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Ergonomic Assembly Line Balancing Problems Evolution and Future Trends with Insights into Industry 5.0 Paradigm

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Abstract. This comprehensive review paper presents the state of the art on assembly line balancing problems, with a specific focus on considering ergonomics aspects (Ergo-ALBPs) and providing insights into the emerging Industry 5.0 paradigm. Traditional assembly line balancing approaches often overlook ergonomic factors, which can lead to work-related injuries and long-term expenses for manufacturing systems. However, recent advancements have seen the integration of human factors and ergonomic (HFE) indicators alongside operational factors in optimization problems, aiming to prevent future ergonomic-related costs. Through a systematic review of the literature published from 2011 to 2022, this study analyzes 57 selected studies, examining their content on operational and ergonomics aspects individually and concurrently. Additionally, this paper highlights the significant implications of the Industry 5.0 paradigm in Ergo-ALBPs, emphasizing the importance of human-centered design, collaboration between workers and advanced technologies, and the challenges faced during implementation. The review also identifies research trends, gaps, and opportunities through comparative content analysis, keyword frequency analysis, and co-occurrence (co-word) analysis, offering valuable insights for future research in this domain.

Keywords: Assembly line balancing problem, ergonomic risks, human factor, ergonomic assessment tools, Ergo-ALBP, Industry 5.0, worker-centric design.

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1. INTRODUCTION

*Assembly line*s (*AL*s) play a crucial role in enhancing the efficiency of mass and lean manufacturing systems by reducing per-unit costs. This pursuit of productivity gives rise to *assembly line balancing problems* (*ALBP*), which involve modeling and solving optimization problems. The objective of balancing is to eliminate any unbalancing points, such as bottlenecks, which cause idle times and increase in-process inventories in other workstations. To achieve a balanced workload across workstations, assembly tasks need to be organized while considering several constraints and optimizing productivity measurements.

In the past, balancing was primarily based on the process time of tasks at different workstations to address the required production rate. While this remains a key variable, real-world manufacturing systems must also contend with market fluctuations and evolving customer needs. Consequently, *AL*s, as the final stage of most production systems, must be flexible. This requires the inclusion of manual tasks to accommodate the required flexibility (Vig, 2020). However, the performance of operators handling these manual operations has a direct impact on the overall system efficiency. Additionally, workers in *AL*s are exposed to ergonomic risks and work-related injuries due to the repetitive and prolonged nature of assembly tasks. These ergonomic issues can adversely affect line efficiency, making it crucial to prioritize the health and well-being of operators as integral components of such systems. The efficiency of manual assembly line systems relies on effectively incorporating ergonomic factors into the balancing process (Ozdemir et al., 2021), leading to the emergence of *Ergo-ALBP*-related research studies to address this goal.

While there have been separate review studies focusing on *ALBP*s (Eghtesadifard et al., 2020) and ergonomics (Joshi & Deshpande, 2019), the literature reveals a gap in systematic review studies specifically in the *Ergo-ALBP* field. In recent years, there has been a growing interest in exploring innovative approaches to manufacturing that prioritize not only productivity and efficiency but also the well-being and satisfaction of workers. Therefore, present paper aims to fill this gap by conducting an in-depth analysis of research studies focused on *Ergo-ALBP*. This study not only helps predict future trends but also explores hot topics and identifies research gaps in this domain.

Over the past few years, the advent of Industry 5.0 has provided a new paradigm that emphasizes harmonious collaboration between human workers and advanced technologies. This paradigm shift holds immense potential for advancements in *Ergo-ALBP*s, where the integration of *augmented reality* (*AR*), *virtual reality* (*VR*), *artificial intelligence* (*AI*), and collaborative robots can revolutionize the *AL* optimization process. By focusing on worker-centric design principles, Industry 5.0 offers opportunities to enhance worker comfort, productivity, and safety while fostering a culture of continuous improvement and learning. This paper delves into the evolution and future trends of *Ergo-ALBP*s within the framework of the Industry 5.0 paradigm, shedding light on the transformative potential and highlighting key aspects and challenges for successful implementation in the manufacturing industry.

The current systematic review employs explicit methods, including bibliometric and quantitative analysis, to investigate research studies published in the *Ergo-ALBP* field from 2011 to 2022. The *PRISMA* (*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*) method was applied to the indexed papers in the *Web of Science* and *Engineering Village* databases, resulting in the inclusion of 57 articles for a comprehensive review. This review employs knowledge mapping methodology to explore foundational knowledge, developmental trends, and future research opportunities. Furthermore, comparative content analysis, keyword frequency analysis, and co-occurrence (co-word) analysis are conducted to identify research gaps.

This manuscript is organized as follows: section 2 provides a brief background on *ALBP*s, *human factors and ergonomics* (*HFE*) considerations, and the *Ergo-ALBP* field. Section 3 introduces the approach used in this study to explore the *Ergo-ALBP* literature, including content analysis and descriptive analysis. Section 4 investigates the Industry 5.0 paradigm. Section 5 discusses the findings of this research and highlights the research gaps that should be addressed in future studies. Finally, section 6 presents the summary and concluding remarks.

2. PRINCIPLES AND LITERATURE REVIEW

This review concentrates on the overlap of two important fields: the *ALBP*s and the *HFE*, see Figure 1. In this section, first, an overview of the fundamental concepts of *HFE* and *ALBP*s is presented. Then, a brief explanation of *Ergo-ALBP* is provided.

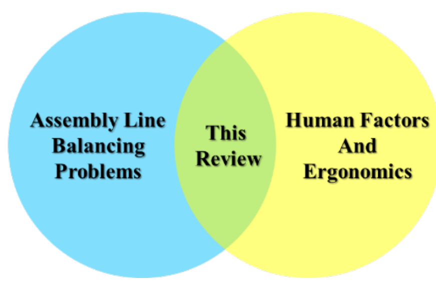


Figure 1. *Overlap of ALBPs and HFE fields is the focus of this review*

2.1. Human Factor and Ergonomic (HFE) Aspects

HFE is a scientific discipline focused on understanding the interactions between humans and other elements of a system, such as machines or work environments, as defined by the *International Ergonomics Association* (*IEA*). The primary goal of ergonomic considerations is to adapt job activities in a way that ensures worker safety and enhances overall system performance. Worker health and safety issues are often associated with repetitive tasks, awkward postures, prolonged activities, mental stress, and job satisfaction concerns. Consequently, various methods exist for evaluating ergonomic risks in workplaces. These methods, known as *ergonomic assessment tool*s (*EAT*s), include a range of techniques, from simple preliminary evaluations to more sophisticated assessments that require expertise and complex equipments (Chengalur, 2004).

In production systems, ergonomic risks encompass physical, cognitive, and psychosocial aspects. Physical work refers to muscular activities with or without movement, either dynamic or static. Such activities can lead to excessive fatigue, discomfort, pain, and, if not addressed adequately, *musculoskeletal disorders* (*MSD*s). Engineers and ergonomics practitioners aim to evaluate risk factors and find ways to reduce them in the workplace. For example, frequent or prolonged static muscular effort can result in *work-related MSD* (*WMSD*). To mitigate *WMSD*s, a practical approach is to design rest allowances to reduce fatigue in the relevant muscle groups (El ahrache & Imbeau, 2009).

Cognitive aspects involve the perceptual and mental abilities required to perform work tasks. The interaction between operators and their environment is crucial, as an increase in cognitive workload or an imbalance between cognitive and physical load can lead to ergonomic risks (Kong, 2019).

Psychosocial factors pertain to operators' subjective perception of various organizational aspects of work, including work-rest cycles, management style, psychological aspects of work, and workplace culture (Sekkay et al., 2018). Different methods are available for evaluating psychosocial risk factors, such as Karasek's *job content questionnaire* (*JCQ*) (Karasek et al., 1998) and the *effort-reward imbalance* (*ERI*) model (Siegrist, 1996).

Chengalur (2004) categorized *EAT*s into three main groups based on the type of data they use:

- Qualitative evaluation techniques rely on observational data and are primarily used for job monitoring. Typically, qualitative data are analyzed using checklists and job safety studies.
- Semi-quantitative assessment methods, such as *Rapid Entire Body Assessment* (*REBA*), *Rapid Upper Limb Assessment* (*RULA*), *Occupational Repetitive Action* (*OCRA*), others, combine qualitative and/or quantitative data. Through a set of decision rules, these techniques classify the occupational risks or rank job demands. They provide essential information for prioritizing interventions or allocating budgets.
- Quantitative analysis methods are data-driven approaches that facilitate continuous improvement and assess the reduction of ergonomic risks over time. These techniques can also be employed to develop guidelines and specify ergonomic interventions during the system design stage.

Li and Buckle (1999) divided *EAT*s into four classes based on data collection methods:

- Direct (or instrumental) methods utilize specialized software and equipment to measure the *physical workload* (*PWL*) of a task based on physiological indicators.

- Observational methods assess the position of body parts during task performance to calculate required force and identify deviations from their neutral positions.
- Subjective methods, or self-reports, are the most commonly used techniques due to their ease of application and generally valid results.
- Other psychophysiological methods, such as electrocardiography, electromyography, and thermal imaging.

In their survey, Takala et al. (2010) compared nineteen observational *EAT*s used in studies from 1965 to 2008 and concluded that no single measurement tool can be considered superior to others. However, most *EAT*s include a classification of ergonomic risk levels, as illustrated in Figure 2.

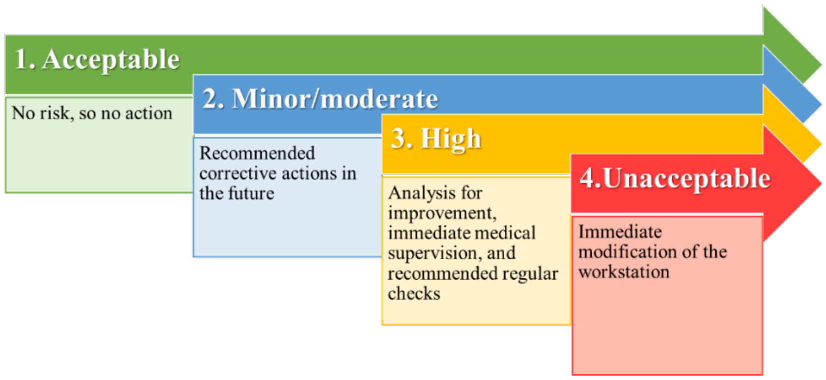


Figure 2. *Classification of ergonomic risk levels*

2.2. Assembly Line Balancing Problems (ALBPs)

Since Henry Ford's introduction of mass production, *AL*s have experienced significant improvements, transitioning from fast-paced single-model lines to more adaptable systems. Today, there are different types of *AL*s, and extensive studies have led to notable advancements in various aspects of their operation. In general, *AL*s consist of multiple workstations arranged in a specific order to produce one or more products by following a predefined sequence of tasks. The primary objective of *AL*s is to efficiently produce and deliver large volumes of standardized products. Thus, *ALBP*s arise as optimization problems that involve assigning tasks to different workstations to achieve the required production rate while satisfying various constraints and optimizing performance measures (Becker & Scholl, 2006). These problems aim to optimize one or more objective functions, which can be broadly classified into three main groups: capacity-related objectives, cost-related objectives, and profit-related objectives (Eghtesadifard et al., 2020).

*ALBP*s involve the combinatorial problem of task assignment. However, when the assignment of tools or equipment to workstations is considered, *ALBP*s become more complex and are referred to as *assembly* *line design problems* (*ALDP*s) (Finco et al., 2019). *ALDP*s encompass equipment selection and assignment in addition to task allocation to workstations.

In the literature, *ALBP*s are classified in various ways, but the most widely recognized classification is proposed by Baybars (1986), who divided *ALBP*s into two main groups: *simple ALBP* (*SALBP*) and *general ALBP* (*GALBP*).

*SALBP*s focus on one-sided straight *AL*s that mass-produce a single-type product with a predetermined operation time (deterministic *cycle time* (CT)) to optimize the desired objective while considering precedence and time cumulative constraints (Becker & Scholl, 2006). According to Rekiek et al. (2002), *SALBP*s can be further classified into four groups. The first type aims to minimize the number of workstations based on a given *CT*. Conversely, the second type considers a fixed number of workstations to minimize the *CT*. The other two types of *SALBP*s either check the feasibility of the problem with a fixed number of workstations and *CT* or aim to minimize both factors.

Although significant research has focused on *SALBP*s, there is still a need to address more complex real-world problems by concentrating on *GALBP*s. In the past decade, there has been a positive trend in considering additional constraints and diverse objectives to tackle more realistic scenarios. Becker and Scholl (2006) presented a comprehensive survey on *GALBP*s, marking a significant milestone. Figure 3 depicts synthesized classifications of *ALBP*s from various studies in this field, allowing for specific characteristics-based classification by considering each group's color in the figure.

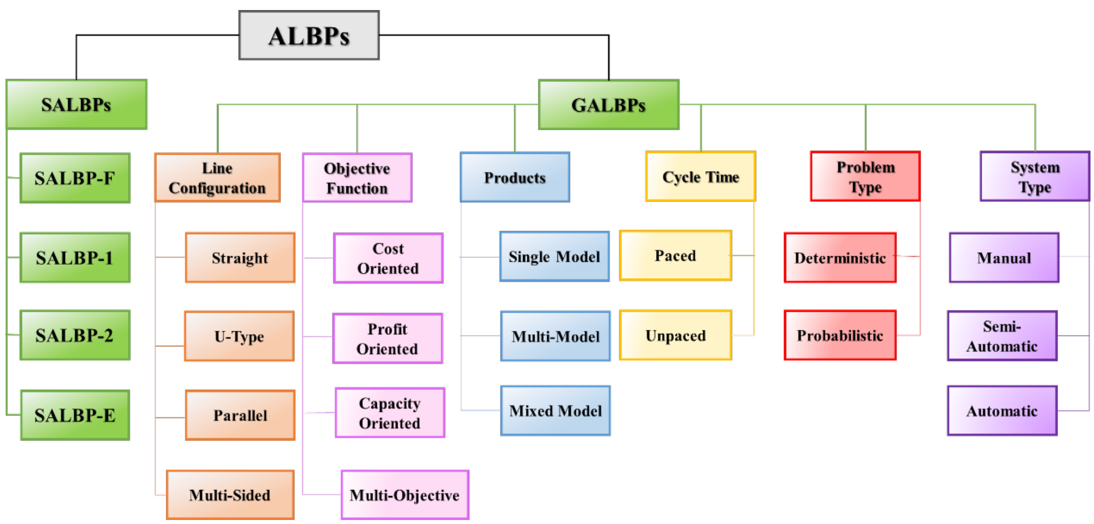


Figure 3. *Comprehensive classification of ALBPs*

In addition to Baybars's (1986) classification (green category), *GALBP*s can be further categorized based on workstation layouts (orange category) or grouped according to their objective functions (pink category). These problems can also be categorized into three groups based on the types of products manufactured (blue category). *GALBP*s can be classified as "paced" and "unpaced" *ALBP*s (yellow category) based on the time interval for parts and materials movement between workstations. In the literature, “unpaced” and “paced” *AL*s are also referred to as “buffered” and “synchronous” *Al*s, respectively (Becker & Scholl, 2006).

Although most *ALBP*s have focused on manual *AL*s, there is a growing trend towards considering the design of semi-automatic *AL*s and developing sustainable *ALDP*s. Consequently, *collaborative* human-robot *ALBP*s (*CALBP*s) and *robotic ALBP*s (*RALBP*s) have emerged as other problem types for modeling and solving the selection and assignment of appropriate collaborative tools and instruments (Stecke & Mokhtarzadeh, 2022). Thus, based on the types of production systems, *AL*s can be categorized into manual, semi-automated, and automated lines (Abdous et al., 2020) (purple category).

Furthermore, *ALBP*s can be classified as deterministic or probabilistic models (red category) based on the nature of the task times (Cakir et al., 2011). However, in addition to stochastic operation time, other aspects of *AL*s can also be indeterministic, and variations may occur due to improvements in the manufacturing process and production systems (Becker & Scholl 2006).

The *ALBP* was initially formulated as a *linear programming* (*LP*) model by Salveson (1955), and Halgeson and Birnie (1961) were the first to study these problems and propose a solution technique. However, for the first four decades, *ALBP*s were primarily solved using trial-and-error methods. They belong to the NP-hard class of *combinatorial optimization problem*s (*COP*s) which are challenging to solve using exact methods. Therefore, solving these complex problems requires sophisticated algorithms to find an effective optimum or at least an approximation through a finite set of feasible solutions.

Various computational methods have been employed to solve *ALBP*s, including exact, heuristic, and metaheuristic methods. Exact methods such as dynamic programming and the branch and bound method have been used, but their efficiency is limited for NP-hard problems. Heuristic and metaheuristic approaches have been found effective in solving different *ALBP*s. The *ranked positional weight technique* (*RPWT*) and Kilbridge & Webster’s method are commonly used heuristic methods. Among metaheuristic algorithms, *genetic algorithm* (*GA*), *particle swarm optimization* (*PSO*), and *ant colony optimization* (*ACO*) have been widely utilized (Eghtesadifard et al., 2020). Hybrid algorithms, which simultaneously apply two or more heuristic and metaheuristic methods, are gaining popularity as they aim to improve solution quality by mitigating the limitations and weaknesses of each method.

2.3. Assembly Line Balancing Problems by Ergonomic Considerations

In contemporary manufacturing systems, manual *AL*s remain prevalent due to their flexibility in addressing market fluctuations and advancements (Ozdemir et al., 2021). However, assembly tasks in *AL*s involve prolonged repetitive activities, exposing workers to ergonomic risks. Therefore, along with other technical productivity factors, it is essential to consider *HFE* indices in the optimization models of *AL*s to reduce ergonomic risks and enhance system efficiency (Weckenborg & Spengler, 2019).

Profit maximization is a crucial goal for companies, and traditional *ALBP*s primarily focus on economic parameters such as production rate, *CT*, and operation costs, while overlooking influential ergonomic factors. Neglecting ergonomic considerations in conventional *ALBP* can lead to indirect costs in the long term, such as absenteeism and medical or healthcare expenses. Additionally, Falck et al. (2010) reported that in the short term, disregarding ergonomic factors can result in costs for the car manufacturing industry, including health and safety expenses, productivity losses (e.g., line stoppages), and quality issues (e.g., scraps, reworks). Increased ergonomic risks can lead to chronic injuries, imposing significant costs on both organizations and society. Hendrick (2008) found that "good ergonomics projects typically provide a direct cost-benefit of from 1 to 2, to 1 to 10, with a typical payback period of 6–24 months."

Falck and Rosenqvist (2014) developed a model to calculate the cost of ignoring ergonomics in the design step. According to their study, the cost of corrective actions for ergonomic errors was 9.2 times higher than the cost of preventive actions taken during the design stage. Therefore, it is imperative to incorporate comprehensive ergonomic risk assessment into optimization models to achieve a more efficient and sustainable assembly system.

Gunther et al. (1983) were the first researchers to consider physical ergonomic risks in *ALBP*s (Otto & Battaïa, 2017). Their contribution served as a motivating starting point for subsequent discussions on ergonomics in *ALBP*s. Among the few studies conducted in this field, Otto and Scholl (2011) were the first to introduce an ergonomic objective. Their work marked a turning point in the literature on *Ergo-ALBP*s, inspiring several other studies in this area. Otto and Battaïa (2017) conducted a survey on optimization models for reducing physical ergonomic risks in *AL*s through line balancing and job rotation. However, to the best of the authors' knowledge, there is no systematic review of literature in the *Ergo-ALBP* domain. Therefore, the next section comprehensively reviews the relevant literature using content and descriptive analyses.

3. SYSTEMATIC REVIEW METHODOLOGY

In previous research studies conducted before 2011, ergonomic risks were rarely taken into account in the context of *ALBP*s. Therefore, this study focused on exploring articles published after 2011 that specifically address *Ergo-ALBP*s. To conduct a systematic literature review, the *PRISMA* method developed by Moher et al. (2009) was employed. This method consists of four main steps, as illustrated in Figure 4.

In the first step, "Identification", a specific search phrase was used to query the "*Web of Science*" and

"*Engineering Village*" databases, outlined in Table 1. Subsequently, in the second step, titles and abstracts were screened to remove duplicate papers. Following this, all the remaining articles (77 papers) underwent a thorough assessment for "Eligibility". Ultimately, a total of 57 research papers were included for qualitative analysis.

***Table 1**. Literature search for ergonomic consideration in ALBPs*

Block1	"assembly line balanc*" **OR** "assembly line"
	AND
Block2	ergonom* **OR** ergonom* risk **OR** "human factor*"

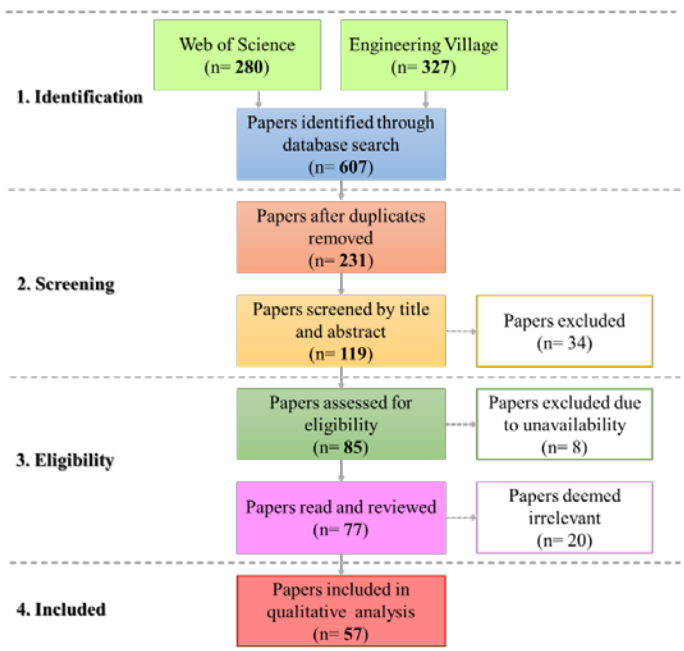


***Figure 4**. The PRISMA flowchart of the systematic literature review of this research*

3.1. Content Analysis

In this section, the reviewed literature was analyzed from the ergonomic perspective and also from the operational perspective separately. Table 2 summarizes key aspects of these studies.

***Table 2**. Summary of Ergo-ALBPs papers published between 2011–2022*

Authors	Problem Type	Mathematic Model	Ergo Factor	EAT	Objective Function	Solution Method	Case Study
Otto & Scholl 2011	SALBP-1	NLP	Posture	OCRA, EAWS, NIOSH	Min (#workstations & Ergo-Risk)	two stage heuristics	
Xu et al. 2012	SALBP-1	MILP	Hand/Arm extremities	ACGIH* guideline	Min (#workstations & Ergo-Risk)	Exact Method (CPLEX)	x
Mutlu & Özgörmüş 2012	SALBP-1	Fuzzy LP	PWL constraints	Subjective method	Min (#workstations)	Bellman-Zadeh approach	x
Cheshmehgaz et al. 2012	SALBP-2	Fuzzy GP	Posture	OWAS	Min (CT & ARP & PWL)	GA	
Bautista et al. 2012	TSALBP-1	LP	somatic risk constraints	-	Min (#workstations & Ergo-Risk)	Exact Method (CPLEX)	x
Bautista et al. 2013	TSALB-1	MILP	Posture	-	Min (#workstations & Ergo-Risk)	Exact Method (CPLEX)	
Otto 2014	SALBP-1	-	Posture	OCRA, EAWS	Min (#workstations & Ergo-Risk)	two stage heuristics	
Öksüz & Satoğlu 2014	UALBP	-	learning effect	-	Max (competency level)	heuristic	
Kara et al. 2014	GALBP	MILP	Workers' skill & posture	-	Min (workers & equipment costs)	Exact Method (XPRESS Solver)	
Battini et al. 2015	SALBP-2	LP	Energy expenditure	Garg et al. 1978	Min (CT) & Max (ESI)	Pareto frontier	
Bautista et al. 2015a	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (max Ergo-Risk)	GRASP	x
Bautista et al. 2015b	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (average Ergo-Risk)	Exact Method (CPLEX)	x
Bautista et al. 2015c	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (average max Ergo-Risk)	Exact Method (CPLEX)	x
Polat et al. 2015	SALBP-2	GP	PWL	REBA	Min (CT & PWL deviation)	Exact Method (CPLEX)	
Barathwaj et al. 2015	MMALBP	MILP	ARP	RULA	Min (#workstations & Ergo-Risk)	GA	x
Battini et al. 2016a	IALBFP	MIP	Fatigue	Garg et al. 1978	Min (#workers)	Exact method (CPLEX)	
Battini et al. 2016b	SALBP-2	MO-LP	Energy expenditure & rest allowance	PMES	Min (CT & Energy expenditure)	Pareto frontier analysis	x
Bautista et al. 2016a	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (max & absolute deviation of Ergo-Risk)	GRASP	x
Bautista et al. 2016b	TSALBP	MILP	Posture	semi-quantitative customized set	Min (max Ergo-Risk)	Exact method (CPLEX)	x

Bortolini et al. 2017	SALBP-2	MO-LP	Posture	REBA	Min (CT & Energy expenditure)	Pareto frontier	x
Battini et al. 2017	SALBP-2	MIP	Energy expenditure	-	Min (CT & Energy deviation)	Hierarchical planning approach	x
Baykasoğlu et al. 2017	SALBP-1	preemptive GP	Posture	OCRA	Min (#Red Stations & OCRA index)	Constructive search algorithm	x
Bautista et al. 2018	MMALBP	MILP	Posture	-	Min (max & average absolute deviation of Ergo-Risk)	Exact method (CPLEX)	x
Bautista & Alfaro 2018a	MMALBP	MILP	Posture	-	Min (Ergo-Risk dispersion)	GRASP	x
Bautista & Alfaro 2018 b	TSALB	MILP	Posture	four risk levels by Bautista et al. 2016a	Min (average Ergo-Risk)	Exact method (CPLEX)	x
Polat et al. 2018	SALBP-2	MIP	PWL	REBA	Min (CT & PWL deviation)	Exact method (CPLEX)	
Finco et al. 2018	SALBP-2	-	Energy expenditure & rest allowance	Price 1990	Min (CT & Energy expenditure)	Heuristic approach	
Tiacci & Mimmi 2018	Stochastic MMALBP	NLP	Posture	OCRA	Min (Normalized design cost for corrected OCRA)	GA	x
Abdous et al. 2018	SALBP-1	MO-MILP	fatigue & recovery	Ma et al. 2009	Min (#workstations & fatigue)	Pareto frontier & ε-constraint	
Alghazi & Kurz 2018	MMALBP	IP & CP	ergonomic risk constraints	-	Min (#workers)	Branch & bound algorithm	x
Kahya & Şahin 2019	SALB-1	-	Posture	REBA	Min (#workstations)	Heuristic approach	x
Dalle Mura & Dini 2019	SALBP-1	-	Energy expenditure	RULA	Min (#skilled workers & cost & energy expenditure variance)	GA	x
Weckenborg & Spengler 2019	CALBP	MILP	Energy expenditure	Price 1990	Min (Cost per cycle)	Exact method (CPLEX)	
Akyol & Baykasoğlu 2019	ALWABP	GP	Posture	OCRA	Min (Ergo-Risk)	Multi-start greedy heuristic method	
Finco et al. 2019	ALDP	MILP	Vibration	ISO 5349-1	Min (Design cost)	Heuristic approach	x
Finco et al. 2020	SALBP-2	MILP	Energy expenditure & rest allowance	OCRA	Min (Smoothness index)	Heuristic approach	
Zhang et al. 2020	UALWABP-2	LP	Posture	OCRA	Min (CT & Ergo-Risk)	Restarted Iterated Pareto Greedy	
Abdous et al. 2020	CALDP	MO-MINLP	fatigue & recovery	Ma et al. 2010	Min (Design cost) & Max (Ergonomics level)	Iterative Local Search	
Mokhtarzadeh et al. 2021	Parallel U-shaped	MIP & CP	Posture	BWM	Min (#workstations & Ergo-Risk)	Heuristic approach	x

	MMALBP						
Vollebregt 2021	MMALBP	MIP	Posture	REBA	Min (CT, max & sum Ergo-Risk)	GA & pareto frontier	x
Zamzam et al. 2021	2sided-ALBP	GP	Posture	ESI	Min (#workstations & #mated stations, ESI)	GA	
Ozdemir et al. 2021	SALBP-2	Fuzzy MO	Posture	DHM & ESM	Min (CT, Ergo-Risk imbalance)	Pareto frontier	x
Bortolini et al. 2021	SALBP-1	Tri-objective LP	Fatigue	-	Min (annual costs, time & fatigue difference)	Pareto frontier	x
Katiraee et al. 2021	SALBP-2	LP	Workers' diversity	Borg scale	Min (CT & max physical effort)	ε-constraint approach	x
Finco et al. 2021	MMALBP	LP	Fatigue and rest allowance	-	Min (CT & rest allowance)	Heuristic approach	x
Weckenborg et al. 2022	CALBP	MIP	Energy expenditure	Biomechanical method	Min (cost & workers' biomechanical load)	Pareto frontier	
Stecke & Mokhtarzadeh 2022	CALBP	MILP & CP	Energy expenditure	Garg et al. 1978	Min (weighted sum of CT and ergonomic indicators)	Benders decomposition algorithm	
Quenehen et al. 2022	RALBP-2	-	fatigue	PMES	Min (CT, accumulated fatigue)	Hybridization metaheuristic (list algorithm)	x
Chutima & Khotsaenlee 2022	Parallel U-shaped CALBP	MILP	Energy expenditure	PMES	Min (workload & energy expenditure variance) & Max (tax benefit & line's efficiency)	Non-dominated Sorting Teaching-Learning-Based heuristic method	
Dalle Mura & Dini 2022	CALBP	CP	Energy expenditure	-	Min (cost & energy expenditure variance)	GA	x
Tkitek & Triki 2022	SALBP-1	LP	Arm measurement	-	Min (#workstations)	Exact method (LINGO)	
Abdous et al. 2022a	SALBP-F	ILP	Fatigue & recovery	Quantitative analytical model	Max (level of ergonomics)	Iterative Dichotomic Search Algorithm	
Abdous et al. 2022b	CALDP	MILP	Fatigue & recovery	Ma et al. 2010	Min (cost & fatigue)	ε-constraint approach	x
Katiraee et al. 2022	SALBP-2	Bi-objective LP	Perceived physical effort	Borg scale	Min (CT & workload variance)	ε-constraint approach	x
Yetkin & Kahya 2022	SALBP-2	Bi-objective LP	Posture	REBA	Min (CT & Ergo-Risk)	conic scalarization method	x
Keshvarparast et al. 2022	CALBP	MILP	Workers' diversity	Borg scale	Min (CT & workload imbalance)	ε-constraint approach	x
Cimen et al. 2022	ALWARBP	GP	Posture	OCRA	Min (rebalancing cost & Ergo-Risk)	Constructive rule-based heuristic method	x

3.1.1. Ergonomic Component of Ergo-ALBPs:

The literature review highlighted that only a limited number of *EAT*s were predominantly used in *Ergo-ALBP*s studies, despite the availability of numerous ergonomic analysis techniques. While semi-quantitative and quantitative methods were suitable for task evaluations (Chengalur 2004), qualitive techniques were employed in only 10% of the papers (6 cases). However, semi-quantitative approaches were utilized in more than half of the articles. Among various semi-quantitative methods, *OCRA* was the most popular, followed by *RULA*, the revised *NIOSH* lifting equation, and *REBA*, as shown in Figure 5.

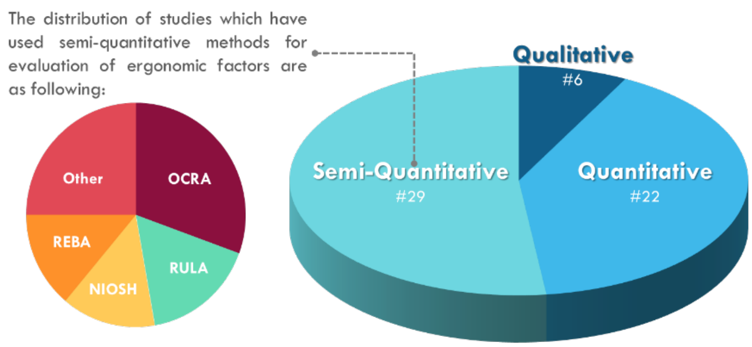


***Figure 5**. Distribution of various EATs in Ergo-ALBPs*

Figure 6 illustrates the distribution of ergonomic factors considered in *Ergo-ALBP*s. The data from the studies revealed that 82% of the articles focusing on posture risk factors used semi-quantitative *EAT*s. Quantitative methods were employed in all studies considering localized fatigue, while the rate for generalized fatigue indicators was 75%. It is important to note that fatigue can be experienced as either localized muscle fatigue (i.e., fatigue in specific muscle groups) or generalized fatigue (whole-body fatigue). To quantify generalized fatigue, the energy expenditure or metabolic rate is evaluated when the activity involves approximately 70% or more of the body's muscular mass (e.g., upper-body non-walking activity without carrying an object). For assessing localized fatigue in specific muscle groups (e.g., shoulder, arm, back), other indices and methods such as the Borg scale for different body parts should be considered.

The first study to incorporate the smoothness of ergonomic factors in *ALBP*s was conducted by Battini et al. (2016b). They applied a multi-objective *SALBP*-2 to optimize the time and energy evenness indexes. Energy expenditure was estimated using the *predetermined motion energy system* (*PMES*), initially developed by Garg et al. (1978). The *PMES* includes formulations for calculating energy expenditure for each task by breaking them down into basic movements like lifting, carrying, and walking.

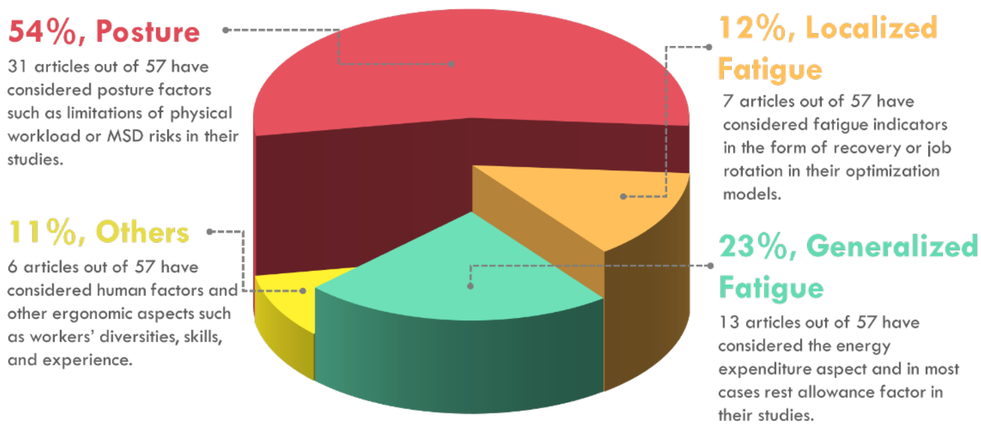


Figure 6. *Distribution of various ergonomic aspects in Ergo-ALBPs*

Different problem types in *Ergo-ALBP*s entail other methods and considerations. For instance, Alghazi and Kurz (2018) utilized the task difficulty indicator, which was computed based on a weighted ergonomic score and task duration. They aimed to control the cumulated difficulty of tasks assigned to each workstation using *constraint programming* (*CP*). Finco et al. (2019) sought to minimize the cost of applying automatic tools in workstations based on vibration levels compliant with ISO 5349-1. Additionally, Zamzam et al. (2021) aimed to minimize the *effort smoothness index* (*ESI*), which represented the standard deviation of the metabolic rate among workers, thereby measuring the variation in physical effort across operators.

3.1.2. Assembly Line Worker Assignment and Balancing Problem with Ergonomics Consideration (Ergo-ALWABP):

On the ergonomic side, individual characteristics of operators, such as gender, age, and weight, result in varying levels of energy expenditure when performing the same task (Garg et al., 1978). In the *Ergo-ALBP* literature, several studies have addressed these differences. For example, Öksüz and Satoğlu (2014) investigated the learning effect as a crucial human factor in balancing U-shaped assembly lines. They incorporated operators' competence levels for each task and aimed to maximize competency in their model. Dalle Mura and Dini (2019) developed an optimization algorithm to assign tasks with required skill levels to operators with diverse technical skills. They then evenly distributed energy loads to workstations based on operators' physical capabilities.

On the other hand, the *assembly line worker assignment and balancing problem* (*ALWABP*) extends the *SALBP* when the operation time for each task varies depending on the worker performing it, resulting in the double assignment problem of tasks and workers to workstations concurrently. Introduced by Miralles et al. in 2007, the *ALWABP* incorporates the concept of *sheltered workcenter for disabled* (*SWD*) and was initially presented through a case study in an *AL* with a fixed number of workstations. In contrast to the

SALBP, where tasks have fixed execution times, in the *ALWABP*, each task's execution time varies based on the skill level of the selected worker (Katiraee et al., 2022). The primary objective of the *ALWABP* is to optimize the assignment of tasks and workers to workstations to enhance *AL* productivity. However, many studies in this field focus solely on operational aspects such as time and costs, neglecting *HFE* considerations.

The first study to consider ergonomic aspects in the *ALWABP* was proposed by Akyol and Baykasoğlu (2019). They developed a multiple-rule-based constructive randomized search algorithm to solve *ALWABP* while considering ergonomic risk factors (*Ergo-ALWABP*). Since then, three other studies have aimed to improve the efficiency and effectiveness of *Ergo-ALWABP* algorithms. For example, Katiraee et al. (2021) employed the *Borg* scale, a subjective assessment tool, to evaluate workers' perceived physical effort and categorized tasks based on their difficulty level for individual workers. This allowed them to determine optimal worker assignments and balancing. Another study by Katiraee et al. (2022) proposed an approach to consider workers' expertise and perceived physical effort in the *ALWABP*. They took into account workers' skill levels, experience, and physical conditions when assigning tasks and balancing the workload. Additionally, Cimen et al. (2022) presented an algorithm to rebalance an existing assembly line and assign workers to minimize ergonomic risk factors. They considered workers' physical abilities, job rotation, and workload distribution to reduce ergonomic risk factors. These studies emphasize the importance of considering ergonomic factors in the *ALWABP* and propose various approaches to optimize worker assignment and balancing.

3.1.3. Operational Component of Ergo-ALBPs:

Incorporating ergonomic aspects alongside operational factors in *ALBP*s introduces conflicting objective functions. To address this, three papers utilized *fuzzy set theory* (*FST*). Mutlu and Özgörmüş (2012) considered the assembly task's *PWL* as a fuzzy set and developed a fuzzy *LP* model based on Bellman and Zadeh’s (1970) approach to solve their *SALBP*. Cheshmehgaz et al. (2012) proposed a fuzzy *goal programming* (*GP*) method and a *GA* to solve the fuzzy mathematical *SALBP* model. They introduced a novel ergonomic factor, the *accumulated risk of postures* (*ARP*), to evaluate steady posture levels during assembly tasks, considering three conflicting objectives: *CT* minimization, *ARP* minimization, and *PWL* smoothness. Ozdemir et al. (2021) employed simulation software to analyze the ergonomic risk of assembly tasks and developed a fuzzy multi-objective model accordingly.

For solving NP-hard problems like *ALBP*s, as explained in the previous section, exact methods are not efficient enough, and it is recommended to employ heuristic and meta-heuristic approaches to find effective or near-optimal solutions. As shown in Table 2, 44% of *Ergo-ALBP*s have been solved by exact methods. Heuristic approaches, constituting 33% of the studies, are more popular than meta-heuristic methods (23%). Among the meta-heuristic approaches, *GA* is widely used individually or in combination with other methods. Innovative solution methods have also been employed in recent studies. For example, Abdous et al. (2022) developed an iterative dichotomic search algorithm for the feasibility study of their *SALBP*. Chutima and Khotsaenlee (2022) applied a *non-dominated sorting teaching-learning-based optimization* (*NSTLBO*) method to solve a parallel *U-shaped ALBP* (*UALBP*) considering the energy expenditure factor using the *PMES* technique.

Regarding the types of problems addressed, 47% of the studies focused on *SALBP*s, with an equal distribution between Type 1 (minimizing the number of workstations) and Type 2 (minimizing the cycle time), except for Abdous et al. (2022a), who considered Type F (feasibility study), and Cimen et al. (2022), who aimed to maximize the line's efficiency (Type E). On the other hand, 53% of the papers with *GALBP* models tackled various types of general problems, as shown in Figure 7.

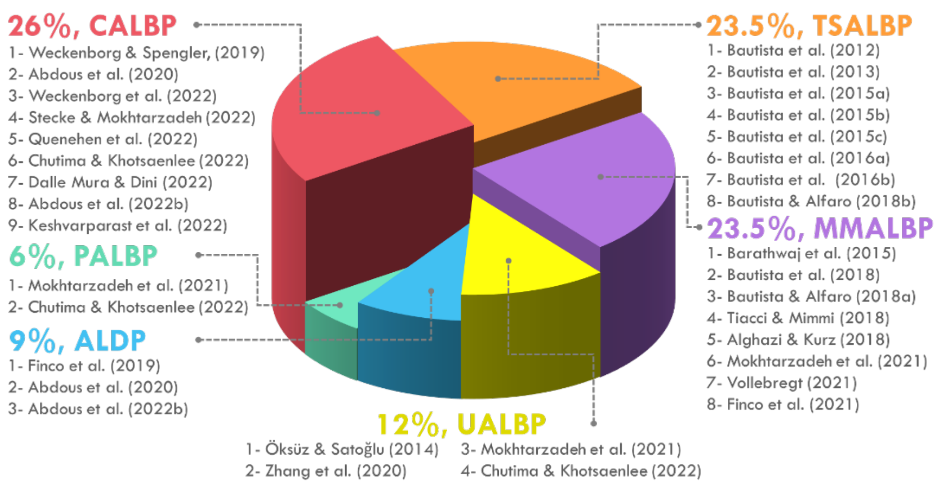


Figure 7. *Distribution of GALBPs in ergonomic-related studies*

One commonly studied problem is the *time and space constrained assembly line balancing problem* (*TSALBP*). Bautista et al. (2012) introduced *TSALBP* by ergonomic considerations (*TSALBP-erg*). They proposed a model that balances conflicting goals related to time, space, and ergonomic risks. *TSALBP*s are classified based on the number of workstations, CT, and available space, resulting in eight different problem models, each of which can be mono-objective or multi-objective. This research group further developed these sorts of problems and since 2015, they employed the Nissan engine company as a case study. Bautista et al. (2015a) used the *greedy randomized adaptive search procedure* (*GRASP*), a multi-start metaheuristic approach, to solve *TSALBP*s. In subsequent studies, they combined *EAT*s such as *RULA*, *OCRA*, and the revised *NIOSH* lifting equation (Bautista et al., 2015a, 2015b, 2015c, 2016a, Bautista & Alfaro 2018b).

The need for more realistic models motivated researchers to study *mixed-models assembly line balancing problems* (*MMALBPs*), which represent 26% of the papers addressing general problems (Figure 7).

*Parallel ALBP*s (*PALBP*s) were less common, with only two hybrid models found. Chutima and Khotsaenlee (2022) investigated the *Parallel U-shaped ALBP*, while Mokhtarzadeh et al. (2021) considered the *Parallel U-shaped mixed-model ALBP*, indicating the increased use of hybrid models.

Operational aspects were incorporated in various ways in the optimization models, either as objective functions or constraints. The most frequently used operational objective functions were *CT* minimization (29%), number of workstations minimization (27%), and cost minimization (19%). Additionally, 25% of the articles considered operational aspects solely as constraints without an operational objective.

A small portion (7%) of the reviewed papers addressed ergonomic balancing problems in the design phase (*ALDP*). Baykasoğlu et al. (2017) proposed a heuristic solution method for the design problem in a *SALBP*. Finco et al. (2019) analyzed vibration in semi-automatic *ALDP* and aimed to minimize design costs. Abdous et al. (2020, 2022b) also considered ergonomic aspects in the design phase, particularly in an Industry 4.0 context.

3.1.4. New Trend in Industry 4.0 Era:

Industry 4.0 is revolutionizing the manufacturing industry by integrating advanced technologies like cyber-physical systems, the *internet of things* (*IoT*), and big data analytics. This digital transformation and automation are also influencing *ALBP*s. Recent studies have highlighted the potential of Industry 4.0 in addressing ergonomic considerations in *ALBP*s. Collaborative robots and exoskeletons, for instance, have been employed to reduce ergonomic risks in *AL* tasks. Moreover, *CALBP*s or *RALBP*s can optimize *CT* and ergonomic risk, leading to improved economic and ergonomic performance in assembly processes.

There is a growing trend in recent years towards integrating ergonomic aspects in collaboration with robots and exoskeletons, Figure 7 demonstrates that out of 57 studies, nine papers focused on *CALBP*s, with seven published in 2022.

Weckenborg and Spengler (2019) were the first to propose a cost-oriented approach for *ALBP* that considers collaborative robots and ergonomics. Their approach aims to reduce workers' PWL, balance energy expenditure, and increase productivity by incorporating collaborative robots.

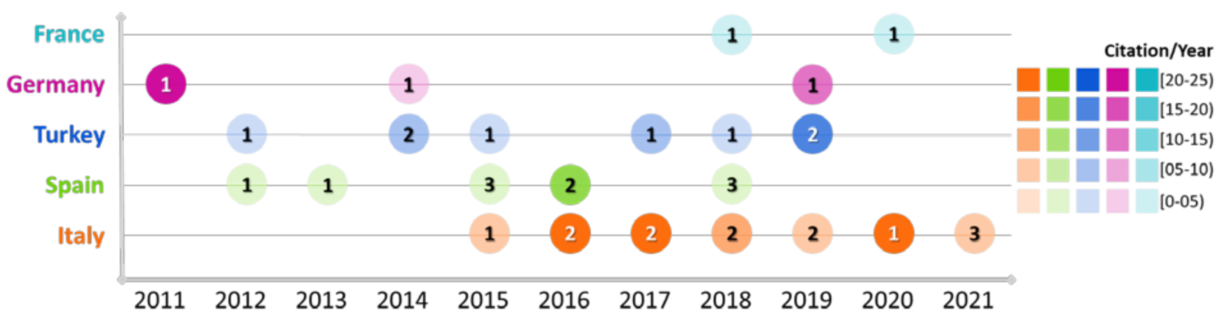
Abdous et al. (2020) subsequently investigated the collaborative problem in the design phase (*CALDP*) to minimize the design cost of *AL*s while also reducing the ergonomic risk level. They assessed dynamic muscle fatigue based on the formula proposed by Ma et al. (2009) for assigned tasks at each workstation. Two years later, Abdous et al. (2022b) proposed a multi-objective approach to *CALDP*, optimizing ergonomic criteria such as workload, body posture, and repetitive motions, as well as economic factors like production cost, equipment cost, and space utilization.

Weckenborg et al. (2022) and Stecke and Mokhtarzadeh (2022) incorporated the energy expenditure factor in their semi-automatic *AL*s. They solved their model using exact methods and tested them on numerical examples. Quenehen et al. (2022), on the other hand, employed the *PMES* to measure fatigue in the *RALBPs* and solved the problem using a hybrid metaheuristic approach (list algorithm), considering a specific case study.

3.2. Descriptive Analysis

This section presents the findings from the quantitative data analysis using bibliometric approaches. These findings, along with those from the content analysis approach (Section 3.1), were utilized to identify research gaps and main trends in the field of study.

The review of 57 *Ergo-ALBP* papers revealed that 79% of the studies were conducted in five countries: Italy, Spain, Turkey, France, and Germany, with 16, 10, 10, 5, and 4 articles, respectively. Figure 8 visually illustrates the distribution of articles from these countries based on their citation rate (i.e., number of citations per year). The citation rates were collected up until October 2022, so publications from 2022 were not considered for a fair analysis.

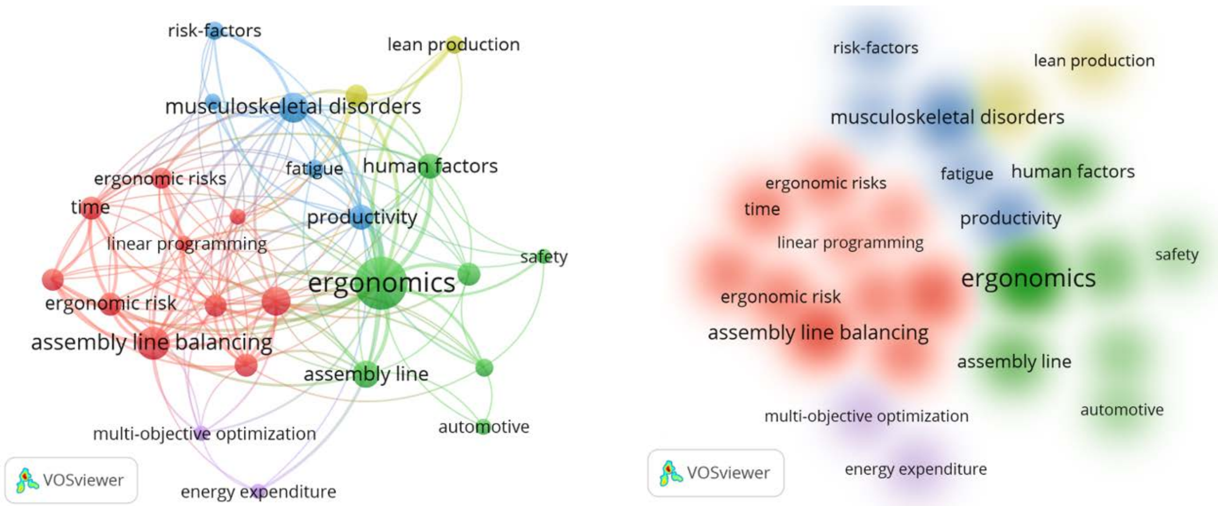


Note: The numbers in circles identify the number of studies at the same point and the citation rate is cumulative.

Figure 8*. Research contributions of the top-five pioneer countries in the field of Ergo-ALBPs*

Furthermore, nearly 60% of the reviewed papers (34 articles) included a case study in their research, while the remaining studies employed numerical examples to validate their models. Automotive manufacturers accounted for more than half of the case studies in the literature (19 articles), with Bautista's research group utilizing the Nissan engine plant in nine of their studies. Additionally, four studies focused on electronic appliance assembly lines (Xu et al., 2012; Bortolini et al., 2017; Kahya & Şahin, 2019; Ozdemir et al., 2021). Among all the reviewed articles, 63% were journal papers, 35% were conference papers, and one article was a thesis.

Finally, the *VOSviewer* software was used to conduct co-occurrence (co-word) analysis and identify trends in the studies. This analysis employs statistical methods to cluster main keywords based on the strength of their relationships in the literature. Figure 9 displays the keyword co-occurrence network as an output of *VOSviewer*.



(a) Co-occurrence map of the keywords *(b) Cluster density of the keywords*

***Figure 9**. The map of connections between the keywords within 2011–2022*

The analysis of the information in the co-word map provides insights into research gaps and future trends, which will be discussed in the following sections.

4. INDUSTRY 5.0 PARADIGM

Industry 5.0 represents a significant transformation in manufacturing, emphasizing collaboration between human workers and advanced technologies to achieve improved productivity, efficiency, and innovation. Unlike Industry 4.0, which focused on automation, Industry 5.0 places greater emphasis on mass customization and recognizes the importance of human intelligence and creativity in manufacturing processes (Baicun et al., 2020). By integrating advanced technologies like *AR*, *VR*, *AI*, and collaborative robots, Industry 5.0 has the potential to assist workers in performing complex tasks, reducing ergonomic risks, and optimizing *AL* performance.

Within the context of *Ergo-ALBP*s, Industry 5.0 offers several potential benefits. Firstly, it acknowledges the importance of worker well-being and safety, aiming to incorporate ergonomic design principles into *ALBP*s. This can lead to improvements in worker comfort, productivity, and job satisfaction. Secondly, Industry 5.0 solutions incorporate human feedback and input into the *ALBP*s, enabling a more flexible and adaptive production environment that can better accommodate variations in worker behavior and physical abilities. Thirdly, Industry 5.0 facilitates the integration of advanced technologies, such as wearables and *AR*, which can enhance worker performance and reduce the risk of injuries. Lastly, Industry 5.0 promotes a culture of continuous learning and improvement, encouraging workers and organizations to adopt a growth mindset and explore new ways to optimize the *ALBP*s.

The core values of Industry 5.0 can be categorized into three main aspects: human-centricity, resilience, and sustainability (Xu et al., 2021). Furthermore, Leng et al. (2022) discussed relevant concepts related to

Industry 5.0, including Industry 4.0, Operator 5.0, and Society 5.0. However, there are commonalities between the main aspects of Industry 5.0 and its related concepts.

The following subsections provide an explanation of the related concepts and aspects of Industry 5.0 and demonstrate their potential future impacts on *Ergo-ALBP*s, as briefly depicted in Figure 10

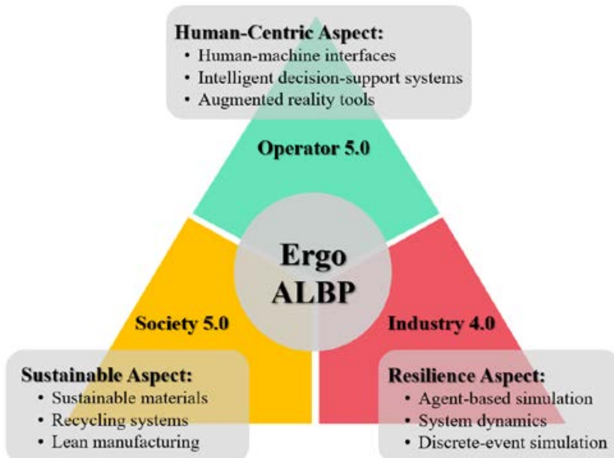


***Figure 10**. Concepts related to Industry 5.0 and their applications in Ergo-ALBPs*

4.1. Paradigm Shift from Industry 4.0

As mentioned earlier, Industry 4.0 is a manufacturing paradigm that relies on interconnected machines, data analytics, and *AI* to create a highly efficient and automated production environment. While Industry 4.0 has revolutionized many aspects of manufacturing, it has limitations when it comes to addressing *Ergo-ALBP*s. For example, Industry 4.0 tends to focus primarily on optimizing production throughput and minimizing costs, often neglecting worker well-being. It treats workers as passive participants in the production process, rather than recognizing them as active agents capable of contributing to the overall efficiency and ergonomics of the assembly line. Furthermore, Industry 4.0 solutions often fail to consider the variability in human behavior and physical abilities, resulting in potential safety hazards and reduced worker productivity. Therefore, there is a need to explore new manufacturing paradigms, such as Industry 5.0, that can address these limitations and incorporate worker-centered design principles into *ALBP*.

Industry 5.0 represents a new paradigm that builds upon the strengths of Industry 4.0 while placing a greater emphasis on human-centered design and collaboration between workers and machines (Leng et al., 2022). Industry 4.0 is closely linked to the resilience aspect of Industry 5.0, which establishes the technical foundations for leveraging digital technologies to enhance the flexibility and agility of manufacturing processes (Zizic et al., 2022).

In the context of *Ergo-ALBP*s, the resilience aspect of Industry 5.0 can involve the use of simulation tools to optimize the *AL* and proactively identify potential issues. Various simulation approaches, including discrete-event simulation, agent-based simulation, and system dynamics, can be employed.

Additionally, Industry 4.0 offers technologies that assist companies in adapting to changes and disruptions, such as predictive maintenance systems or adaptive manufacturing systems.

4.2. Operator 5.0

Operator 5.0 is a concept that describes a new generation of workers who are empowered by advanced technologies and trained to collaborate with machines to optimize production processes. Operator 5.0 signifies a transition towards a more collaborative and team-based production environment, where workers are trained to work alongside machines as partners rather than mere operators. This concept highlights the crucial role of human skills, creativity, and problem-solving abilities in the manufacturing process, with advanced technologies supporting operators to achieve higher levels of productivity, quality, and flexibility.

In the context of *Ergo-ALBP*s, Operator 5.0 represents a paradigm shift from the traditional view of workers as passive participants in the production process to active agents who contribute to the optimization of the *AL*. The concept of Operator 5.0 aligns with the human-centric aspect of Industry 5.0, which emphasizes placing human needs and values at the core of manufacturing processes. One key characteristic of Operator 5.0 is the use of wearable technology and sensors to monitor worker behavior and physical capabilities. This data can be utilized to optimize *ALB* and reduce the risk of injuries or *MSD*s. For instance, wearables can track worker posture and movements, identifying potential ergonomic hazards and providing real-time feedback to help workers adjust their posture or movements. Wearables can also monitor worker fatigue and issue alerts when workers need to take breaks or switch tasks to prevent injuries.

Moreover, Operator 5.0 entails the adoption of human-machine interfaces, *AR* and *VR* technologies, and intelligent decision-support systems. These technologies offer workers real-time information on *ALB* and guide them through complex tasks. For example, *AR* can overlay instructions or images onto physical objects, enabling workers to precisely place components or perform specific tasks. *VR* can simulate various balancing scenarios, providing workers with virtual training and feedback on their performance. An operator wearing an *AR* headset can receive real-time feedback on assembly tasks and receive suggestions for optimal work postures to prevent ergonomic injuries. Additionally, there are advancements in the development of intelligent exoskeletons that enhance the strength and endurance of workers involved in physically demanding tasks, such as lifting heavy objects or working in awkward postures.

These technologies possess the potential to enhance the cognitive and physical abilities of human operators, enabling them to perform their tasks more efficiently, safely, and comfortably. As a result, they can improve the overall ergonomics of assembly processes and enhance the well-being and job satisfaction of workers (Gervasi et al., 2023).

4.3. Society 5.0

Society 5.0 represents a shift towards a more inclusive and diverse production environment that benefits all members of society. This concept emphasizes integrating advanced technologies with societal needs and values to create a sustainable future. It requires organizations to adopt a holistic and human-centric approach to production that considers the diverse needs and perspectives of workers, customers, and other stakeholders. By promoting diversity and inclusion, organizations can enhance creativity, innovation, and collaboration, while ensuring that their products and services meet the needs of a diverse customer base. Society 5.0 envisions a production system that balances economic, social, and environmental considerations to create value for all stakeholders. This concept aligns closely with the sustainable aspect of Industry 5.0, which emphasizes the importance of creating an environmentally and socially responsible manufacturing industry.

In the context of *Ergo-ALBP*s, Society 5.0 can be applied to create *AL*s that are not only efficient but also sustainable and human-centered. For example, advanced sensors and *AI* algorithms can monitor workers' physical and mental states and adjust the *AL* to reduce physical strain and improve workers' well-being. Integrating social values and ethics ensures that the *AL* is designed to meet the needs of workers, customers, and society as a whole. The principles of Society 5.0 can involve using sustainable materials and processes, such as biodegradable materials, closed-loop systems, and lean manufacturing principles, to reduce waste and minimize the environmental impact of manufacturing.

Therefore, in *Ergo-ALBP*s, it is important to consider technologies that support sustainable manufacturing practices, such as employing renewable energy sources or implementing recycling systems. Additionally, efforts can be made to prevent the environmental impact of production in the design phase by incorporating eco-design principles or closed-loop manufacturing. These actions align with the principles of Society 5.0 and contribute to the creation of a more sustainable and socially responsible manufacturing industry.

4.4. Potential Challenges of Industry 5.0 in Ergo-ALBPs

While Industry 5.0 holds great potential for revolutionizing *Ergo-ALBP*s, there are several challenges that organizations may encounter during its implementation. One key challenge is the investment required in new technologies and training programs to support worker-centered design and collaboration. This entails upfront costs and a shift in organizational culture and mindset. Resistance from workers who may be apprehensive about new technologies or fear job loss due to automation is another challenge to address

(Zizic et al., 2022). Involving workers in the planning and implementation process and giving them a voice in decision-making can help reduce these concerns. Additionally, regulatory and legal barriers may obstruct the adoption of Industry 5.0 solutions, particularly in industries with strict safety and health regulations. Moreover, organizations need to develop new performance metrics and evaluation frameworks to effectively measure the impact of Industry 5.0 on improving *Ergo-ALBP*s. Despite these challenges, the potential benefits of Industry 5.0 in creating a more efficient, safe, and worker-centered production environment make it an area of significant interest and investment for many organizations.

To address the challenges posed by Industry 5.0, Baicun et al. (2020) suggest focusing education and training programs on enhancing workers' interdisciplinary skills, such as engineering, information technology, and psychology, to meet the demands of human-centered intelligent manufacturing. Additionally, Industry 5.0 requires a new organizational structure that prioritizes collaboration, communication, and flexibility to adapt to evolving customer needs and technological advancements.

5. FINDINGS AND DISCUSSION

The content and quantitative analysis of this literature review yielded several trends in *Ergo-ALBP* research studies, shedding light on the current research gaps in this field. The systematic review identified the following research gaps and future study trends:

(1) In recent years, studies have explored the ALBP with human-machine or human-robot collaboration within the context of Industry 4.0. However, this is a newly emerged field in the Ergo-ALBP domain, which requires further investigation and offers numerous research opportunities. Cyber-physical systems, such as sensors and robots, can provide real-time data on AL process, enabling better decision-making and optimization. AR and VR technologies can enhance the design and planning phases by enabling workers to visualize and test different scenarios. The integration of AI and machine learning algorithms can automate ALB processes and improve efficiency over time. These opportunities have the potential to significantly improve productivity, quality, and worker safety in manufacturing.

(2) The integration of *HFE* considerations with practical aspects represents a major trend in *Ergo-ALBP* research (Boysen et al., 2022). While many studies have focused on time and space-constrained (*TSALBP*) or mixed-model problems (*MMALBP*s), there is a new trend of studying ergonomic factors in more complex ALs, such as parallel U-shape mixed-model (Mokhtarzadeh et al. 2021) and Parallel U-shape (Chutima & Khotsaenlee, 2022) *ALBP*s. Although progress has been made in incorporating task features, performance indicators, restrictions, and objective functions in *ALBP*s, there remains a gap between real-world problems and mathematical models.

(3) While heuristic and meta-heuristic approaches have been commonly used to solve *Ergo-ALBP*s and find near-optimum solutions, there is a growing interest in applying hybrid methods and machine learning techniques. Hybrid methods, as demonstrated in recent studies such as Chutima and Khotsaenlee (2022) and Quenehen et al. (2022), can lead to more effective solutions. Learning techniques, such as neural networks, have been used to model ergonomic factors and incorporate them into optimization algorithms. These new optimization methods hold promise in achieving better assembly line balancing considering ergonomic factors, leading to improved worker health and productivity.

(4) Uncertainty in *Ergo-ALBP*s can be classified as environmental and system uncertainty (Ho 1989). Environmental uncertainty relates to market variations and customer behavior, while system uncertainty includes uncertainties within the production process, including human aspects. Moreover, the findings of some studies (Golabchi et al. 2016; Golabchi et al. 2017) proved the imprecision of inputs in *EAT*s which significantly affects the results. Stochastic programming models can incorporate variability by treating certain parameters as stochastic values. However, only one study in the *Ergo-ALBP* domain (Tiacci & Mimmi, 2018) has included stochastic task times in their model. Fuzzy programming models, employing fuzzy numbers, can be useful when historical data is insufficient. Additionally, a small number of studies have applied fuzzy set theory to handle conflicting objectives (Mutlu & Özgörmüş 2012; Cheshmehgaz et al. 2012; Ozdemir et al. 2021). Future research should explore the application of stochastic and fuzzy programming models to address the uncertain nature of *Ergo-ALBP*s.

(5) The robustness of solutions in *Ergo-ALBP*s, considering indeterministic factors, is an important aspect to measure and evaluate. No research has explored robustness objectives in this area. A robust configuration of *AL*s, considering both ergonomic and operational aspects, can ensure long-term efficiency.

(6) The integration of lean tools in *ALBP*s can simplify computational optimization models and improve results (Qattawi & Chalil 2019). Several studies have recommended incorporating ergonomic indicators in lean production methods to enhance production system efficiency (Oliveira et al. 2018). However, none of the *Ergo-ALBP* studies reviewed in this research have incorporated the lean approach, presenting an opportunity for future investigation.

(7) The design phase is critical for considering ergonomic aspects to prevent health-related issues and minimize the need for corrective actions. While most reviewed articles focus on existing *AL*s, there are only a few studies that consider ergonomic factors in the design phase such as Baykasoğlu et al. (2017), Finco et al. (2019) and Abdous et al. (2020). Thus, further research is needed in the area of *Ergo-ALDP*.

(8) More research is needed to examine the range of available methods for addressing ergonomic factors in optimization problems in production industries. The methods used in the reviewed papers are very few compared to the large range of available methods (ex., Takala et al. 2010). One research opportunity is investigating newer methods and evaluating their effectiveness in optimization problems can contribute to the advancement of *Ergo-ALBP*.

(9) The advent of Industry 5.0 as a value-driven concept represents a paradigm shift towards resilient, sustainable, and human-centric systems (Leng et al., 2022). While Industry 4.0 focuses on technology-driven solutions, Industry 5.0 integrates human-centric initiatives. Ergo-ALBP is expected to become a popular research domain in the context of Industry 5.0. Further research is needed to explore the full potential of Industry 5.0 in coping with *Ergo-ALBP*s and other manufacturing challenges.

In conclusion, the main future trend in *Ergo-ALBP*s is to develop more realistic models and propose efficient solutions. Considering the variability and uncertainty of environmental aspects, finding sustainable solutions that remain efficient in the long term is essential. Exploring the implications of emerging paradigms such as Industry 4.0 and Industry 5.0 can further improve *Ergo-ALBP*s.

6. CONCLUSIONS

Given the significant role of efficiency in *AL*s and the crucial importance of *HFE* in optimizing *ALBP*s, this paper provides a comprehensive literature review of *Ergo-ALBP*s. This review aims to benefit process engineers, ergonomic practitioners, and researchers interested in simultaneously addressing operational and ergonomic considerations for achieving optimal *AL* balancing and design. Utilizing the *PRISMA* methodology, a total of 57 research articles published after 2011 were analyzed.

The analysis of the literature revealed notable trends in *Ergo-ALBP*s. While early studies primarily focused on simple *ALBP*s, current studies have expanded to investigate more complex problems. For instance, there are investigations into collaborative *AL*s and mathematical aspects such as balancing parallel U-shape mixed-model assembly lines. Additionally, hybrid algorithms have been employed in solution methodologies to improve the efficiency of finding optimal solutions.

Several research gaps were identified, indicating potential future research directions. There is a growing emphasis on modeling more realistic problems by addressing indeterministic parameters and handling uncertainties in the environment and system using stochastic or fuzzy programming approaches. Furthermore, considering the dynamic nature of markets and industry conditions, ensuring the robustness of optimal solutions poses a new challenge for researchers. The importance of incorporating HFE aspects in the design stage presents a motivating factor for further exploration of *Ergo-ALDP*. Integrating lean tools into *Ergo-ALBP*s is another promising area to simultaneously enhance ergonomic and operational aspects.

The advent of Industry 4.0 and Industry 5.0 has the potential to revolutionize *Ergo-ALBP*s. Industry 4.0, characterized by automation and advanced technologies, has already shown promise in addressing ergonomic concerns in *AL* tasks. However, there is still ample room for exploration, with cyber-physical systems, *AR*, and *AI* offering further improvements to *ALBP*s. Industry 5.0, with its human-centered approach and emphasis on collaboration between humans and machines, can further enhance *Ergo-ALBP*s by utilizing advanced technologies to assist workers in complex tasks and mitigate ergonomic risks. Addressing challenges such as skills training and organizational restructuring will be pivotal in harnessing the benefits of Industry 5.0.

In conclusion, future research should continue to investigate the impact of Industry 4.0 and 5.0 on worker well-being and organizational performance. It is essential to develop innovative solutions that promote human-centered intelligent manufacturing. By leveraging advanced technologies and promoting collaboration between humans and machines, the manufacturing industry can achieve greater efficiency, productivity, and worker safety in *Ergo-ALBP*s.

DATA AVAILABILITY

Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

CONFILICTS OF INTEREST

The authors declare that they have no conflict of interest regarding the publication of this research. There are no financial, personal, or professional relationships that could be perceived as influencing the content or findings presented in this manuscript.

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