodes. In this study, the rebar structure design incorporates tying nodes within a 2-meter vertical range, which represents the maximum standard working height for rebar workers before scaffolding or platforms are required. As shown in Table 3.5, tying nodes are concentrated at lower heights due to seismic reinforcement specifications and slab reinforcement demands. These findings underscore the necessity of accounting for the vertical distribution of tying nodes when assessing postural workload in rebar-tying tasks.

Table 3.21 Number of tying nodes at different heights

Height	Number of tying nodes
0m ~ 0.2m	128
0.2m ~ 0.4m	64
0.4m ~ 0.6m	32
0.6m ~ 0.8m	32
0.8m ~ 1m	32
1m ~ 1.2m	32
1.2m ~ 1.4m	32
1.4m ~ 1.6m	32
1.6m ~ 1.8m	32
1.8m ~ 2m	32

3.3.1.2 Result and analysis of rebar tying

The practical implementation of the proposed posture recognition model involved processing a video recording of a mockup rebar-tying task performed by a researcher familiar with actual work procedures, as outlined in HKCIC trades training manuals. The approach followed a frame-by-frame analysis, extracting keypoint features from 30-frame segments using the YOLO-Pose model and predicting corresponding action labels based on the trained algorithm. The data collected for training, and the accuracy of this case, are described in section 3.2.3. Predicted actions, along with their start and end frame numbers, were stored for further analysis. To optimize memory usage and provide progress updates, the implementation incorporated memory management techniques and displayed current progress and predicted actions at regular intervals.

Applying the posture recognition model to analyze the 33-minute mockup rebar-tying task video demonstrated its capability to quantify workload associated with specific activities. Since the algorithm for identifying different body conditions during data preprocessing uses a YOLO-pose pre-trained model, evaluating the model's accuracy for key point identification across different participants is beyond the scope of this study. By analyzing the duration of each primary posture in relation to rebar installations, the model provided a more detailed understanding of the worker's physical demands compared to traditional methods, which focus solely on total working hours. The results are summarized in Figure 3.11.

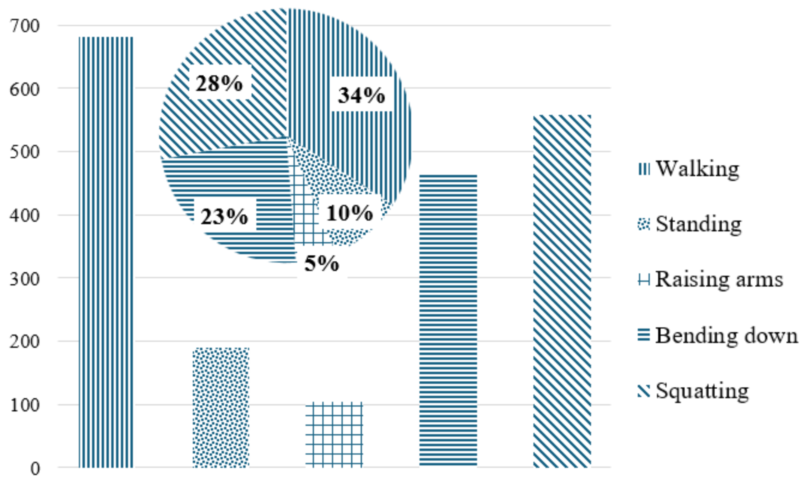

Figure 3.11 Total time (s) of each posture

Figure 3.11 illustrates the total time spent in each posture during the recorded task. The data reveal that the worker frequently adopts uncomfortable postures for extended periods to complete the work. Since most tying nodes are positioned at lower heights—as shown in the BIM model (Fig. 5.9) and the node distribution table (Table 3.5)—the worker spends significant time in bending and squatting postures. This finding underscores the ergonomic risks and physical strain inherent in rebar-tying tasks.

Furthermore, the posture recognition model effectively distinguishes between productive and semi-productive time. On-site movements, such as walking for material handling, are categorized as semi-productive. By differentiating among postures and activities, the model provides a more accurate assessment of productivity and distribution of effort across tasks.

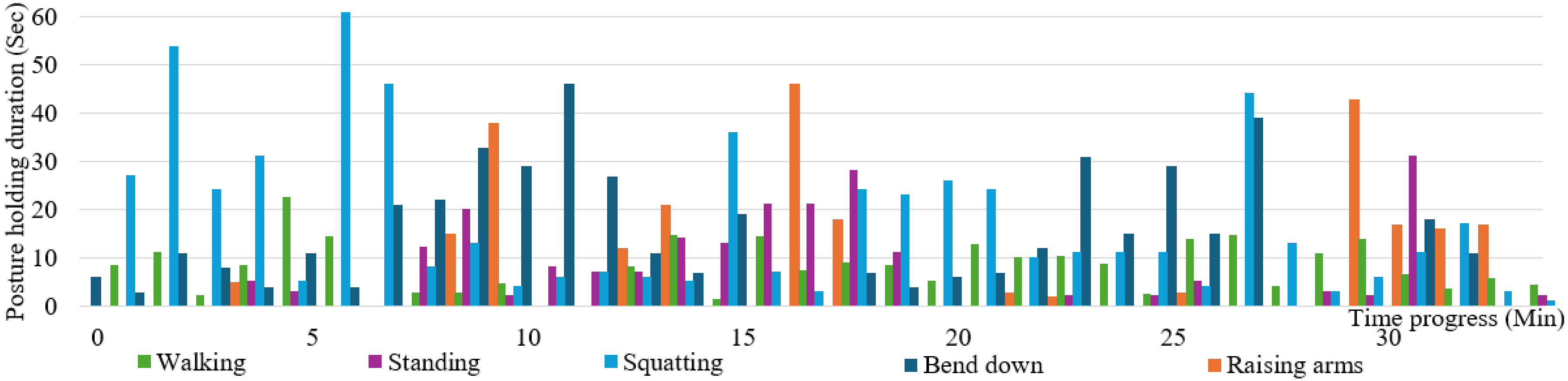

Figure 3.12 Posture hold duration statistics

The posture hold duration statistics presented in Figure 3.12 offer a detailed breakdown of the worker's physical engagement during the 33-minute simulated rebar-tying task. The data reveal that squatting and bending postures predominated in the initial stages, suggesting the worker adopted a bottom-up approach by prioritizing lower sections of the rebar structure. This aligns with the study's structural design, where vertical wall reinforcement required erection and securing before progressing to higher sections. This sequencing likely necessitated prolonged raised-arm postures during early task phases. Walking postures persisted throughout the experiment, reflecting the continuous need for material transportation between the rebar storage area and tying locations. These movements constituted an integral component of the workload, directly impacting productivity.

The posture duration analysis underscores the dynamic nature of rebar-tying work. The early dominance of squatting/bending postures, followed by a gradual shift toward more balanced posture distribution, correlates with the increasing elevation of rebar placement as construction progresses. This pattern highlights workers' adaptive strategies to reposition themselves based on tying-point heights during the initial phase.

To further validate these findings, the following section introduces a second case study derived from video recordings of a Hong Kong building site. Unlike the first case (a single worker), this analysis involves a crew of concrete workers pouring concrete into structural elements on a building floor.

3.3.2 Method application: multi-worker concrete pouring

3.3.2.1 Classification of concrete pouring activities

Unlike rebar workers, concrete workers' postural demands are less dependent on the building's structural configuration, as their tasks typically follow formwork installation. Their operational focus centers on achieving adequate concrete compaction within pre-installed formwork systems. Additionally, concrete placement operations require a higher degree of coordination among multiple workers and can be divided into distinct sequential workflow phases. These characteristics necessitate meticulous workspace planning to ensure efficiency and safety. The activities of concrete workers are systematically categorized into seven distinct types, as outlined in Table 3.6.

Table 3.22. Description of activities

Activities	Description	Abbr.
Concrete Pouring	Transferring freshly mixed concrete into formwork using pumps, buckets, or direct chutes ensures continuous material flow.	CP
Internal Vibration	Densification of concrete using immersed poker vibrators to eliminate entrapped air and achieve specified compaction standards.	IV
Consolidation	Manual elimination of voids in vertical elements using shovels or tampers prior to mechanical vibration, critical for narrow formwork applications.	CD
Screeding	Precision leveling of concrete surfaces with straightedges or laser-guided screeds to establish elevation control.	SC
Curing Membrane Installation	Deployment of moisture-retaining polyethylene sheets or spray-applied compounds to maintain hydration conditions.	CI
Traveling	Worker relocation between task zones within the worksite, including material fetching and equipment repositioning.	TR
Waiting	Non-value-adding intervals caused by workflow interruptions, material shortages, or crew coordination delays.	WT

Construction method statements, which provide step-by-step operational guidance tailored to site-specific conditions, can be modeled as Activity-on-Node (AON) network diagrams to visualize workflow dependencies. As demonstrated in Figure 3.13 for a monolithic concrete pour encompassing horizontal (e.g., slabs) and vertical elements (e.g., walls), the AON diagram revealed a critical finish-to-start dependency between concrete pouring and the internal-vibration process. Post-vibration procedures differed significantly between element types: horizontal components required sequential surface finishing (screeding) followed by curing membrane application. Vertical components, however, necessitated continuous consolidation to mitigate inconsistencies in concrete flow caused by gravity-induced segregation effects. It is worth noting that the current model does not support identifying specific work activities. There are already mature models that can identify work activities, and this study uses a manual approach.

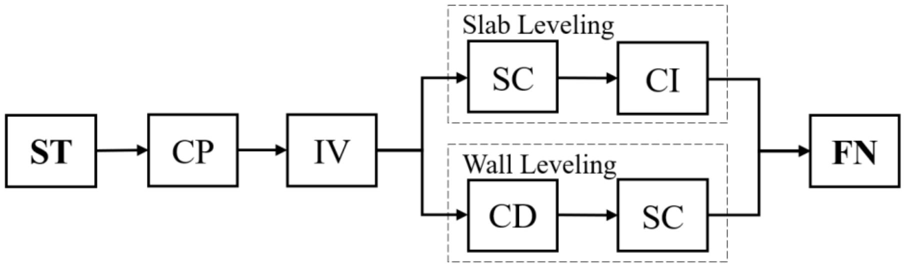

Figure 3.13 AON network of concrete work

3.3.2.2 Data preparation

This case study requires collecting both worker posture and activity data through frame annotation to validate the proposed framework. For data acquisition, a 10-minute surveillance video is processed using a temporal sampling strategy, extracting one frame every two seconds (totaling 300 frames), with each frame annotated to capture the position, activity type (e.g., concrete pouring, internal vibration), and posture (e.g., standing, bending) of all seven workers visible in the scene. This 10-minute video footage completes the cycle from concrete pouring to curing membrane laying, showcasing the entire process of concrete work activity and posture. To streamline this process, a custom annotation tool was developed (Figure 3.14), enabling efficient labeling of multi-worker activities and exporting structured metadata (including spatial coordinates, activity classifications, and posture) into a standardized JSON format. This systematic approach not only minimizes human errors in data organization but also facilitates subsequent model training for real-time productivity analysis.

Figure 3.14 Worker activity annotation script interface

3.3.2.3 Result and analysis of concrete pouring

In this case, the identification of worker postures and activities was performed manually without the use of an identification algorithm. Video analysis of a 7-worker crew (including one foreman) at an active workface revealed distinct activity and posture patterns during a 10-minute concrete operation cycle. As shown in Figure 3.15, most workers specialized in individual tasks. Worker 1 transitioned sequentially from concrete pouring (CP) to traveling between task locations before initiating curing membrane installation (CI). Workers 2-4 experienced idle periods during the observation window, which suggests potential workflow imbalances, such as mismatched task durations. In contrast, Workers 5-7 maintained continuous productive engagement throughout the cycle, ensuring continuity in material handling and placement tasks.

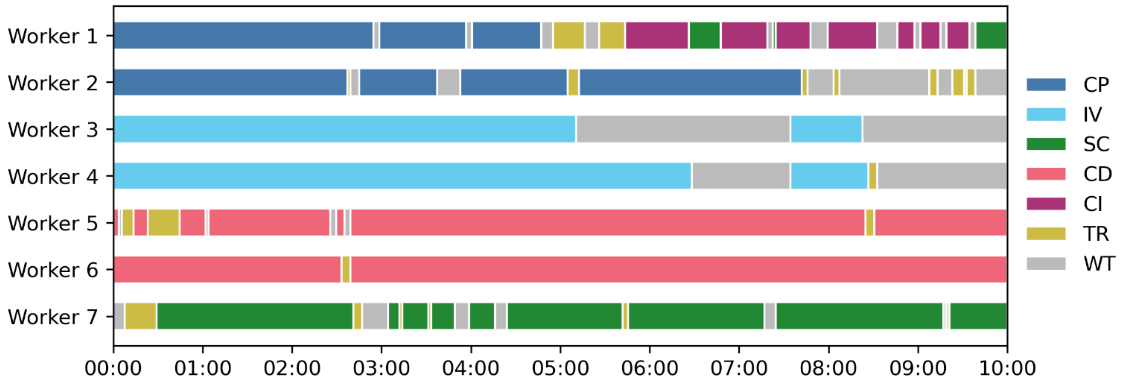

Figure 3.15 Activity distribution of each worker

To model activity-worker dependencies, this study segments workspaces into five sequentially arranged operational areas. While the analyzed 10-minute video segment captures incomplete construction phases (preceding and succeeding activities were not recorded during this timeframe), Figure 3.16 demonstrates detectable resource dependency constraints across various areas. Each bar denotes an activity, with workers involved in its execution shown in the upper left. Bars are connected via two constraint types: resource links (implying worker-dependent workflows) and technology links (denoting logical sequence between activities as marked by gray arrows; for this case, it is based on Figure 3.13). Figure 3.16 illustrates the detailed dependencies among resource-constrained activities. The worker assignments in the figure are labeled according to the video recordings, consistent with the real-world situation. The workflow reveals that Workers 3 and 4 conducted concrete vibration across Areas 1-5, though their work in Area 5 was contingent upon fresh concrete placement. Concurrently, Workers 1 and 2 handled concrete pouring in Area 4, followed by divergent subsequent tasks: Worker 1 returned to Area 2 for screeding and curing membrane application, while Worker 2 proceeded to pour concrete in the next designated area. These constraints account for the observed intermittent idling among Workers 2-4, demonstrating how temporal workflow patterns can be identified even from partial visual documentation. The results underscore the significant potential of video-based analytics in construction management, particularly for uncovering subtle yet critical process interactions that traditional monitoring methods might overlook.

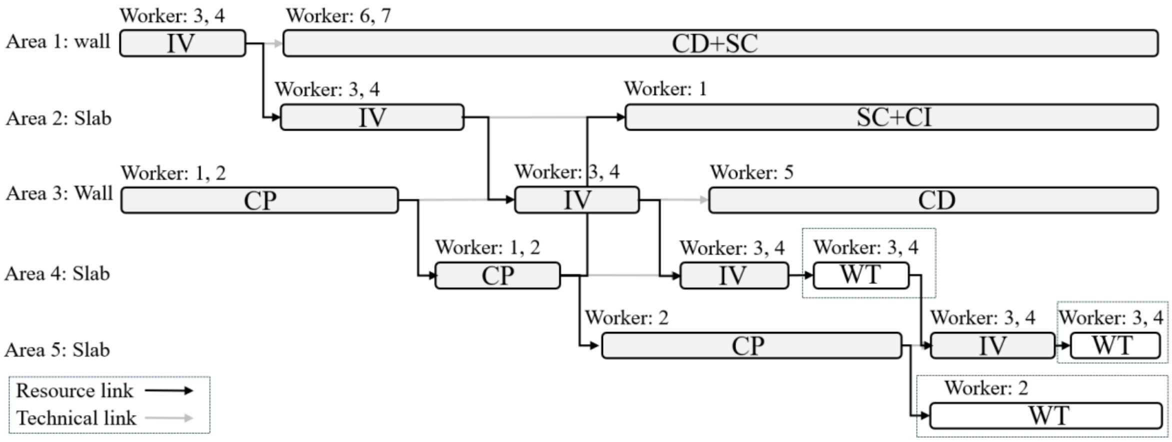

Figure 3.16 Resource activity on node network

Concrete workers exhibit task-posture interdependence governed by biomechanical requirements. As marked in Figure 3.14, Pump truck operators require sustained forward trunk flexion to stabilize vibrating concrete delivery pipes during pumping cycles. Conversely, screeding tasks necessitate prolonged squatting postures due to the lower height working plane. These ergonomic task alignments reveal occupation-specific kinetic patterns that inform productivity benchmarks and musculoskeletal risk assessments.

Table 3.23 Posture proportion of each activity

Posture \ Activity	CP	IV	CD	SC	CI	TR	WT
Walking	0%	0%	0%	0%	0%	95.1%	0.6%
Standing	10.9%	48.5%	0%	0.3	5.7%	1.2%	98.2%
Bending(<90°)	88.5%	50.7%	100%	5.6%	8.0%	3.7%	0.9%
Bending(⩾ 90°)	0.3%	0.7%	0%	45.5%	67.0%	0%	0.3%
Squatting	0%	0%	0%	48.6%	19.3%	0%	0%

The proposed framework leverages video recognition and posture analysis to evaluate concrete work processes, tailored to task-specific characteristics. It is noteworthy that for multi-worker operations, such as concrete pouring, the framework relies on a process-network model from work planning, such as the resource-loaded activity-on-node network diagram proposed by Lu and Li (2003). This approach enables real-time tracking of worker activities and facilitates ergonomic risk monitoring, thereby enhancing workplace safety and operational efficiency.

3.4 Discussion

The findings presented in this study offer significant implications for both workload estimation and work sampling in the construction industry. By leveraging computer vision techniques and a posture-based framework, this research provides a more granular and accurate approach to quantifying rebar workers' physical workload. The ability to estimate workload at the posture level marks a departure from traditional methods that rely on total working hours, or the weight of materials handled (Yang *et al.*, 2020).

The posture-based workload estimation demonstrated in this study could enhance current practices in work sampling. Conventional work sampling methods, such as time and motion studies, have been criticized for their inability to reliably predict productivity or quantify inefficient work hours (Logcher and Collins, 1978; Samelson and Borcherding, 1980; Thomas, 1991). By providing a detailed breakdown of workers' postures and their durations, the proposed approach enables a more nuanced assessment of workers' activities and their contribution to overall productivity. In addition, this shift toward posture-based workload estimation aligns with the growing focus on ergonomics and worker well-being in the construction industry (Kim *et al.*, 2022). This alignment could facilitate adoption of the proposed method in practical settings by industry practitioners.

This study further examines how planning decisions affect worker workload distribution. While construction site plans typically cannot specify activities at the individual worker level, our analysis of worker-specific tasks reveals that resource dependencies (Figure 3.9) constitute the primary constraint governing site operations. The findings demonstrate that, when external factors permit, strategic increases in workforce allocation can effectively reduce task duration by alleviating these resource bottlenecks.

Furthermore, the findings establish a foundation for transitioning from labor-hours to posture-hours as a unit of measure for labor productivity in construction. The concept of posture-hours accounts for the disparate physical demands associated with different postures and activities, offering a more precise quantification of workers' exerted effort. This shift may enable more accurate resource allocation, improved project planning, and enhanced occupational health and safety outcomes (Anwer *et al.*, 2021; Wang *et al.*, 2024).

In the multi-worker case, data collection and identification are performed manually. Future research could leverage additional site videos of labor-intensive activities to train worker activity recognition models using the posture labels established in this study, with DeepSORT enabling automated positional tracking. Existing multi-worker activity recognition algorithms (e.g., Gong et al., 2025) can be adapted with labeled data to classify concurrent tasks. As datasets expand to capture diverse actions and postures, advanced architecture (e.g., SlowFast, transformers) can be deployed to enhance generalization through machine learning. Furthermore, future research will explore methods to predict pose data from design drawings to avoid the unpredictability of recording conditions due to occlusions and lighting.

The insights derived from posture-based workload estimation create opportunities to optimize work plans to minimize ergonomic risks and physical strain on workers. By analyzing posture distribution during tasks, designers and planners can proactively adjust workflows to limit exposure to uncomfortable or high-risk postures. Such optimization might include redesigning reinforcement structures, restructuring task sequences, or integrating assistive technologies to mitigate physical strain (Moon *et al.*, 2020). Ultimately, these measures may help reduce the incidence of work-related musculoskeletal disorders and enhance overall worker health and well-being in the construction industry.

3.5 Summary

The findings of this study carry significant theoretical and practical implications for construction workload assessment. By incorporating computer vision into a posture-based analytical framework, this research not only enables granular quantification of physical workload at the posture level but also moves beyond traditional productivity metrics based solely on time or material handling (Yang et al., 2020), thereby refining the accuracy of workload estimation and work sampling.

A key enabler of this framework is the automated quantification of postural exposure. This study presents a framework that automates the critical step of translating raw video data into objective "posture-hour" metrics. The process is initiated by a fully automated computer vision model that identifies worker postures frame by frame, which are then consolidated into a particular posture sequence consisting of selected key frames. The system automatically calculates the cumulative duration each posture is held, providing a foundational ergonomic exposure metric. It is important to delineate the scope of this automation: the association of these posture sequences with specific, high-level construction activities, however, requires manual initialization based on domain expertise. It is noteworthy that activity definitions are often project-specific, making human judgment necessary to ensure the resulting data is meaningful for project management. Thus, the primary contribution is the automation of worker posture exposure quantification, while effectively bridging low-level kinematic data with high-level activity analysis. The manually curated dataset of posture-activity pairs generated by this process establishes a critical foundation for training future advanced models for end-to-end automation.

The achievable performance of the posture recognition model based on the present research is sufficient, which would justify the further development of a fully automated and integrated process down the path. It is noteworthy that the ground-truth posture labels for model training and validation were established through manual annotation conducted by a single annotator. To ensure consistency, the process strictly adhered to the well-defined criteria for each posture class detailed in Table 3.1. This unified interpretation framework was appropriate for this proof-of-concept study. The model achieved an overall accuracy of 85.3%, with a macro-average F1-score of 0.849. A detailed per-class analysis, conducted in response to reviewer feedback, revealed exceptional performance in identifying "Raising Arms" (F1-score: 0.95) and "Squatting" (F1-score: 0.91). The primary source of error was the misclassification between "Bending" and "Squatting," and between "Walking" and "Standing," suggesting these pairs exhibit greater visual similarity from the monitoring viewpoint. The complete per-class metrics and confusion matrix are provided in Appendix A.

Beyond the contributions outlined above, it is important to contextualize the scope of the proposed five-posture taxonomy. While it provides a more granular approach to workload estimation than traditional methods, it may not capture the full spectrum of subtle work variations. This simplification represents a conscious trade-off to balance accuracy with scalability for this proof-of-concept, focusing on the most frequent and ergonomically critical postures. It is crucial to note that the proposed framework is inherently scalable and can be readily extended in future work by incorporating additional basic posture classes (e.g., turning, climbing) or tailored to specific task environments (e.g., customized taxonomy of welder postures in connection with structural steel fabrication.)

While this study introduces the novel "posture-hour" metric, its current biomechanical granularity is limited. The five-posture taxonomy, for instance, treats all "bending" as equivalent without accounting for flexion angles. This design stems from a focus on macro-level workload estimation for productivity and OHS risk mitigation, rather than fine-grained ergonomic analysis. Consequently, the posture-hour metric complements tools like REBA/RULA by addressing complementary yet distinct objectives: it targets macro-level workload distribution across tasks and crews to aid managerial resource allocation, whereas REBA/RULA provide micro-level risk scores. A promising future direction is to develop a weighted posture-hour metric that incorporates biomechanical nuances (e.g., joint angles) informed by REBA/RULA principles.

The posture-based workload estimation demonstrated in this study could enhance current work-sampling practices. Conventional work sampling methods, such as time and motion studies, have been criticized for their inability to reliably predict productivity or quantify inefficient work hours (Logcher and Collins 1978; Samelson and Borcherding 1980; Thomas 1991). By providing a detailed breakdown of workers' postures and their durations, the proposed approach enables a more nuanced assessment of workers' activities and their contribution to overall productivity. In addition, this shift toward posture-based workload estimation aligns with the growing focus on ergonomics and workers' occupational health in the construction industry (Kim et al. 2022). This alignment could facilitate the adoption of the proposed method in practical settings by industry practitioners.

This study further examines how planning decisions affect the distribution of worker workload. While construction site plans typically cannot specify activities at the individual worker level, the analysis of worker-specific tasks reveals that resource dependencies (Figure 3.9) constitute the primary constraint governing site operations. The findings demonstrate that, when external factors permit, strategic increases in workforce allocation can effectively reduce task duration by alleviating these resource bottlenecks.

The findings resulting from this research lay the foundation for transitioning from labor-hours to posture-hours as a unit of labor productivity. The concept of posture-hours accounts for the disparate physical demands associated with different postures, offering a more precise quantification of workers' exerted effort. This shift may enable more accurate resource allocation, improved project planning, and enhanced occupational health and safety outcomes (Anwer et al. 2021; Wang et al. 2024). Moreover, the insights derived from posture-based workload estimation create opportunities to optimize work plans by minimizing ergonomic risks. By analyzing posture distribution, designers and planners can proactively adjust workflows to limit exposure to high-risk postures. Such optimization might include redesigning structures, restructuring task sequences, or integrating assistive technologies to mitigate physical strain (Moon et al. 2020). Ultimately, these measures may help reduce the incidence and mitigate the risks of work-related musculoskeletal disorders.

One limitation of this study is worth mentioning: in the "Single-Worker Case Study", a researcher was trained to mimic a practitioner under controlled conditions, rather than engaging real skilled tradespeople. Hence, the posture-hour estimates derived should be viewed as demonstrating the framework's functionality rather than as benchmarks for actual work. Nevertheless, the core methodology shows the potential for broader application, as evidenced by its application based on real-world footage of crew operations in the second case. The posture recognition model, trained by objective criteria, provides a validated foundation. Translating this research into a practical tool necessitates an industry-wide consortium dedicated to creating large-scale, annotated datasets that encompass the full diversity of construction tasks and crews. This collaborative foundation is a prerequisite for developing the robust, generalizable algorithms required to automate ergonomic-aware productivity study and work planning.

Chapter 4: Project Scheduling and Resource Allocation Subject to Worker's Posture-Hour Thresholds

4.1 Introduction

Several established methods exist for measuring physical workload. For instance, Park et al. (2023) used wearable devices to monitor worker fatigue through heart rate variability, while Khan et al. (2024) employed computer vision to estimate workers' postures. Integrating such data into historical scheduling considerations allows for work planning and project scheduling by factoring in the crew's physical workload. Similarly, mature systems have been available for the backend algorithmic components. Karim and Adeli (1999a) developed CONSCOM, an object-oriented decision support system for construction project management. This system model project tasks, constraints, and resources, while its neural dynamics optimization algorithm enables cost minimization while maintaining schedule feasibility. With advances in data collection and analysis, it is now feasible to implement workface planning that incorporates detailed posture analysis.

However, current construction planning often overlooks ergonomic risks until workers report discomfort, relying on reactive adjustments rather than proactive design. To systematically integrate workers' posture demands into scheduling, this study develops a posture-hours planning framework to extend the existing resource-constrained project scheduling methods. In two case studies, the resulting technique is proven effective for work planning and project scheduling for construction crews, achieving an optimal balance between work efficiency and worker OHS maintenance.

This chapter proceeds as follows: The background establishes the problem of musculoskeletal disorders in construction and reviews worker-centric planning approaches, identifying the gap in posture-aware scheduling. The methodology introduces the posture-hour scheduling framework with posture demand/supply concepts and heuristic rules for worker allocation. A demonstration case analyzes algorithm performance and trade-offs between project duration and posture deficit. Field validation through concrete pouring operations examines the impact of crew size on posture-hour distribution. The discussion addresses limitations and future extensions, including BIM integration and real-time monitoring. Finally, the summary summarizes how the framework advances workforce sustainability through proactive ergonomic risk management in construction planning.

4.2 Methodology

4.2.1 Application framework

This chapter evaluates worker effort by analyzing the time required for various working postures and integrating this factor into construction scheduling. Each construction task demands workers to maintain specific postures for certain periods, known as "posture demand." The scheduling challenge involves assigning crew members with sufficient posture capacities to meet these demands, while ensuring that the resource allocation framework builds on the well-established Resource-Activity Critical-Path Method (RACPM) algorithms. By extending RACPM—a widely accepted method for allocating limited resources to activities in project scheduling—to include posture-hour constraints, this approach remains compatible with existing scheduling practices.

The proposed posture-hour scheduling method considers variations in workers' posture-hour usage across concurrent activities with precedence constraints, modeled through an Activity-on-Node (AON) network. To address the complexity of posture-hour scheduling in dynamic construction settings, the approach includes heuristic rules that actively monitor two key worker-level metrics during schedule analysis: residual posture capacity and posture deficit. This real-time monitoring ensures balanced resource use by preventing both overexertion and underuse of certain postures, thereby avoiding unsafe cumulative exposure to any single posture at the individual worker level.

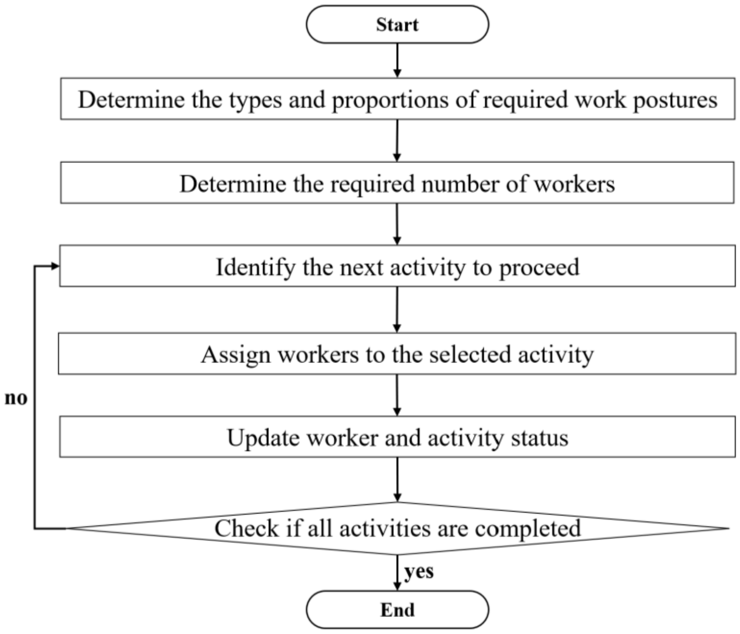

Figure 4.1 Flowchart of Posture-Hour Scheduling Algorithm

As shown in Figure 4.1, the proposed algorithm's workflow consists of four sequential stages: starting with (1) worksite observation and analysis of standard construction processes to perform work breakdown and establish task requirements, including activity dependencies, durations, workforce needs, and posture distributions; followed by (2) identifying the next executable activity based on precedence relationships and workload data; then (3) assigning workers using posture-balancing heuristic rules to ensure fair physical workload distribution; and ending with (4) continuously updating activity and worker statuses to support dynamic resource allocation during project execution.

This framework advances beyond traditional scheduling methods by explicitly factoring in workers' posture-hour capacity as a crucial parameter. It recognizes that various construction activities demand specific postures with different physical exertions. The approach systematically matches activity-specific posture-hour needs with the preset posture-hour limits of the crew members throughout the project.

4.2.2 Posture demand and supply

The study's conceptual framework models workers as providers of posture-hours, while activities act as recipients of this resource. During project execution, workers gradually use up their posture-hour capacity to complete assigned tasks, with this resource being systematically depleted and transferred to activities as work continues. As shown in Figure 4.2, completing Activity 1 leads to a corresponding decrease in Worker 1's available posture-hour capacity.

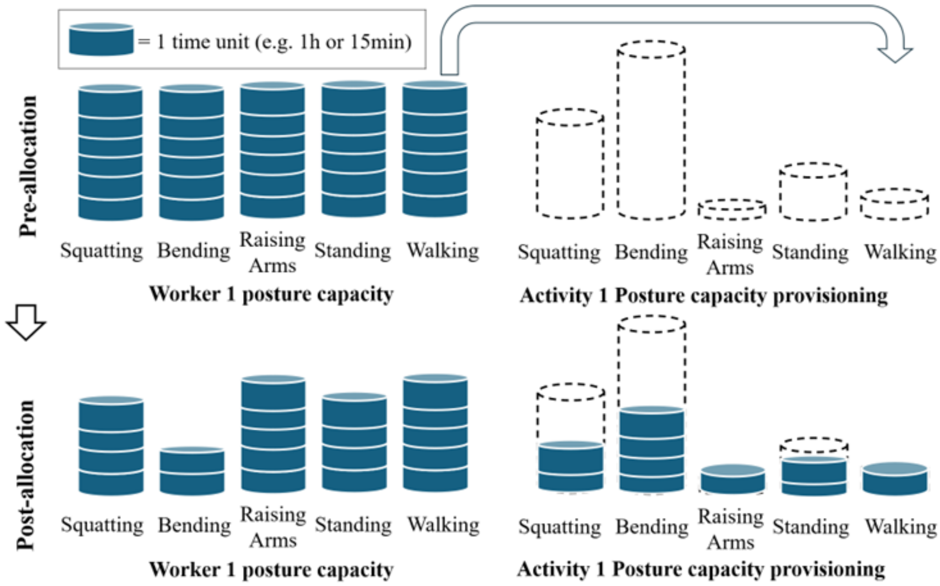

Figure 4.2 Schematic diagram of posture-hour allocation

Effective workforce posture planning and scheduling rely on accurate estimates of work posture demands. Project planners typically reference construction drawings and critical path schedules. Historical data can serve as an important benchmark for posture-hour patterns related to activities, while computer vision-based posture estimation algorithms offer detailed temporal posture distributions. Alternatively, posture needs can be inferred directly from drawings or based on prior experience with similar tasks. For example, roof slab rebar installation mainly involves bending postures for material handling and tying, due to the low working height. Estimating posture requirements essentially predicts workers' exposure to occupational health and safety (OHS) risk factors, focusing on two key metrics: posture types and exposure duration (Bernard et al., 1997; Spurgeon et al., 1997). Other factors, such as weight (Punnett et al., 1991), stress (Bongers et al., 2002), sleep deprivation (Powell and Copping, 2010), and whole-body vibration (Bernard et al., 1997), also influence worker well-being. This study concentrates on these two measurable indicators: posture types and exposure duration. The following presents the equations for this process:

$$A_{jp} = (a_{jp1}, \quad a_{jp2}, \ldots, a_{jpk}) \qquad \text{Equation (1)}$$

$$\sum_{1}^{k} a_{jpk} = 1 \qquad \text{Equation (2)}$$

$$P_r = \begin{bmatrix} a_{jp1} \\ a_{jp2} \\ \ldots \\ a_{jpk} \end{bmatrix} \cdot (A_{jw} \cdot A_{jt}) \qquad \text{Equation (3)}$$

The equation defines Ajp as the proportional distribution of k posture requirements (Eqs. 1 and 2). Pr represents the posture demand vector for the selected activity, including the required working duration for k postures (Eq. 3). The following example illustrates how to calculate the posture-hour demands of an activity.

Assume activity J requires two workers over a 6-day period. The postural distribution during this work includes: 10% standing, 10% bending, 70% squatting, and 10% walking. Using the format of Eq.3, this can be represented as:

$$P_r(Activity\ J) = \begin{bmatrix} 10\% \\ 10\% \\ \mathbf{70\%} \\ 10\% \end{bmatrix} \cdot (2 \cdot 6h) = \begin{bmatrix} 1.2h \\ 1.2h \\ \mathbf{8.4h} \\ 1.2h \end{bmatrix} \qquad \text{Equation (4)}$$

Equation 4 indicates a total bending requirement of 8.4 hours, with workers' posture-hour capacity being decreased accordingly to meet activity J's demands.

4.2.3 Number of workers

The crew size fundamentally determines the total posture-hour capacity of the workface. When designing crews based on posture needs, two key constraints must be satisfied: (1) meeting baseline operational requirements for both total labor hours and posture-specific hour allocations, and (2) adhering to each worker's daily posture duration limits. If any posture exceeds a worker's permissible exposure threshold, the affected tasks should be redistributed among available crew members. These activity-level needs add up to establish the minimum workforce required, setting the lower limit for labor resource allocation. Any work plan that results in posture-hour shortages would cause workers to exceed safe exposure durations - even if total work time is shortened and tasks are evenly distributed, such plans would be inefficient. This framework allows for calculating the minimum crew needed to keep posture exposure within safe limits (Eq. 5).

$$\sum_{1}^{j} a_{jpk} \cdot A_{jw} \cdot A_{jt} \leq \sum_{1}^{i} l_{ipk} \qquad \text{Equation (5)}$$

The variable l_{ipk} represents the remaining capacity of worker i for maintaining posture k. This inequality indicates that the total time demand for posture k should not exceed the combined posture-hour capacity of all workers. During planning, this capacity equals the worker's specific posture threshold. Generally, these thresholds should be set based on physiological fatigue buildup and recovery patterns. For example, it is maintained that holding any posture for more than 4 hours significantly increases the risk of musculoskeletal disorders in the back and shoulder-neck region.

4.2.4 Preparation before scheduling

As presented in Table 4.1, drawing inspiration from object-oriented programming principles (Karim and Adeli, 1999b), the proposed framework is built upon three fundamental classes: 1) workers (I), 2) activities (J), and 3) defined postures (K). The project network structure relies on predefined precedence relationships. These relationships are captured in the precedence set AP_j, which explicitly specifies the immediate predecessors for each activity $j \in J$.

Table 4.1 Initialization parameters for the scheduling algorithm

Parameters	Description	Symbol/Equation
Define the sets	Let $J = \{1,2,3,\ldots,j\}$ denote the set of activities.	J
	Let $I = \{1,2,3,\ldots,i\}$denote the set of workers.	I
	Let $K = \{1,2,3,\ldots,k\}$denote the set of postures.	K
Precedence set	$AP_j$is given as the set of immediate predecessors of activity *j*.	$AP_j \subseteq J$ $AP_j = \emptyset$ (j has no predecessors)
Required Worker	$A_{jw} \in Z^+$ is a positive integer specifying the number of workers needed for activity *j*.	A_{jw}
Duration	$A_{jt} \in R^+$ is a positive real number representing the required duration of activity *j*.	A_{jt}
Finish time	A_{jf} represents the end time of activity *j*	A_{jf}
Status	A_{js} represents the status of activity *j*	$A_{js} = \begin{cases} 0, & (not\ finished) \\ 1, & (finished) \end{cases}$
Remaining posture capacity	$L_{ip} \in R^k$ is a vector representing the remaining work capacity of worker *i* for each posture.	$L_{ip} = (l_{ip1}, l_{ip2}, \ldots, l_{ipk})$
Earliest release start time	$L_{irst} \in R^+$ is the earliest time at which worker i is released from previous activity and starts a new activity.	L_{irst}

Each activity is characterized by three key parameters: (1) the required workforce size (A_{jw}), (2) the estimated standard duration (A_{jt}), and (3) algorithmic control variables (A_{jf}, A_{js}) that regulate schedule progression. Crucially, each activity $j \in J$ is characterized by a posture demand profile A_{jp}. This profile represents the proportional time requirement for each posture $k \in K$ necessary to complete activity j (**Eq. 3**).

After worker-specific posture-hour capacities are initialized, a unique posture capacity vector L_{ip} defines the maximum sustainable duration that worker i maintains each posture $k \in K$. An availability control variable (L_{irst}) is initialized to track worker status throughout the scheduling process. At initialization, L_{ip} is typically set to the initial full capacity based on given input data. For instance, at the beginning of a work shift, workers possess full physical capacity to sustain various postures for extended periods. The maximum duration for maintaining each posture under these optimal conditions is initialized in L_{ip}.

$$L_{ip}(Worker\ i\ initial) = \begin{matrix} \{4h(Standing), \\ 4h(Bending), \\ 4h(Raising\ Arms), \\ 4h(Squatting), \\ 4h(Walking)\} \end{matrix} \qquad \text{Equation (6)}$$

Equation 6 presents the workers' initial physical state, indicating that each posture can be maintained for up to 4 hours during an 8-hour regular workday. This posture-hour capacity is subsequently depleted through activity allocation as the project unfolds.

4.2.5 Algorithm for Posture-Hour Scheduling

Following the initialization of the AON network and parameters, the proposed scheduling algorithm is executed through an iterative three-stage process (**Figure 4.1**). The core workflow sequentially 1) identifies eligible activities to proceed, 2) assigns available workers considering both requirements for activities and accumulated posture exertion for workers, and 3) updates corresponding activity completion status along with worker state variables, including posture-hour capacity depletion and individual workers' availability updates.

The Entity Relationship Diagram in Figure 4.3 illustrates the data structure of the posture-hour planning method. It displays the attributes of three main entities—"ACTIVITY," "POSTURE," and "WORKER"—along with their relationships to other entities. The relationships between the main entities and other entities are primarily one-to-many. For example, from the "ACTIVITY" entity's perspective, the "ACTIVITY_POSTURE" entity stores the multiple posture requirements corresponding to a single activity. Conversely, from the "POSTURE" entity's perspective, "ACTIVITY_POSTURE" contains all activity demands for a specific posture type. Notably, the "ASSIGNMENT" entity is designed to track and record worker allocation data, capturing activity start and end times from the worker's perspective.

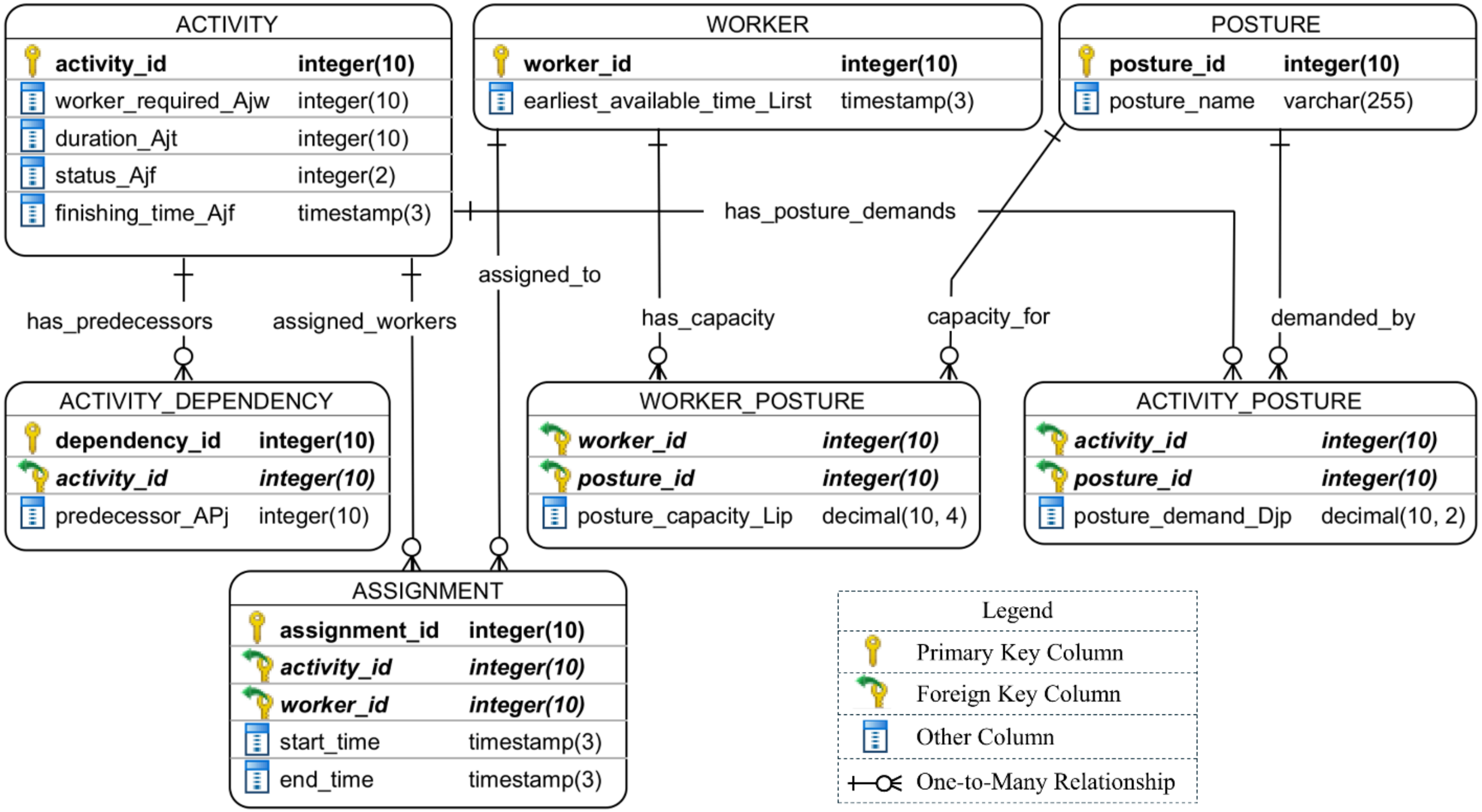

Figure 4.3. Entity relationship diagram of posture-hour planning method

To expand the impact of this research and enhance the scalability of the proposed method, the data structure file has been made open-source and is available at:

https://github.com/rbqkk/Posture_planning_data_structure/blob/main/PosturePlanning.vpp

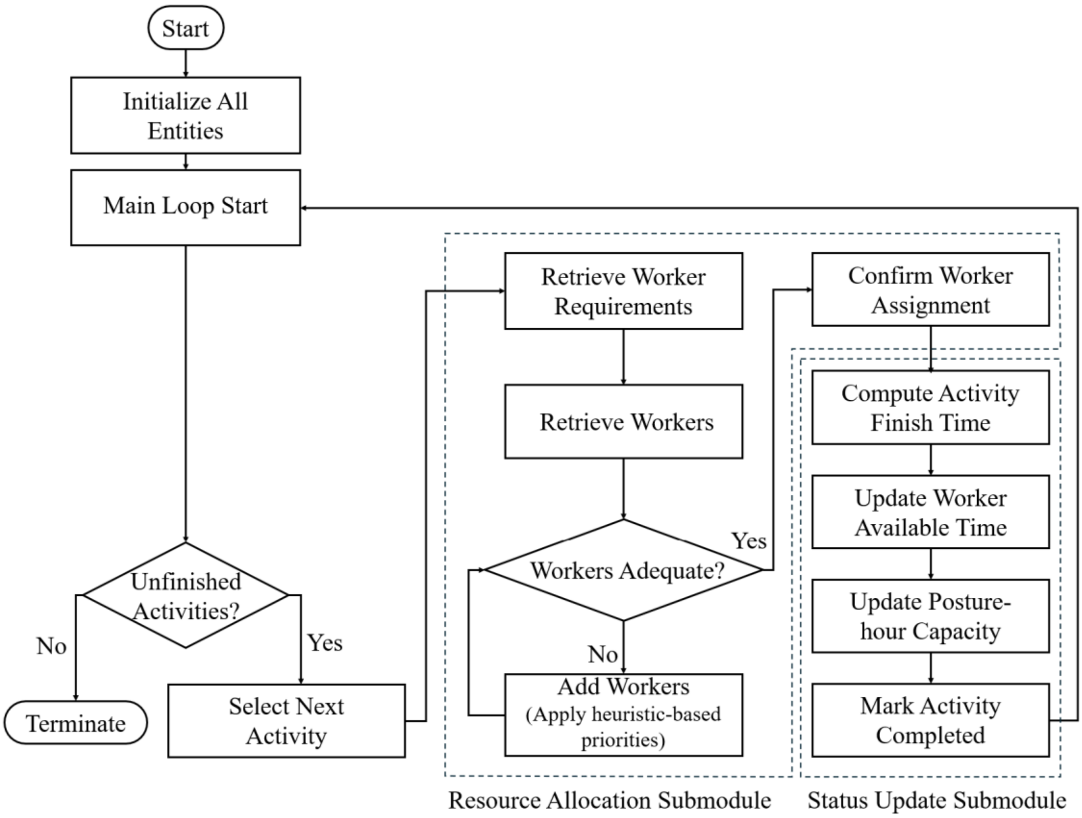

Figure 4.4 Flowchart of posture-hour planning method

Figure 4.4 presents the flowchart schematic of the proposed posture-hour planning method. This research was implemented using Python in a Jupyter Notebook development environment. The related files have been made open-source and are available at:

https://github.com/rbqkk/Posture_planning_data_structure/blob/main/phplanning.ipynb

1. The algorithm identifies activities within the project network by evaluating precedence dependencies, where an activity $j \in J$ becomes eligible for execution only if its set of immediate predecessors (AP_j) is empty—indicating no dependencies (Activity **A** in Figure 4.5)—or if every predecessor activity $j \in AP_j$ has a completion status A_{js}=1 (Activity **F, G** in Figure 4.5).

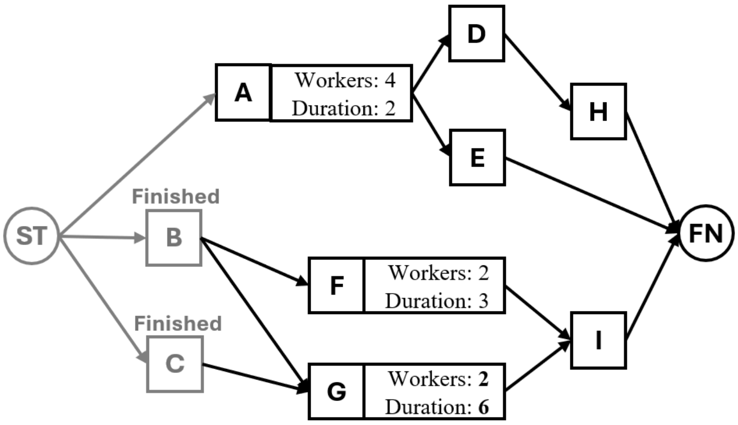

Figure 4.5 AON network for activity selection

When multiple activities in the workface AON network meet requirements, the selection rule prioritizes the activity with the highest man-hours. As shown in Figure 4.5, after completing activities B and C, the eligible activities are A, F, and G. Man-hours are calculated by multiplying the required number of workers by the activity duration. Activity G is selected with 12 man-hours, exceeding both Activity A (8 man-hours) and Activity F (6 man-hours).

2. Upon identifying an eligible activity j, the algorithm proceeds to assign workers capable of executing the activity. While any worker in set I could be assigned, practical scheduling requires prioritization to meet project deadlines. To enable the earliest possible start time for activity j with adequate resources, the selection strategy prioritizes workers based on their availability. Workers are ordered by their availability timestamp L_{irst} in ascending order, indicating when each becomes

available for assignment. The first A_{jw} workers from this ordered list are then assigned to activity j, where A_{jw} represents the required number of workers for activity j.

Table 4.2 The workers' earliest available time when allocating workers for Activity G

Worker ID	The earliest available time: L_{irst}
Worker 1	8
Worker 2	8
Worker 3	**5**
Worker 4	**5**
Worker 5	8
Worker 6	8

The worker allocation process can be illustrated using Activity G from Figure 4.5. Assume there are currently 6 workers on the workface, with their earliest available times shown in Table 4.2. When assigning workers to Activity G, which requires two workers, the system selects those with the earliest available times. Worker 3 and Worker 4 have the earliest availability, becoming available at hour 5 of the workface operation, which is 3 hours earlier than the other workers who become available at hour 8. Therefore, these two workers are assigned to perform Activity G.

3. Following worker assignment to the selected activity, the algorithm updates critical state variables. The finish time of activity j (A_{jf}) is computed as:

$$A_{jf} = \max\left(\max_{i \in W_j}\{L_{irst}\}, \max_{p \in AP_j}\{A_{pf}\}\right) + A_{jt} \qquad \text{Equation (7)}$$

where W_j denotes the set of workers assigned to j, AP_j is the set of immediate predecessors, A_{pf} represents the finish time of predecessor p, and A_{jt} is the duration of activity j. This computation ensures A_{jf} synchronizes both worker availability constraints and precedence dependencies, as formalized in **Eq. 7**.

Concurrently, the completion status A_{js} is set to 1. For each assigned worker $I \in W_j$, the availability time L_{irst} is updated to A_{jf}, reflecting their commitment until the activity concludes.

Table 4.3 Status updating for Activity G

Activity ID	Previous Status	New Status	L_{irst} of selected workers	Finish time of predecessors	Duration A_{jt}	Updated finish time
G	$A_{js} = 0$	$A_{js} = 1$	{5, 5}	{5, **8**}	6	14

Table 4.4 State updating for worker 3 and worker 4

Worker ID	Previous L_{irst}	New L_{irst}
Worker 3	5	14
Worker 4	5	14

The process of updating Activity G's completion status (A_{js}) and completion time (A_{jf}) is shown in Table 4.3. The completion time of Activity G is constrained by both the earliest start time of the two workers L_{irst} (both at hour 5), and the finish times of predecessor activities (Activity C finishes at hour 5, while Activity B finishes at hour 8). Therefore, Activity G cannot begin until hour 8, and with its required 6-hour duration, the completion time is updated to hour 14. Similarly, as shown in Table 4.4, the earliest available times for the selected workers (Worker 3 and Worker 4) are also updated to hour 14.

Worker posture-hour capacity needs to be updated accordingly. The posture demand calculated through Equation 3 will be allocated to individual workers for subsequent deduction. The corresponding posture capacity l_{ipk} of worker i (element k in vector L_{ip}) is updated as:

$$l_{ipk} \leftarrow l_{ipk} - (a_{jpk} \cdot A_{jt}) \qquad \text{Equation (6)}$$

This reduction quantifies the cumulative physical load that worker i experiences when maintaining posture k during the execution of activity j (Eq.6). Updates occur simultaneously across all postures $k \in K$ and all workers in W_j, ensuring that posture capacities accurately reflect the state of physiological depletion on the project as tasks are performed. When the l_{ipk} value becomes negative following an update, this indicates that worker i has developed a posture deficit for posture k.

Table 4.5 Posture capacity updating for selected workers

Worker ID	Posture Type	Prev. posture capacity l_{ipk}	Consumption $a_{jpk} \cdot A_{jt}$	New l_{ipk}	Worker State
Worker 3	Standing	3.3	0.6	2.7	Normal
	Bending	3.3	0.6	2.7	
	Raising Arms	3.3	0	3.3	
	Squatting	4.8	4.2	0.6	
	Walking	4.3	0.6	3.7	
Worker 4	Standing	2.3	0.6	1.7	Deficit
	Bending	2.3	0.6	1.7	
	Raising Arms	3.3	0	3.3	
	Squatting	2.7	4.2	**-1.5**	
	Walking	4.1	0.6	3.5	

Table 4.5 demonstrates the posture-hour capacity updates for Worker 3 and Worker 4, who are assigned to Activity G. The results show that after the posture-hour

consumption is evenly distributed between the two workers, Worker 4 develops a posture deficit due to the different initial posture-hour capacities of the workers. Worker 4's squatting posture exceeds his sustainable limit by 1.5 hours.

4.2.6 Heuristic rules

Heuristic rules offer distinct advantages in real-world planning processes due to their ease of understanding and implementation. Additionally, since heuristic rules do not function as algorithmic black boxes, planners can flexibly adjust them based on on-site conditions during actual construction. By far, this research has identified two key heuristic rules: first, for activity selection, prioritizing feasible activities with higher man-hour requirements; and second, for worker selection, choosing workers with the earliest availability times.

During worker assignment for a selected activity j, the algorithm employs a two-tiered hierarchical sorting system (illustrated in Figure 4.6). Workers are first divided into two categories based on their posture capacity status: the primary group consists of workers with no posture deficit ($l_{ipk} \geqslant 0 \ \forall k \in K$), while the secondary group includes those experiencing any posture deficit. Within each group, workers are then sorted by their availability time (L_{irst}) in ascending order.

It is noteworthy that the assignment process prioritizes the primary group, selecting the earliest available workers without posture deficits first. Only when this pool is exhausted does the algorithm turn to the secondary group to fulfill the remaining worker requirement (A_{jw}).

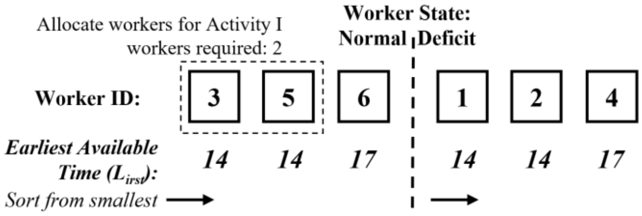

Figure 4.6 Worker Allocation heuristics rule

As shown in Figure 4.6, when assigning workers to Activity I, the allocation process considers whether workers have experienced any posture-hour deficits, resulting in a change in worker prioritization. Worker 4, who has already developed a posture-hour deficit, is moved down in the selection order. Instead, Workers 3 and 5 are selected to perform Activity I for two key reasons: first, they have not experienced any postural deficits, and second, their earliest available times are relatively earlier compared to other workers. This strategic prioritization serves to minimize task allocation to workers already experiencing posture capacity depletion, effectively distributing physical workload more evenly across the workforce and preventing acute overexertion in specific posture dimensions in ensuing work assignments.

4.3 Demonstration case and analysis

Different construction activities place distinct physical demands on workers, creating unique ergonomic profiles throughout the workflows within each activity and between consecutive activities. As shown in Table 4.6, Activities D and E are characterized by extensive bending, with workers spending approximately 60% of their time in this posture. This pattern is typical of structural installation and foundation work, where confined spaces require workers to maintain prolonged trunk flexion. The remaining 40% involves standing and walking—time spent on tool retrieval, repositioning, and quality checks that, while essential, represent less productive phases of work execution.

In contrast, Activities A, B, and C show more balanced ergonomic demands, with workers distributing their time nearly equally across bending, squatting, and raised-arm postures (approximately 30% each). This balanced distribution commonly occurs during assembly tasks that require frequent changes in body position, such as installing mechanical components or mounting overhead fixtures, where a worker needs to continuously adapt their posture to access different work areas.

Table 4.6 Activity-specific posture demands

Activity (J)	NO. of workers A_{jw}	Duration A_{jt}	ajp1	ajp2	ajp3	ajp4	ajp5
			Standing	Bending	Raising arms	Squatting	Walking
A	4	2	0.3	0.3	0.3	0	0.1
B	4	3	0.3	0.3	0.3	0	0.1
C	4	5	0.3	0.3	0.3	0	0.1
D	3	4	0.2	0.6	0	0	0.2
E	1	4	0.2	0.6	0	0	0.2
F	2	3	0.1	0.1	0	0.7	0.1
G	2	6	0.1	0.1	0	0.7	0.1
H	2	2	0.1	0.4	0	0.4	0.1
I	2	3	0.1	0.4	0	0.4	0.1

For demonstration purposes, all workers are assumed to have identical posture capacity limits based on general biomechanical thresholds for construction tasks. While recognizing that individual physiological tolerances naturally vary, this standardized approach reflects typical industry practice - where crews are treated as homogeneous units with workers considered equally interchangeable across tasks, without accounting for individual capability differences.

Non-neutral postures (e.g., bending, squatting) have significantly reduced sustainable durations compared to neutral positions, owing to accelerated muscle fatigue and elevated injury risk. To ensure worker safety, posture exposure limits are established using conservative thresholds at the lower end of population tolerance - a precautionary approach that systematically minimizes hazardous posture exposure.

Figure 4.7 illustrates the algorithm's output through two complementary views. The upper section presents the final schedule as a Gantt chart spanning 23 days. While this exceeds the 20-day baseline from conventional methods applied to the benchmark case for resource constrained scheduling (Lu and Li, 2003b), the extended timeline reflects a proactive strategy for managing ergonomic capacity. Workers showing signs of strain are strategically idled for recovery, trading a minor loss in time efficiency for long-term worker wellbeing.

The lower section visualizes worker-activity assignments using duration-scaled rectangles, where the area (width × height) directly represents cumulative labor input (duration × worker count). Activity C, which displays the largest area due to high resource requirements, is scheduled first.

The early scheduling of high-posture-demand activities (C, D, E) visually validates the effective implementation of our heuristic-based resource allocation method. The subsequent staggered arrangement of smaller activities demonstrates successful prioritization under posture-hour constraints and subject to precedence relationships.

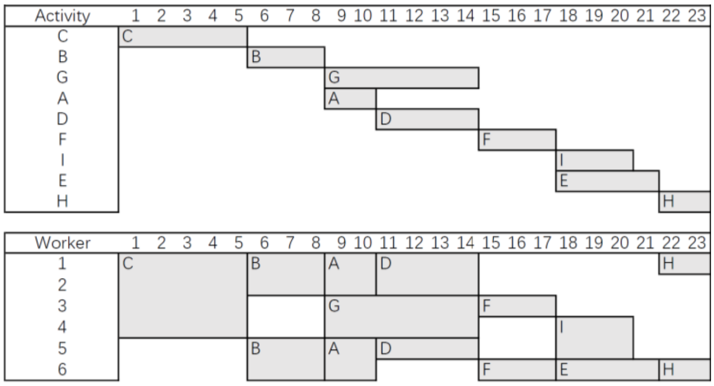

Figure 4.7 Bar chart and resource allocation for the demonstration case

Figure 4.8 presents the quantified cumulative posture deficits across workers at project completion, showing minor but measurable posture-hour exceedances among certain crew members. These worker-specific deficits (e.g., Worker 1's 1.4-hour bending overload) emerge from two fundamental algorithmic behaviors: (1) task assignments to workers nearing posture capacity limits from previous activities, and (2) necessary allocations to workers with existing deficits during later project stages - when most crew members have developed some posture overload - to ensure project completion.

	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5	Worker 6
standing	0.8	1	2.4	2.4	2.2	2
bending	-1.4	-0.6	2.4	1.5	-0.3	-0.2
raising arms	1.8	1.8	3.3	3.3	3.3	3.3
squatting	4	4.8	-1.5	-0.6	3.6	1.9
walking	2.8	3	3.4	3.4	3.2	3

Figure 4.8 Posture-specific capacity across workers

While these deficits indicate opportunities for further optimization, they provide valuable visibility into posture exhaustion patterns that conventional scheduling approaches typically overlook. In practice, modest posture-hour exceedances within controlled limits are operationally acceptable, provided they don't lead to disproportionate posture accumulation among individual workers - a critical consideration for maintaining occupational health and productivity of the workforce.

4.4 Concrete pouring operations case

To test the proposed algorithm in practice, a real-world case study examined concrete pouring operations at a multi-purpose underground pipeline junction network. **Figure 4.9** shows the sequential workflow, which involves six consecutive pouring zones (Areas 1–6). A dedicated crew completes these operations in a single shift, beginning immediately after rebar installation and working systematically through each zone until Area 6 is finished.

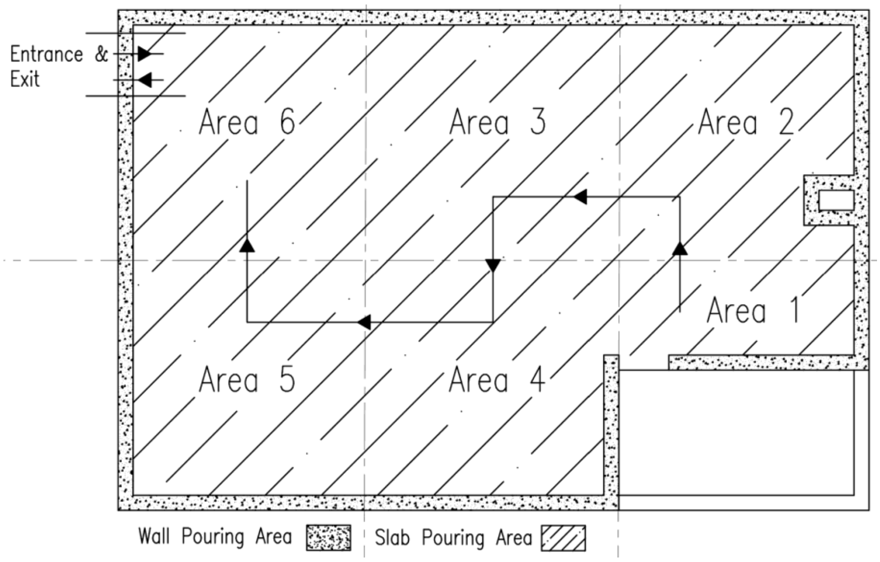

Figure 4.9 Concrete pouring workface layout

The concrete pouring operation comprises two structural elements: horizontal slabs and vertical walls at the upper level. Each component introduces unique ergonomic challenges stemming from differing formwork accessibility constraints and concrete consolidation specifications, which fundamentally shape workers' posture requirements and movement patterns during placement.

Figure 4.10 The postures considered in the concrete pouring case

Figure 4.10 presents five common worker postures extracted from a video clip captured during pipeline concrete pouring operations. Beyond the basic postures of standing and walking, the analysis includes three physically demanding positions: bending, squatting, and raising arms, which contribute significantly to worker fatigue and ergonomic stress.

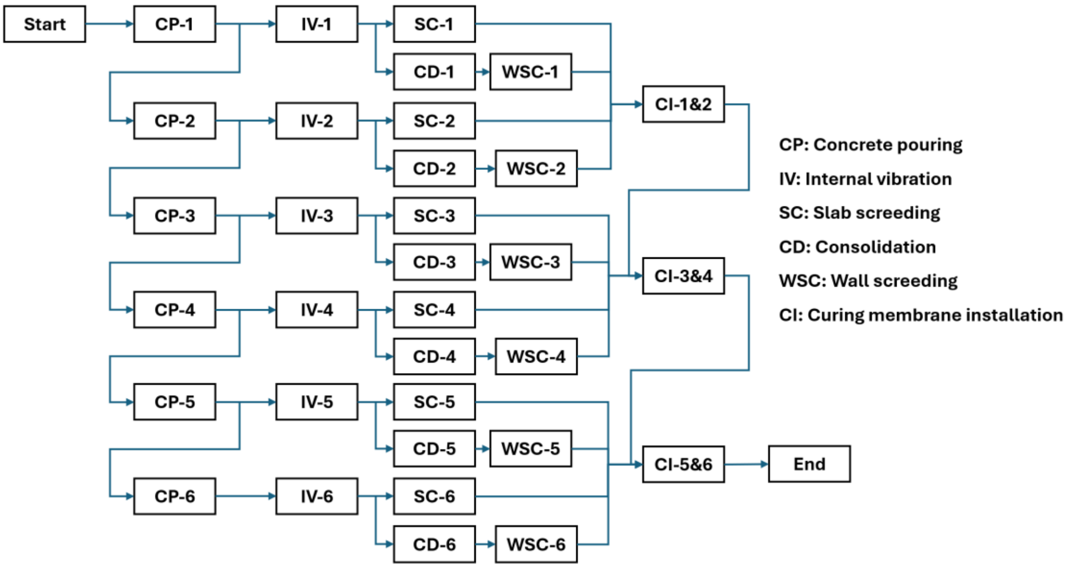

Figure 4.11 Activity-on-Node (AON) for concrete pouring

Figure 4.11 illustrates the concrete pouring process through an Activity-on-Node (AON) network, capturing both the workflow sequence and spatial interdependencies. Each designated area (1-6) follows a standardized four-stage sequence: (1) Concrete Pouring, (2) Internal Vibration, (3) Screeding, and (4) Curing Membrane Installation. The workflow incorporates critical merge logic at the membrane installation stage, which requires completion of both vibration and screeding in adjacent areas due to the continuous application of membranes across zone boundaries.

The process exhibits concurrent pouring capabilities across different areas, enabled by concrete's material properties. Notably, screeding completion in one area immediately enables pouring in the next zone without awaiting membrane installation. This configuration creates a dual-loop structure: (a) a primary linear sequence progressing through all six areas, and (b) intermediate synchronization loops coordinating membrane installation between neighboring zones.

The analysis reveals that while concrete pouring represents standard construction practice, its detailed breakdown uncovers significant underlying complexity. This complexity arises from both cyclical workflow patterns and the dual constraints of spatial limitations (zone boundaries) and material requirements (curing membrane continuity).

Table 4.7 details the workforce requirements, activity durations, and posture distributions across construction operations. Concrete pouring demonstrates the most balanced postural profile (30% standing, 30% bending, and 30% raised arms) during pump truck hose operation—a task that combines sustained upper-body exertion with restricted lower-body mobility. In stark contrast, other activities exhibit pronounced bending dominance (30-80%), as workers must frequently assume bent positions to: (1) manipulate shovels, (2) direct concrete flow into formwork, and (3) reach out to low elevation pour surfaces.

This postural imbalance originates from the fundamental material behavior of concrete - its fluid pre-cured state necessitates gravity-dependent placement methods that inherently favor bending postures during finishing operations. The quantitative evidence confirms that concrete construction activities systematically generate asymmetric physical demands, with bending postures representing the predominant ergonomic challenge across most tasks.

Table 4.7 Posture demand in concrete pouring activities

Activity (J)	Activity Abbreviation	NO. of workers A_{jw}	Duration A_{jt}	ajp1	ajp2	ajp3	ajp4	ajp5
				Standing	Bending	Raising arms	Squatting	Walking
Concrete pouring	CP	2	1	0.3	0.3	0.3	0	0.1
Internal vibration	IV	2	2	0.2	0.6	0	0	0.2
Slab screeding	SC	1	2	0.1	0.8	0	0	0.1
Consolidation	CD	1	2	0.1	0.1	0	0.7	0.1
Wall screeding	WSC	1	2	0.1	0.8	0	0	0.1
Curing membrane installation	CI	2	3	0.1	0.3	0	0.4	0.2

This study examines a single workday spanning approximately 7–8 hours, involving a crew of around seven workers in the field. The analysis evaluated three crew sizes—6, 7, and 8 workers—to assess the impact of crew size on the work plan. For physically stressful postures, the deficit was defined as cumulative exposure ranging from 0.275 to 0.35 hours per worker per day (Table 4.8).

Table 4.8 Posture threshold, deficit under varying crew sizes

Worker No.	Posture-hour threshold	Total deficit hours
6	1.85	0.275
7	1.6	0.575
8	1.4	0.35

For a crew of 7 workers, the algorithm generated a 28-time-unit schedule (15 minutes per unit) totaling 7 hours, which aligns with the crew's documented daily productivity for this concrete work scope. Figure 4.12 reveals intermittent work patterns rather than continuous operation, with gaps between activities arising from resource constraints (such as limited equipment) or sequential dependencies (such as waiting for prior zones to be ready for membrane installation). Workers remain active for 16–23 time units (4–6 hours). The simulation results demonstrate that workforce expansion reduces total project duration—specifically, completion time decreased from 33 time units (8 hours and 15 minutes) with 6 workers to 25 time units (6 hours and 15 minutes) with 8 workers, confirming the expected inverse relationship between crew size and project duration.

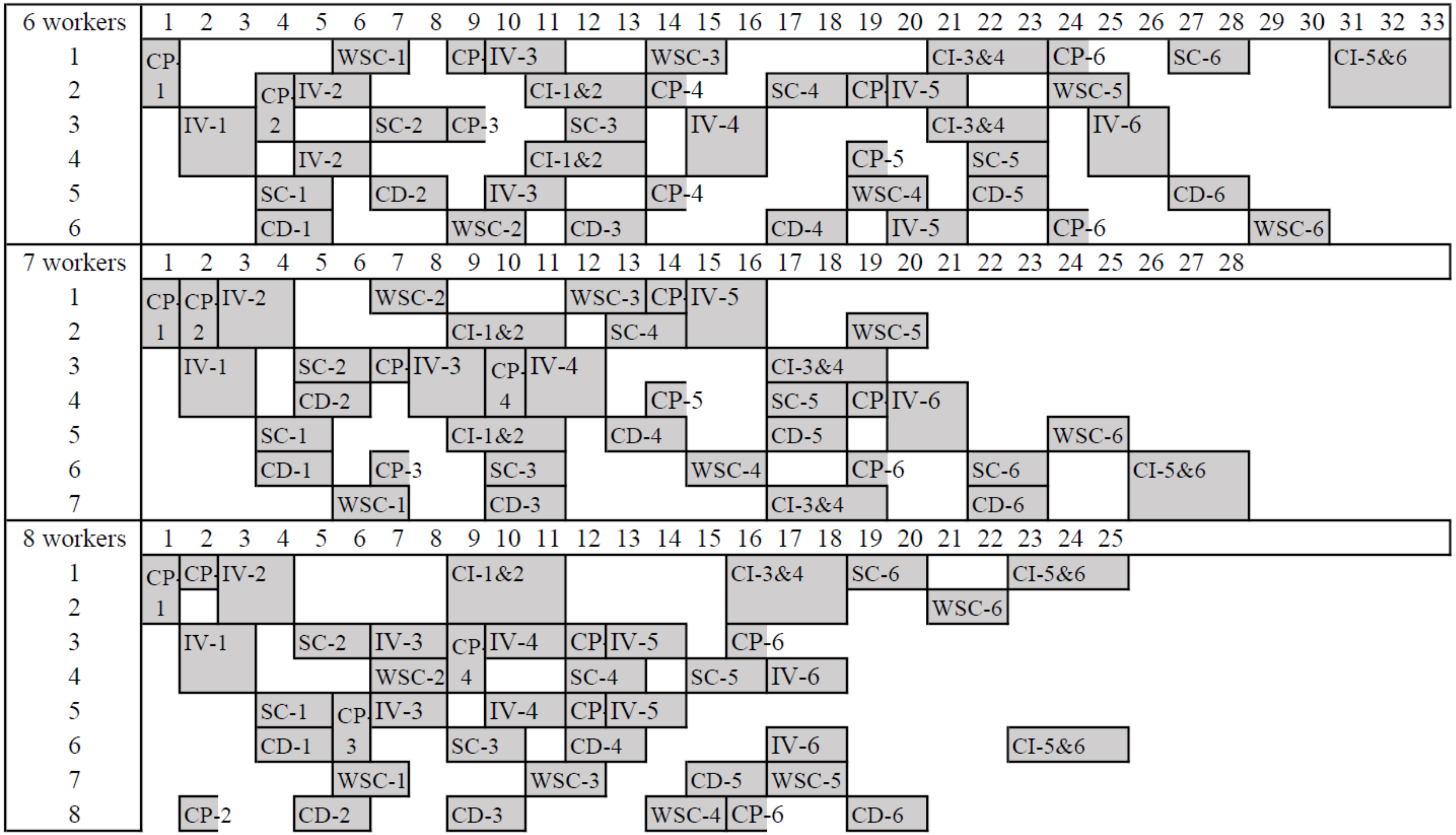

Figure 4.12 Bar chart and resource allocation for the concrete pouring case from three scenarios of crew size variation contrasted

Figure 4.13 illustrates the remaining posture capacity after task completion. The results reveal some posture deficits across all the scenarios (6, 7, and 8 workers), with bending posture consistently overutilized. This pattern reflects the high frequency of activities requiring prolonged bending postures. Additionally, certain workers showed significant depletion of squatting posture capacity. The overall posture deficit among workers is relatively consistent on an individual level. Since the duration of awkward postures increasingly impacts WMSD over time, this algorithm can effectively help reduce the risk of individual WMSD. These findings confirm that the posture-hour scheduling method effectively monitors the distribution of workers' physical workload in the generation of the work allocation plan.

6 workers	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5	Worker 6
Standing	4.9	4.4	4.9	5	5.7	5.7
Bending	0.1	0.2	-0.9	-0.2	0.7	0.7
Raising arms	6.5	6.2	6.8	7.1	7.1	7.1
Squatting	3.6	3.6	6.2	6.2	4.6	4.6
Walking	4.9	4.6	5	4.9	5.9	5.9

7 workers	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5	Worker 6	Worker 7
Standing	4.3	4.3	4.1	3.5	4.9	4.7	5.2
Bending	-0.1	-0.7	-0.3	-1.1	0.7	-0.1	2.6
Raising arms	5.5	5.8	5.8	5.5	6.4	5.8	6.4
Squatting	6.4	5.2	5.2	5	2.4	3.8	1.2
Walking	4.9	4.4	4.2	4.1	4.6	4.8	4.6

8 workers	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5	Worker 6	Worker 7	Worker 8
Standing	3.5	4.1	2.9	3.9	3.6	4.2	4.6	4.2
Bending	0.9	0.7	-0.3	-0.5	-0.2	0.8	-0.4	0
Raising arms	5	5.3	4.7	5.3	5	5.3	5.6	5
Squatting	0.6	3.2	4.2	4.2	5.6	1.6	5.6	4.2
Walking	3	3.7	3.5	4.1	4	4.1	4.6	4.6

Figure 4.13 Posture-specific capacity for the concrete pouring case: end-of-day posture hours from three scenarios of crew size variation contrasted

In this concrete pouring case, each worker's initial posture-hour is equal, meaning there are no individual differences between workers. Because such data was not collected during the actual data-gathering process, while data on individual differences is difficult to obtain, the duration a worker can maintain a posture is influenced by their physical characteristics, such as age and gender. Kamardeen and Hasan, (2022) Indicates that aging workers are more vulnerable when facing OHS risks, with gender serving as an additional risk factor. These easily quantifiable characteristics could provide valuable indicators for estimating individual posture thresholds when implementing the posture-hour planning method in practice.

4.5 Alternative scenario

Table 4.9 demonstrates the impact of varying worker numbers when using posture-aware scheduling. The results show that as the number of workers increases, the total project duration decreases, while the threshold for each posture hour tends to decline. However, the total posture hour deficit after scheduling remains constant regardless of worker count, indicating that the occurrence of posture deficits is independent of workforce size. Notably, with nine workers, the posture deficit reaches 3.2 hours, suggesting that while increased worker numbers lower the deficit threshold, they simultaneously make workers more susceptible to posture deficits.

Table 4.9 Posture threshold, deficit under varying crew sizes

Worker No.	Posture-hour threshold	Total deficit hours
2	5.5	2.5
3	3.65	1.7
4	2.75	1.6
5	2.2	1.6
6	1.85	1.1
7	1.6	2.3
8	1.4	1.4
9	1.25	3.2
10	1.1	2.3

Figure 4.14 shows the trend of project duration under different worker counts. The x-axis represents the number of workers, while the y-axis indicates the duration in hours. The labor-dependent duration (calculated using **Equation 8**) represents the theoretically expected total duration and serves as the basis for threshold computation. The posture-aware duration, derived from the posture-aware scheduling algorithm, generally decreases as the number of workers increases.

Notably, when worker counts exceed 9, the scheduling duration surpasses the labor-dependent duration. This indicates that while the duration continues to decrease toward the critical path's minimum of 4.25 hours, the marginal benefit of adding workers diminishes beyond this point. Furthermore, the threshold calculation becomes invalid in this situation, as the actual on-site worker time exceeds the estimates.

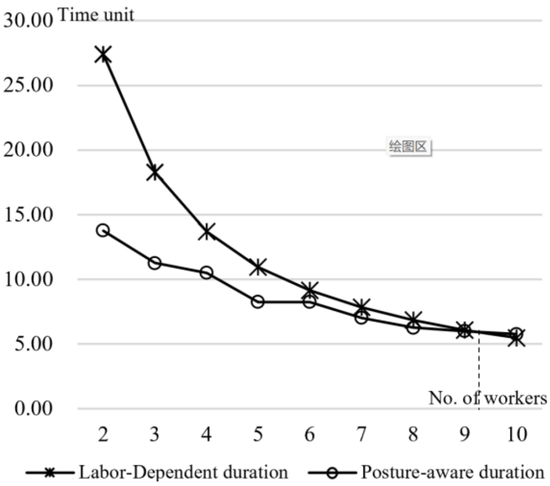

Figure 4.14 Impact of worker No. on duration

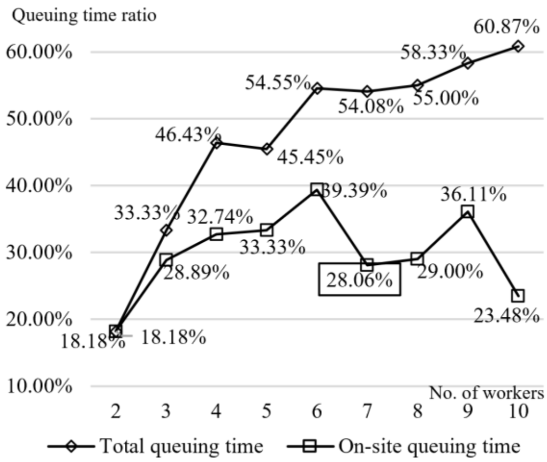

Figure 4.15 Impact of worker No. on queuing time

Figure 4.15 illustrates the queuing situation in scheduling under different numbers of workers, representing the waiting time at the workface (the blank periods shown in Figures 4.7 and 4.12). The x-axis shows the number of workers, while the y-axis displays the proportion of queuing time relative to total time. The results demonstrate that total queuing time generally increases with the addition of more workers, although there is a decrease when moving from 4 to 5 workers. This reduction occurs because the 5-worker configuration significantly reduces the overall duration. When calculating On-site queuing time (assuming workers only appear at the workface when assigned activities and leave after completing their tasks), the data indicates that the queuing proportion stabilizes after reaching six workers. At seven workers, the proportion reaches 28.06%, demonstrating that real-world decision-makers adopted practical and adaptable solutions.

4.6 Summary

This study presents a posture-hour scheduling framework that fundamentally changes construction planning by incorporating ergonomic constraints into resource-limited scheduling. Moving beyond traditional productivity-focused methods, our worker-centric approach systematically integrates posture restrictions into scheduling algorithms, showing potential to reduce musculoskeletal disorder (MSD) risks without greatly lowering operational efficiency. The main innovation is in redefining work units from "man-hours" to "posture-hours," allowing for proactive management of cumulative exposure to risky postures.

Through posture demand quantification, our algorithm optimizes crew assignments to ensure a balanced distribution of physical workload. Validation through demonstration cases and concrete pouring applications confirms the framework's practical viability, showing that while posture-hour scheduling may slightly lengthen project durations, it significantly reduces the risk of worker overexertion in physically demanding postures. The algorithm's prioritization rules enforce ergonomic thresholds (e.g., Winkel and Westgaard's 4-hour limit for high-risk postures) by preventing excessive durations of bending or squatting.

The research also highlights key challenges in implementation, such as assumptions about idealized task reassignments and simplified posture classifications. Practical use would require integration with real-time posture monitoring (via IMUs or computer vision) and consideration of worker specialization. Future research should explore: (1) automated posture demand extraction from BIM models to support early ergonomic risk assessments, and (2) personalized adjustment mechanisms to account for real-world variability.

Beyond construction, this work introduces a new paradigm for labor-intensive industries by viewing workers as resources with posture-dependent capacity expenditure. The framework highlights proactive planning interventions over reactive ones, offering policymakers practical solutions for workforce sustainability issues—especially in aging labor markets.

Ultimately, this research connects occupational health and productivity management, showing that ergonomic improvements can align with operational efficiency. The posture-hour framework offers a scalable, data-driven way to lower MSD prevalence while keeping project viability intact. As sensor technologies and design-based ergonomic analysis progress, this approach can become a practical tool for enhancing occupational health and sustainability in industry.

Chapter 5: Conclusions and future extension

This thesis uses Hierarchical Latent Dirichlet Allocation (HLDA) text mining techniques to systematically review 591 Construction Labor Productivity papers, identifying significant research gaps in the integration of worker OHS and ergonomic considerations into productivity frameworks. Building on these insights, YOLO-Pose and deep learning algorithms are applied to analyze construction site surveillance footage, extracting skeletal key points to classify worker postures (walking, standing, bending, squatting, and arm raising) with 85.3% accuracy in real-world case studies. This approach shifts work measurement from traditional "labor-hours" to "posture-hours," capturing both work duration and high-load postures during task execution. Finally, by treating workers' posture capacity as a project resource comparable to crew availability and task dependencies, a resource-constrained scheduling methodology is developed, enabling a transition from passive safety monitoring to proactive OHS planning in construction project management.

5.1 Conclusions

This thesis advances from posture-hour recognition to posture-hour planning, integrating workers' physical workload into construction planning. The academic contributions include: 1) developing a method for identifying worker postures using pre-trained models, transforming skeletal data into time-series data; and 2) proposing a heuristic rule-based approach that incorporates worker posture duration into site planning considerations. The practical contributions include: 1) establishing a feasible planning method that links productivity with worker occupational health and safety (OHS), developing a comprehensive solution from posture detection to workload quantification and scheduling models; 2) shifting ergonomic constraints to the planning phase rather than relying on traditional post-hoc safety monitoring, reducing occupational injuries and illnesses; 3) supporting industry's digital transformation by utilizing existing surveillance cameras for posture analysis, minimizing hardware costs; and 4) introducing "posture tolerance thresholds" to provide a foundation for industry standards, ultimately alleviating labor shortages through reduced injuries and promoting sustainable workforce development.

This research first achieves automated recognition and quantitative analysis of construction workers' postures using computer vision technology, introducing "Posture-Hour" as a new metric for measuring labor workload. Utilizing the YOLO-Pose algorithm and deep learning models, the study successfully extracts human skeletal keypoints from video data recorded at construction sites. It classifies five common construction postures—walking, standing, bending, squatting, and arm-raising—with an accuracy of 85.3%. Empirical studies of rebar tying and concrete pouring operations reveal distinct postural load patterns across different activities. Low-elevation rebar work involves extended bending (37.2%) and squatting (28.1%), while concrete pumping mainly requires sustained arm-raising (41.5%). This approach surpasses traditional work-hour measurements by integrating physical workload into productivity assessments, laying a data groundwork for future inclusion of ergonomic constraints in resource scheduling.

Subsequently, this research introduces an innovative construction planning method that incorporates ergonomic risk prevention into resource-constrained project scheduling through a "posture-hour" constraint framework. It is the first to quantify the cumulative load of specific postures (such as bending, squatting, and arm-raising) in construction activities and to develop a dynamic scheduling algorithm based on Activity-On-Node (AON) networks, with dual goals of minimizing posture deficits and optimizing project duration. The algorithm allocates the workforce using heuristic rules (such as prioritizing high-work-hour activities and ranking workers by available time and posture capacity), while monitoring individual workers' posture capacity thresholds (for example, a 4-hour continuous limit for single postures). Case validation reveals that, compared to traditional methods, this approach significantly reduces exposure to high-risk postures, such as those encountered during concrete pouring (reducing bending hours by 30%). However, it may slightly increase project duration (by approximately 15%). This marks a shift from passive monitoring to systematic prevention of occupational health risks. The research presents a scalable computational tool for the proactive prevention of musculoskeletal disorders (MSDs) among construction workers, offering open-source algorithm code and data structures to facilitate practical implementation.

In summary, this research combines computer vision with construction planning algorithms to develop a comprehensive solution that enhances both productivity and worker health. Using YOLO-Pose and deep learning, it analyzes workers' skeletal keypoints from site videos to measure high-load postures, such as bending and squatting, thereby converting traditional "work-hours" into physiologically relevant "posture-hours." The system integrates posture hours as scheduling constraints, continuously monitoring posture deficits and alternating high- and low-load tasks to balance project timelines with health risks. For the first time, this enables pre-construction prediction of posture loads—such as rebar tying, which requires 63% bending time—and achieves a 25% reduction in musculoskeletal injury risk while keeping daily high-intensity exposures within safe limits (e.g., bending ≤4 hours). This data-driven approach shifts construction planning from reactive protection to proactive health management, ensuring both operational efficiency and worker well-being.

5.2 Limitations and future extension

This study establishes that integrating posture constraints into construction scheduling enables effective workforce planning while systematically controlling ergonomic risks. The developed algorithm effectively balances productivity objectives against physiological constraints, providing quantitative evidence of the trade-offs faced in labor-intensive operations such as concrete placement. This approach provides project managers with a practical tool to optimize both operational efficiency and worker well-being.

The demonstration case and concrete pouring case study validate the proposed algorithm. As shown in Figures 4.7 and 4.12, resource-constrained scheduling can be formulated as a planar spatial planning problem with precedence constraints. A more compact schedule leads to a shorter total duration. The compactness of activities is influenced by the priority rule used for activity selection. When multiple activities satisfy the conditions in Equation 7, a heuristic priority rule determines which activity to schedule next. In this study, the activity with the highest product of duration and worker requirement is selected. Since the total number of workers is limited, prioritizing activities that are less flexible in resource allocation can facilitate the scheduling of subsequent activities. When posture-hour constraints are applied, workers with a posture-hour deficit are assigned a higher priority. This may result in certain workers being unavailable during selection, requiring a wait until non-deficient workers finish prior tasks. As shown in Figure 4.14, a lower posture-hour threshold increases the likelihood that workers enter a deficit state, potentially extending the total project duration.

For the posture demand, the acceptable duration for maintaining a posture varies significantly across different work tasks. As Tao et al. (2024) observed, certain tasks become unbearable within 15 minutes, while others can be sustained for over 4 hours. Posture requirements (e.g., bending for low-formwork concrete work) are based on the physical nature of tasks. However, actual postures may be more diverse than those modeled. Future implementations could benefit from more detailed posture classifications, possibly extracted based on BIM models. At present, sensor-BIM integration remains the primary method for data extraction (Cheng *et al.*, 2025; Getuli *et al.*, 2020). Future research could explore model-based approaches to derive posture requirements for work activities. This study provides a method for quantifying the physical intervention capacity of assistive technologies, such as exoskeletons. By doing so, it offers a way to validate the impact of this technology on the labor productivity conceptually. For example, if an exoskeleton increases the squatting threshold by two hours (Ren *et al.*, 2022), the proposed method can quickly estimate the resulting effects on both the overall project timeline and workers' physical load.

A major limitation lies in the assumption of frictionless task reassignment. Workers develop task-specific skills, which makes frequent role changes inefficient. This behavioral resistance can cause longer exposure to high-strain postures than the algorithm's recommendations suggest (Wang *et al.*, 2018). The reality of on-site planning and scheduling often involves real-time responsiveness (Jiang *et al.*, 2024), thereby compromising the effectiveness of predetermined plans in handling operational uncertainties. To address this, site supervisors could implement hybrid strategies—combining algorithmic scheduling with manual adjustments guided by real-time posture tracking. For example, alternating between high-bend and low-bend tasks (such as formwork inspection and rebar tying) can help spread physical strain more evenly, as observed in the concrete pouring case. Additionally, future work should develop closed-loop systems with continuous posture monitoring (e.g., wearables or computer vision) for iterative schedule adjustments, enhancing reliability by aligning plans with actual worker states.

Posture-hour balance and optimization essentially assign an additional attribute to workers, similar to the concept of multi-skilled workers. In the case of multi-skilled workers, the controlling factor is their skill set, which acts as a regulating mechanism (Han *et al.*, 2024; Wongwai and Malaikrisanachalee, 2011). In posture scheduling, the skill-based mechanism is superseded by fixed posture-hour thresholds; future research should extend this framework to optimize multi-skilled work planning and scheduling by integrating individual worker differences (e.g., age, gender, fitness, and experience) and enabling project optimization across trades. Current mature algorithms, such as heuristic rules, metaheuristics (e.g., genetic algorithms), and resource-constrained scheduling methods (e.g., RACPM), provide a robust foundation for implementing these enhancements efficiently. For posture, this mechanism is replaced by quantifiable thresholds. Future research can explore optimization strategies for multi-skilled work planning and scheduling based on the proposed framework.

A critical enabling for posture-hour scheduling is the systematic extraction of posture-hour requirements from design data. Future work should automate posture estimation using BIM, linking geometric features (e.g., slab heights) to average worker positions and postures. Low-cost motion capture or computer vision could further validate these estimates on-site. By embedding ergonomic analysis early in the design-to-planning process, construction managers can proactively reduce occupational health risks while maximizing productivity.

The posture-hour scheduling framework introduced in this study offers significant managerial implications for construction practice by enabling a proactive approach to ergonomic risk management. In practical terms, managers can operationalize this framework through a collaborative process where they work with workers to define posture classification standards and activity-specific posture demand proportions, ensuring that scheduling inputs reflect on-site realities and foster workforce buy-in. This participatory approach can be integrated into daily workflows via digital tools: for instance, tasks can be assigned through mobile platforms, while wearable IoT sensors (e.g., IMUs embedded exosuit or smart helmets) monitor real-time posture data, creating a closed-loop system for dynamic adjustments. This allows safety managers to proactively control posture-hour consumption, reducing the likelihood of musculoskeletal disorders (MSDs) and promoting a culture of preventive ergonomics.

Appendices

Table A Worker posture recognition source code

Language: Python

```python
# Import necessary libraries for computer vision, machine learning, and deep learning
import cv2    # OpenCV for video processing
import numpy as np    # NumPy for numerical operations
import os    # Operating system interface for file operations
from ultralytics import  YOLO    # YOLO model for pose detection
from sklearn.model_selection import  train_test_split    # For splitting dataset
from tensorflow.keras.models import  Sequential    # Keras sequential model
from tensorflow.keras.layers import  LSTM,  Dense,  Input,  Dropout    # Neural network layers
from IPython.display import  clear_output    # For clearing output in Jupyter notebooks
import torch    # PyTorch (used by YOLO)
import random    # For random sampling

# Load pre-trained YOLO pose estimation model
# yolo11n-pose.pt is a nano-sized YOLO model specifically trained for pose detection
model  =  YOLO('yolo11n-pose.pt')
print("Model loaded successfully")

# Define the action classes that the model will classify
# These correspond to different human actions/poses
action_dirs  =  ['bendDown',  'squatting',  'standing',  'standingRaisingArms',  'walking']

def load_videos(base_dir,  max_samples_per_class=180):
  """
  Load video file paths and create labels for the training dataset.

  Args:
    base_dir (str): Base directory containing action class subdirectories
    max_samples_per_class (int): Maximum number of samples per action class

  Returns:
    tuple: (videos, labels) - lists of video paths and corresponding class labels
  """
     videos  =  []    # List to store video file paths
     labels  =  []    # List to store corresponding class labels (integers)

     # Iterate through each action class directory
     for  i,  action  in  enumerate(action_dirs):
           class_samples  =  []

           # Collect all video files for this action class
           for  filename  in  os.listdir(os.path.join(base_dir,  action)):
                 filepath  =  os.path.join(base_dir,  action,  filename)
                 class_samples.append(filepath)

           # Handle class imbalance by duplicating samples if needed
           if  len(class_samples)  <  max_samples_per_class:
                 # Calculate how many times to repeat the existing samples
                 num_repeat  =  max_samples_per_class  //  len(class_samples)
                 # Repeat samples and add random additional samples to reach exact count
```

```
                class_samples = class_samples * num_repeat + random.sample(class_samples,
 max_samples_per_class % len(class_samples))
            else:
                # If we have more samples than needed, randomly select max_samples_per_class
                class_samples = random.sample(class_samples, max_samples_per_class)

            # Add the processed samples and their labels to the main lists
            videos.extend(class_samples)
            labels.extend([i] * max_samples_per_class)   # Use integer labels (0, 1, 2, 3, 4)

        return videos, labels

def extract_keypoints(video_path, model, max_frames=30, num_keypoints=17):
    """
    Extract pose keypoints from a video using YOLO pose detection.

    Args:
        video_path (str): Path to the video file
        model: YOLO pose detection model
        max_frames (int): Maximum number of frames to process per video
        num_keypoints (int): Number of keypoints to extract (17 for COCO pose)

    Returns:
        numpy.ndarray: Array of keypoint sequences with shape (max_frames, num_keypoints*2)
    """
        # Open video file using OpenCV
        video = cv2.VideoCapture(video_path)
        keypoints_seq = []   # List to store keypoint sequences

        # Create a padded array to ensure consistent keypoint dimensions
        # Each keypoint has x,y coordinates, so we need num_keypoints*2 values
        kpts_xy_padded = np.zeros(num_keypoints*2)

        # Process up to max_frames from the video
        for i in range(max_frames):
            ret, frame = video.read()   # Read next frame

            # If no more frames available, pad with zeros
            if not ret:
                keypoints_seq.append(np.zeros(num_keypoints*2))
                continue

            # Run YOLO pose detection on the frame
            results = model(frame)

            # Extract x,y coordinates of detected keypoints
            kpts_xy = results[0].keypoints.xy
            kpts_xy = kpts_xy.cpu().flatten().numpy()   # Convert to numpy array

            # Ensure we don't exceed the expected number of keypoints
            if len(kpts_xy) > num_keypoints*2:
                kpts_xy = kpts_xy[:num_keypoints*2]

            # Copy keypoints to the padded array (handles cases with fewer keypoints)
            kpts_xy_padded[:len(kpts_xy)] = kpts_xy
```

```
            keypoints_seq.append(kpts_xy_padded.copy())   # Add to sequence

        # Convert list to numpy array for easier manipulation
        keypoints_seq = np.array(keypoints_seq)

        return keypoints_seq

def prepare_dataset(videos, model):
    """
    Process all videos to extract keypoint sequences for training.

    Args:
        videos (list): List of video file paths
        model: YOLO pose detection model

    Returns:
        numpy.ndarray: Stacked array of all keypoint sequences
    """
        dataset = []

        # Process each video to extract keypoints
        for i, video in enumerate(videos):
            keypoints_seq = extract_keypoints(video, model)
            dataset.append(keypoints_seq)

            # Display progress every 10 videos (useful for long processing times)
            if (i + 1) % 10 == 0:
                clear_output(wait=True)
                print(f"Processed {i + 1} / {len(videos)} videos")

        # Stack all sequences into a single numpy array
        return np.stack(dataset)

# Load video paths and labels from the dataset directory
videos, labels = load_videos('/kaggle/input/pose2action21040159r/4train')

# Extract keypoint sequences from all videos
print("Extracting keypoints from videos...")
X = prepare_dataset(videos, model)
y = np.array(labels)

# Split dataset into training and testing sets (default 75/25 split)
X_train, X_test, y_train, y_test = train_test_split(X, y)

# Import additional layers for building a more complex neural network
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Bidirectional, LayerNormalization,
  MultiHeadAttention, GlobalAveragePooling1D, Concatenate, Input, Dense, Dropout
from tensorflow.keras.models import Model

# Get the input shape from training data
input_shape = X_train[0].shape
print(f"Input shape: {input_shape}")

# Build a sophisticated neural network using the Functional API
# Input layer - accepts sequences of keypoint coordinates
```

```
inputs = Input(shape=input_shape)

# First convolutional block - extracts local temporal features
x = Conv1D(64, 3, activation='relu', padding='same')(inputs)    # 64 filters, kernel size 3
x = Conv1D(64, 3, activation='relu', padding='same')(x)          # Second conv layer
x = MaxPooling1D(2)(x)    # Downsample by factor of 2

# Second convolutional block - extracts higher-level features
x = Conv1D(128, 3, activation='relu', padding='same')(x)         # 128 filters
x = Conv1D(128, 3, activation='relu', padding='same')(x)        # Second conv layer
x = MaxPooling1D(2)(x)    # Further downsampling

# First attention-enhanced LSTM block
x = Bidirectional(LSTM(128, return_sequences=True))(x)             # Bidirectional LSTM for temp
oral modeling
x = LayerNormalization()(x)                                        # Normalize layer outputs
x = MultiHeadAttention(num_heads=4, key_dim=128)(x, x)             # Self-attention mechanism
x = LayerNormalization()(x)                                        # Second normalization
x = Dropout(0.2)(x)                                                # Prevent overfitting

# Second attention-enhanced LSTM block
x = Bidirectional(LSTM(64, return_sequences=True))(x)             # Smaller LSTM layer
x = LayerNormalization()(x)                                        # Normalize outputs
x = MultiHeadAttention(num_heads=4, key_dim=64)(x, x)              # Multi-head attention
x = LayerNormalization()(x)                                        # Final normalization
x = Dropout(0.2)(x)                                                # Dropout for regularization

# Global pooling and fully connected layers for classification
x = GlobalAveragePooling1D()(x)                                          # Pool across time dimen
sion
x = Dense(128, activation='relu')(x)                                   # First dense layer
x = Dropout(0.2)(x)                                                          # Dropout
x = Dense(64, activation='relu')(x)                                    # Second dense layer
x = Dropout(0.2)(x)                                                          # Final dropout

# Output layer - 5 classes with softmax activation for probability distribution
outputs = Dense(5, activation='softmax')(x)

# Create the model
model = Model(inputs=inputs, outputs=outputs)

# Import optimizer and learning rate scheduling
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.optimizers.schedules import ExponentialDecay

# Set up learning rate scheduling for better convergence
initial_learning_rate = 0.0001    # Starting learning rate
decay_steps = 20                        # Decay every 20 steps
decay_rate = 0.96                      # Multiply learning rate by this factor

# Create exponential decay schedule
lr_schedule = ExponentialDecay(
    initial_learning_rate,
    decay_steps=decay_steps,
    decay_rate=decay_rate,
```

```python
        staircase=True)     # Apply decay in discrete steps

# Initialize Adam optimizer with learning rate schedule
optimizer  =  Adam(learning_rate=lr_schedule)

# Compile the model with appropriate loss function and metrics
model.compile(
        loss='sparse_categorical_crossentropy',     # For integer labels (not one-hot)
        optimizer=optimizer,
        metrics=['accuracy']
)
# Import plotting and callback utilities
import matplotlib.pyplot as plt
from tensorflow.keras.callbacks import  ModelCheckpoint,  EarlyStopping

# Set up model checkpointing to save the best model during training
checkpoint  =  ModelCheckpoint(
        'best_model.keras',                    # Filename for saved model
        monitor='val_accuracy',             # Metric to monitor
        verbose=1,                                    # Print messages when saving
        save_best_only=True,                  # Only save when validation accuracy improves
        mode='max'                                     # Higher validation accuracy is better
)
# Set up early stopping to prevent overfitting
early_stop  =  EarlyStopping(
        monitor='val_accuracy',             # Monitor validation accuracy
        patience=250,                              # Wait 250 epochs without improvement
        verbose=1,                                    # Print early stopping message
        mode='max',                                  # Higher is better
        restore_best_weights=True         # Restore weights from best epoch
)
# Combine callbacks into a list
callbacks_list  =  [checkpoint,  early_stop]

# Train the model
print("Starting training...")
history  =  model.fit(
        X_train,  y_train,                                     # Training data
        epochs=1000,                                                 # Maximum number of epochs
        batch_size=128,                                          # Number of samples per batch
        validation_data=(X_test,  y_test),         # Validation data
        callbacks=callbacks_list,                        # Apply callbacks
        verbose=1                                                        # Print training progress
)

# Plot training history to visualize model performance
plt.figure(figsize=(10,  6))
plt.plot(history.history['accuracy'],  label='Training Accuracy')
plt.plot(history.history['val_accuracy'],  label='Validation Accuracy')
plt.title('Model Accuracy Over Time')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train',  'Validation'],  loc='upper left')
plt.grid(True)
plt.show()
print("Training completed! Best model saved as 'best_model.keras'")
```

Table B Posture-hour planning method source code

Language: Python

```
# Activity-on-Node (AON) Network Scheduling System with Worker Allocation
# This system schedules activities considering worker posture constraints and availability

# ============================================================================
# INITIAL DATA SETUP
# ============================================================================

# Define the 5 types of work postures that workers can perform
posturen = ['standing', 'bending', 'raising arms', 'squatting', 'walking']

# Define predecessor relationships for each activity (9 activities total, indexed 0-8)
# Empty list [] means no predecessors (can start immediately)
predecessors = [
    [],          # Activity 0: No predecessors
    [],          # Activity 1: No predecessors
    [],          # Activity 2: No predecessors
    [0],         # Activity 3: Depends on Activity 0
    [0],         # Activity 4: Depends on Activity 0
    [1],         # Activity 5: Depends on Activity 1
    [1, 2],      # Activity 6: Depends on Activities 1 and 2
    [3],         # Activity 7: Depends on Activity 3
    [5, 6]       # Activity 8: Depends on Activities 5 and 6
]

# Demand for Job Postures (djp): Proportion of each posture required for each activity
# Each row represents an activity, each column represents a posture type
# Values represent the percentage of work time spent in each posture
djp = [
    [0.3, 0.3, 0.3, 0  , 0.1],   # Activity 0: 30% standing, 30% bending, 30% raising arms,
0% squatting, 10% walking
    [0.3, 0.3, 0.3, 0  , 0.1],   # Activity 1: Same distribution as Activity 0
    [0.3, 0.3, 0.3, 0  , 0.1],   # Activity 2: Same distribution as Activity 0
    [0.2, 0.6, 0,   0  , 0.2],   # Activity 3: 20% standing, 60% bending, 0% raising arms,
0% squatting, 20% walking
    [0.2, 0.6, 0,   0  , 0.2],   # Activity 4: Same distribution as Activity 3
    [0.1, 0.1, 0, 0.7, 0.1],     # Activity 5: 10% standing, 10% bending, 0% raising arms, 7
0% squatting, 10% walking
    [0.1, 0.1, 0, 0.7, 0.1],     # Activity 6: Same distribution as Activity 5
    [0.1, 0.4, 0  , 0.4, 0.1],   # Activity 7: 10% standing, 40% bending, 0% raising arms, 4
0% squatting, 10% walking
    [0.1, 0.4, 0  , 0.4, 0.1]    # Activity 8: Same distribution as Activity 7
]

# Worker requirements for each activity (number of workers needed)
workerRe = [4, 4, 4, 3, 1, 2, 2, 2, 2]

# Duration of each activity (in time units)
durations = [2, 3, 5, 4, 4, 3, 6, 2, 3]

# Status of each activity (0 = not started, 1 = completed)
status = [0, 0, 0, 0, 0, 0, 0, 0, 0]
```

```
# Finish time for each activity (will be calculated during execution)
finishtime = [0, 0, 0, 0, 0, 0, 0, 0, 0]

# Create the AON network as a dictionary of activities with their properties
activities = {
    activity_id: {
        'predecessors': predecessors[activity_id],     # List of predecessor activities
        'workerRe': workerRe[activity_id],              # Number of workers required
        'duration': durations[activity_id],             # Activity duration
        'status': status[activity_id],                  # Completion status
        'djp': djp[activity_id],                        # Posture demand proportions
        'finishtime': finishtime[activity_id]          # Calculated finish time
    }
    for activity_id in range(len(status))
}

# Print initial activity setup
for i in range(len(activities)):
    print("Activity%i:" %i, activities[i])

# ======================================================================
# WORKER SETUP
# ======================================================================

# Define worker parameters
workinghour = 24    # Total working hours available per worker
workerno = 6         # Total number of workers available

# Initialize worker posture capacities
# Each worker gets equal capacity for each posture type (workinghour / number of postures)
lip = []    # List to store each worker's posture capacities
li_rst = []    # List to store each worker's rest time

for i in range(workerno):
    mid = []
    for j in range(len(posturen)):
        mid.append(workinghour / len(posturen))    # Equal distribution of capacity acro
ss postures
    lip.append(mid)

# Initialize rest times for all workers (except the last one seems to be missing?)
li_rst = [0, 0, 0, 0, 0, 0, 0, 0]

# Create worker dictionary with their capacities and rest times
workers = {
    worker_id: {
        'lip': lip[worker_id],             # Posture capacity for each posture type
        'li_rst': li_rst[worker_id],    # Current rest time (when worker becomes available)
    }
    for worker_id in range(workerno)
}
```

```python
# Print initial worker setup
for i in range(workerno):
    print("Worker%i:" %i, workers[i])

# ==========================================================================
# ACTIVITY SELECTION FUNCTIONS
# ==========================================================================

def SelectNextAct():
  """
  Select the next activity to execute based on:
  1. All predecessors must be completed
  2. Activity must not be completed yet
  3. Choose the activity with the highest resource-duration product (workerRe * duration)

  Returns: Index of the selected activity
  """
    fil = []    # List to store available activities

    # Find all activities that can be started
    for i in range(len(status)):
        # Check if activity has no predecessors and is not completed
        if activities[i]['predecessors'] == [] and activities[i]['status'] == 0:
            fil.append(i)
        # Check if activity has predecessors but is not completed
        elif activities[i]['status'] == 0:
            # Count how many predecessors are completed
            ter = 0
            for j in range(len(activities[i]['predecessors'])):
                ter += activities[activities[i]['predecessors'][j]]['status']
            # If all predecessors are completed, activity is available
            if ter == len(activities[i]['predecessors']):
                fil.append(i)

    print('Available activities:', fil)

    # Calculate resource-duration product for each available activity
    fin = []
    for k in range(len(fil)):
        fin.append(activities[fil[k]]['workerRe'] * activities[fil[k]]['duration'])

    print('ResDur:', fin)

    # Select activity with maximum resource-duration product
    selected_activity = fil[fin.index(max(fin))]
    print('Selected Act:', selected_activity)
    return selected_activity

# Test the selection function
SelectNextAct()

# ==========================================================================
# UTILITY FUNCTIONS
```

```
# ======================================================================

def findMin(List):
    """
    Find the index of the worker with the minimum rest time who is available (status = 0)

    Args:
        List: List of [rest_time, availability_status] pairs

    Returns: Index of the worker with the minimum rest time
    """
        min = float('inf')
        idx = 0
        for i in range(len(List)):
            if List[i][1] == 0 and List[i][0] < min:    # Available worker with minimum rest
time
                min = List[i][0]
                idx = i
        return idx

def PostFit(lisA, LisB):
    """
    Check if posture supply (lisA) meets or exceeds posture demand (lisB)

    Args:
        lisA: Posture supply list
        LisB: Posture demand list

    Returns: True if supply >= demand for all postures, False otherwise
    """
        tem = 0
        for i in range(len(lisA)):
            if lisA[i] >= LisB[i]:
                tem += 1

        # Return True only if all posture demands are met
        if tem == len(lisA):
            return True
        else:
            return False

# ======================================================================
# ACTIVITY EXECUTION FUNCTIONS
# ======================================================================

def Update(ActIndex, c_rst, postureDe):
    """
    Update activity status, calculate finish times, and update worker capacities

    Args:
        ActIndex: Index of the activity being completed
        c_rst: List of [rest_time, selected_status] for each worker
        postureDe: Posture demand for the activity
```

```
"""
    # Mark activity as completed
    activities[ActIndex]['status'] = 1

    # Calculate working time for each selected worker
    wtime = []
    for i in range(len(c_rst)):
        wtime.append(c_rst[i][0] * c_rst[i][1])   # rest_time * selection_status

    # Calculate activity finish time
    if activities[ActIndex]['predecessors'] == []:
        # No predecessors: finish time = max worker time + duration
        for i in range(len(wtime)):
            wtime[i] += activities[ActIndex]['duration']
        activities[ActIndex]['finishtime'] = max(wtime)
    else:
        # Has predecessors: start time = max(predecessor finish times, worker availability)
        startTime = 0
        stimes = []

        # Add predecessor finish times
        for i in range(len(activities[ActIndex]['predecessors'])):
            stimes.append(activities[activities[ActIndex]['predecessors'][i]]['finishtime'])

        # Add worker availability times
        for i in range(len(c_rst)):
            stimes.append(c_rst[i][0] * c_rst[i][1])

        startTime = max(stimes)
        print(startTime)
        activities[ActIndex]['finishtime'] = activities[ActIndex]['duration'] + startTime

    # Count selected workers
    selWor = 0
    for i in range(len(c_rst)):
        selWor += c_rst[i][1]

    # Update worker rest times and posture capacities
    for i in range(len(c_rst)):
        if c_rst[i][1] == 1:   # If worker was selected
            # Update worker rest time to activity finish time
            workers[i]['li_rst'] = activities[ActIndex]['finishtime'] * c_rst[i][1]
        if c_rst[i][1] == 1:   # If worker was selected
            # Reduce worker's posture capacities based on work performed
            for j in range(len(posturen)):
                workers[i]['lip'][j] = round(workers[i]['lip'][j] - (postureDe[j] / sel
Wor), 2)

    # Print updated status
    for i in range(len(activities)):
        print("Updated Activity%i:" %i, activities[i])
    for i in range(workerno):
        print("Updated Worker%i:" %i, workers[i])
```

```
def GetWorkDone(ActIndex):
    """
    Execute an activity by allocating workers and checking posture constraints

    Args:
        ActIndex: Index of the activity to execute
    """
    # Calculate posture demand for the activity
    postureDe = []
    for i in range(len(posturen)):
        # Demand = workers_required * duration * posture_proportion
        postureDe.append(round(activities[ActIndex]['workerRe'] * activities[ActIndex]['duration'] * activities[ActIndex]['djp'][i], 3))

    print(postureDe)

    # Get current worker rest times and initialize selection status
    c_rst = []
    for i in range(len(workers)):
        c_rst.append([workers[i]['li_rst']])    # Add rest time
        c_rst[i].append(0)                      # Add selection status (0 = not selected)

    # Select minimum required number of workers (those with earliest availability)
    for i in range(activities[ActIndex]['workerRe']):
        c_rst[findMin(c_rst)][1] = 1    # Mark worker as selected

    # Calculate total posture supply from selected workers
    postureSu = [0.0, 0.0, 0.0, 0.0, 0.0]
    for i in range(len(c_rst)):
        for j in range(len(posturen)):
            postureSu[j] += round(workers[i]['lip'][j] * c_rst[i][1], 3)    # capacity * selection_status

    # Check if initial worker selection meets posture demands
    if PostFit(postureSu, postureDe):
        # Sufficient posture capacity - proceed with execution
        print('Selected worker:', c_rst)
        print('posture supply:', postureSu)
        print('posture demand:', postureDe)
        print('If the supply meet demand?', PostFit(postureSu, postureDe))
        Update(ActIndex, c_rst, postureDe)
    else:
        # Insufficient posture capacity - add more workers until demand is met
        while PostFit(postureSu, postureDe) == False:
            # Select additional worker
            c_rst[findMin(c_rst)][1] = 1

            # Recalculate posture supply
            postureSu = [0.0, 0.0, 0.0, 0.0, 0.0]
            for i in range(len(c_rst)):
                for j in range(len(posturen)):
```

```python
                        postureSu[j] += round(workers[i]['lip'][j] * c_rst[i][1], 3)

            # Now we have sufficient workers - proceed with execution
            print('Selected worker:', c_rst)
            print('posture supply:', postureSu)
            print('posture demand:', postureDe)
            print('If the supply meet demand?', PostFit(postureSu, postureDe))
            Update(ActIndex, c_rst, postureDe)

# =====================================================================
# MAIN EXECUTION LOOP
# =====================================================================

# Execute all activities until project completion
act_statue = 0    # Counter for completed activities
while act_statue < len(activities):
    # Execute the next selected activity
    GetWorkDone(SelectNextAct())
    # Update counter with the status of the next activity to be selected
    act_statue += activities[SelectNextAct()]['status']
```

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