

Ergonomics and Human-Centered Industrial Engineering:

From Human Data to Intelligent Work-System Design

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Assist. Prof. Dr. Ahmet CİHAN

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EDITORS' PREFACE

For many years, ergonomics was often perceived primarily as a field concerned with working postures, anthropometric fit, physical workload, and workplace design. Contemporary work systems, however, require attention not only to the physical capacity of the worker but also to cognitive workload, individual differences, decision-making processes, trust in technology, and responses to changing working conditions. Digitalization, artificial intelligence, human–robot collaboration, wearable technologies, big data and data analytics, and digital twins are redefining the relationship between people and work systems. This transformation is broadening the scope of ergonomics and bringing it into closer integration with the decision-making, modeling, and optimization tools of industrial engineering.

This book does not aim to describe this transformation in ergonomics merely as a series of emerging technologies. Its central premise is that ergonomics is evolving from a reactive field focused on identifying risks in work systems toward a more integrated decision-oriented discipline that measures human performance and system behavior, anticipates future risks, optimizes work systems, and adapts to changing conditions. Accordingly, the conceptual backbone of the book is organized around four interrelated stages: assessment, prediction, optimization, and adaptation.

Chapter 1 examines the historical and conceptual transformation of ergonomics from a human-centered industrial engineering perspective. The sociotechnical systems approach, the transition from Industry 4.0 to Industry 5.0, human-centered manufacturing, sustainability, resilience, and inclusive ergonomics are discussed as major components of this transformation. In this context, ergonomics is presented not merely as a field concerned with protecting the individual worker, but as a systems discipline that requires the joint design of relationships among people, technology, organizations, and production systems.

Chapter 2 focuses on the transformation of physical ergonomic risk assessment. Although conventional observational methods remain important, sensors, computer vision, artificial intelligence, and real-time monitoring systems are making ergonomic assessment more continuous and data-driven. The chapter therefore treats classical methods and new technologies not as substitutes for one another, but as complementary elements within an integrated process of measurement, interpretation, and decision-making.

Chapter 3 turns to the cognitive and technological dimensions of ergonomics. Mental workload, neuroergonomics, automation, trust in artificial

intelligence, explainability, human–AI interaction, and human–robot collaboration are considered together. The main question is not simply how advanced a technology is, but which tasks should appropriately be performed by humans, supported by artificial intelligence, or shared with robots. For this reason, the chapter emphasizes task-allocation decisions that jointly consider human capabilities, technological capacity, ergonomic cost, uncertainty, and the consequences of error.

Chapter 4 directly integrates ergonomics with decision problems in industrial engineering. Work design, job rotation, scheduling, mathematical programming, multi-objective optimization, decision-support systems, and dynamic replanning constitute the central topics of the chapter. The core argument is that ergonomic criteria should not be treated as additional constraints checked only after a production plan has been established. Instead, these criteria should be embedded in the decision model from the outset as integral components of system performance.

Chapter 5 addresses the future of ergonomics. Digital human models, digital human twins, three-dimensional anthropometry, data science, predictive ergonomics, prescriptive ergonomics, and adaptive work systems are considered within a common framework. The chapter extends ergonomic decision-making from a structure that merely identifies current risk toward a closed-loop structure that anticipates future risk, selects an appropriate intervention, and adapts the system accordingly. The Adaptive Ergonomic Intelligence framework proposed at the end of the book integrates this transformation through the cycle Observe → Measure → Assess → Predict → Select → Adapt → Learn.

Chapter 6 returns to a foundational concern in ergonomic design: the reliability and temporal validity of anthropometric data used in product and workplace design. Focusing on ratio scaling, the chapter examines whether body-dimension-to-stature ratios remain stable over time by comparing the 1988 ANSUR1 and 2012 ANSUR2 databases. Ratio scaling is evaluated alongside stature-based regression, BMI-based regression, and multiple linear regression methods using stature and body weight. The findings indicate that ratio scaling may remain useful over shorter time intervals and for selected anthropometric dimensions, but its long-term applicability is limited because body proportions do not remain equally stable across all measurements. Models incorporating both stature and body weight generally produce lower prediction errors for many dimensions. The chapter therefore emphasizes measurement-specific method selection, subgroup representation, and periodic validation of

anthropometric databases as essential conditions for reliable human-centered product and workplace design.

When these six chapters are considered together, the central argument of the book becomes clearer: the future of ergonomics does not lie solely in more sophisticated measurement devices or greater automation. The more fundamental transformation concerns how reliable knowledge about people is generated, validated, and translated into system design, operational decisions, and dynamic adaptation mechanisms. From anthropometric data and physical risk assessment to cognitive workload, intelligent technologies, optimization, and adaptive systems, ergonomic decision-making depends on the quality of the human data and models on which design choices are based. In other words, the ergonomics of the future must not only protect people, but also understand them, represent their variability accurately, anticipate system behavior, evaluate alternatives, and design work systems in which humans and technology can perform better together.

This perspective is particularly important from the standpoint of industrial engineering. Industrial engineering has traditionally emphasized performance measures such as productivity, cost, quality, capacity, and resource utilization. In contemporary work systems, however, sustainable performance cannot be considered independently of human factors. Fatigue, mental workload, skill fit, health-related constraints, trust in technology, error probability, and individual differences are not external to production performance; rather, they are intrinsic components of it. Human-centered systems design should therefore be regarded as an important research direction that reduces the boundaries between ergonomics and industrial engineering and brings both fields together within a shared decision-science perspective.

In preparing this book, emphasis has been placed not only on presenting findings from the literature but also on establishing connections among those findings and providing readers with an integrated conceptual structure. The conceptual models and author syntheses included throughout the chapters are not intended to replace established ergonomic approaches. Rather, they are offered to reorganize existing knowledge from the perspective of human-centered industrial engineering and to propose discussable frameworks for future research.

This book is intended to be useful not only for researchers working in ergonomics, industrial engineering, human factors, production systems, occupational health, and anthropometric design, but also for graduate students and practitioners. In particular, it is designed to provide an integrated starting point for readers who wish to approach ergonomics not only through risk-

assessment methods, but from a broader perspective extending from reliable human-data representation and measurement to prediction, optimization, and adaptive system design.

Ultimately, this book is an effort to understand the future of ergonomics while preserving the lessons learned from its past. In an era in which human-centered manufacturing, artificial intelligence, robotics, digital systems, and data-driven design are becoming increasingly important, the fundamental question remains unchanged: How can work systems and products be designed to support human capabilities, account for human limitations and variability, and simultaneously sustain system performance? Despite the variety of methods and technologies discussed throughout the book, every chapter is, at its core, an attempt to contribute to answering this common question.

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Chapter 1

The Transformation of Ergonomics: Human-Centered Industrial Engineering and Ergonomics 5.0

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ABSTRACT

Ergonomics emerged historically as a discipline concerned with improving the fit between the physical and cognitive characteristics of people and the demands of work, but its scope has expanded substantially as production and service systems have become more complex. Today, ergonomic design is no longer limited to improving working postures, workstations, or physical loads. Digitalization, advanced automation, artificial intelligence, human-robot collaboration, wearable technologies, and data-driven decision systems are redefining the role of the human within production systems. This transformation also requires a reconsideration of the relationship between ergonomics and industrial engineering. While industrial engineering addresses system performance in terms of productivity, quality, cost, and resource utilization, ergonomics brings human performance, safety, health, usability, and well-being into the system. The Industry 5.0 emphasis on human-centricity, sustainability, and resilience makes the integration of these two fields even more explicit. This chapter examines the historical and conceptual transformation of ergonomics together with the sociotechnical systems perspective and human-centered industrial engineering. Its central argument is that ergonomics is evolving from a reactive assessment discipline that mainly identifies existing risks toward a proactive decision science that anticipates risk, optimizes work systems, and adapts to changing human-technology conditions. This transformation is conceptualized along the assessment-prediction-optimization-adaptation continuum, which also provides a common framework for the subsequent chapters of the book.

Keywords: ergonomics, human factors, industrial engineering, human-centered manufacturing, Industry 5.0, sociotechnical systems, sustainability, resilience

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1. INTRODUCTION

The history of production systems can also be read, to a large extent, as the history of changing relationships among people, technology, and organizations. Mechanization changed the nature of physical labor; mass production fragmented work into narrower tasks; automation partially reduced direct human involvement in production; and digitalization has increasingly transformed the human from an actor who performs physical operations into one who processes information, makes decisions, supervises systems, and collaborates with technology. These changes have transformed not only production technologies but also the basic assumptions about how work should be fitted to people.

Ergonomics and human factors lie at the center of this transformation. The fundamental aim of ergonomics is to understand interactions between people and other system components and to design systems in ways that improve both human well-being and overall system performance. This perspective requires systems to be designed around human characteristics, capabilities, and limitations rather than requiring people to adapt to the system. Ergonomics is therefore not concerned solely with preventing accidents or work-related musculoskeletal disorders; it is also directly related to performance, usability, error, quality, reliability, and system resilience (Dul et al., 2012; Wilson, 2000).

A natural intersection between ergonomics and industrial engineering emerges at this point. Industrial engineering is concerned with the design and improvement of integrated systems composed of people, machines, materials, information, energy, and other resources, whereas ergonomics brings the characteristics of the human component into system design. Decisions such as balancing a production line, distributing workload, selecting work methods, designing shift and job-rotation schedules, or introducing a new automation system have both technical and human consequences. Nevertheless, a substantial proportion of traditional decision models either omit human factors or represent them through highly simplified parameters.

This approach is becoming increasingly inadequate in smart manufacturing systems. Following the Industry 4.0 vision of production based on cyber-physical systems, connected machines, data analytics, and automation, Industry 5.0 emphasizes the use of technology not merely to achieve higher productivity but to create human-centered, sustainable, and resilient production systems (European Commission, 2021; Xu et al., 2021). This shift repositions the human not as an element left outside automation but as an indispensable and complementary actor within the production system.

Accordingly, the questions posed by next-generation ergonomics are also changing. Whereas the traditional approach asks, 'What is the risk associated with this working posture?', the emerging approach asks more complex questions such as,

'How will this risk evolve over time?', 'Which worker should perform which task, and for how long?', 'How should tasks be allocated between humans and robots?', and 'Can the system detect increasing fatigue before it becomes excessive and reorganize the work accordingly?' The progression from ergonomic assessment to ergonomic prediction, then to optimization, and ultimately to adaptive work systems strengthens the position of ergonomics within industrial engineering.

This chapter traces that transformation from the historical development of ergonomics to contemporary human-centered production systems. The aim is not to present a detailed chronology of ergonomics, but rather to show how the forms of ergonomic thinking that emerged in different periods have contributed to current human-centered system design. In this way, the chapter establishes a common conceptual foundation for later discussions of intelligent ergonomic risk assessment, human-AI interaction, ergonomic optimization, and digital human twins.

2. HISTORICAL DEVELOPMENT OF ERGONOMICS: FROM FITTING THE HUMAN TO THE JOB TO FITTING THE JOB TO THE HUMAN

It is insufficient to interpret the historical development of ergonomics merely as a chronological sequence of methods or measurement tools. A more meaningful perspective is to examine how the discipline has positioned the human within the production system over time. From this viewpoint, the development of ergonomics can be understood as a transition from periods in which people were expected to adapt to machines toward a contemporary perspective that seeks mutual adaptation between people and technology and integration at the system level.

In the early stages of industrialization, the primary goals of production systems were to increase output through mechanization and reduce production costs. Work methods were determined largely by the requirements of technology and the production process, while human physical capacity was often treated as a constraint on production. Scientific management introduced detailed task analysis, standardization, and motion study, generating important productivity gains; however, integrated consideration of the physical, cognitive, and psychosocial dimensions of human performance remained limited.

Time and motion studies became characteristic tools of this period. These studies were highly influential in the development of industrial engineering because they enabled systematic analysis of work and provided an analytical basis for eliminating unnecessary motions and improving methods. Yet making work faster or more standardized is not equivalent to making it compatible with human capabilities and limitations. The development of ergonomic thinking accelerated as this distinction became increasingly visible.

The development of complex military systems, in particular, clearly demonstrated the critical importance of human-machine interaction for system performance. Technological systems could not be considered adequate merely because they operated correctly from a technical perspective; people also had to perceive displays correctly, use controls effectively, make decisions under high workload, and operate within systems designed to constrain the likelihood of error. This experience helped ergonomics move beyond physical work design to include perception, attention, decision making, and human-machine interfaces.

In later stages of development, the systems perspective became decisive. Wilson (2000) emphasized that ergonomics cannot be restricted to the measurement of individual human characteristics and that relationships among the person, task, technology, environment, and organization must be considered together. Similarly, Karwowski (2005) highlighted the integrative role of ergonomics across science, engineering, design, technology, and management. This perspective moved ergonomics beyond a collection of applied techniques for determining, for example, the 'correct sitting height' at a single workstation, toward a discipline that contributes to the design of complex work systems.

Three major domains have become prominent in modern ergonomics: physical ergonomics, cognitive ergonomics, and organizational ergonomics. Physical ergonomics addresses anthropometry, biomechanics, working postures, manual handling, and musculoskeletal loading, whereas cognitive ergonomics focuses on perception, memory, attention, mental workload, and decision making. In particular, mental workload analysis provides a means of examining the relationship between task demands and the cognitive resources available to the individual, with implications for performance, error, decision quality, and safety (Fırlalı & Fırlalı, 2025). Organizational ergonomics concerns higher-level system properties such as communication, work design, teamwork, work-time arrangements, and the optimization of sociotechnical systems. In practice, these domains are not independent. In a highly automated assembly line, for example, physical load may decrease while cognitive monitoring demands or monotony increase. Evaluating an intervention against only one risk dimension may therefore create unintended consequences elsewhere in the system.

One of the most important outcomes of this historical development is the strengthening of the idea that ergonomics should pursue system optimization rather than isolated local improvements. Dul et al. (2012) argue that human factors and ergonomics should simultaneously improve human well-being and overall system performance. This emphasis is especially important from an industrial engineering perspective because ergonomic performance and production performance can be treated not as competing alternatives but as different outcome variables within the same system design problem.

Table 1. Key characteristics of the historical transformation of ergonomic thinking

Historical approach	Human role in the system	Central question	Primary ergonomic focus
Fit-the-human-to-the-job approach	Worker adapting to the production system	How efficiently can the person perform the job?	Motion, time, physical capacity
Human-machine fit	Operator interacting with technology	How can the machine be adapted to human characteristics?	Controls, displays, anthropometry, error
Systems ergonomics	Component of a sociotechnical system	How should people, technology, and organization be designed together?	Physical, cognitive, and organizational interaction
Human-centered production	Partner who creates value and makes decisions	How can technology support human capabilities?	Collaboration, trust, well-being, competence
Adaptive ergonomics	Dynamic actor in continuous interaction with the system	How can the system adapt to changing human states?	Data, prediction, optimization, adaptation

The final two stages in Table 1 should not be interpreted as completed historical periods, but as directions that are becoming increasingly prominent today. Sensor technologies, artificial intelligence, and real-time data analytics enable ergonomic design to move from static measurements toward dynamic assessment. Consequently, next-generation ergonomics considers not only relatively stable characteristics such as worker stature, body mass, or joint angles, but also time-dependent variables such as fatigue during the day, task history, mental workload, and changes in individual performance.

This transformation does not mean abandoning the fundamental principles of ergonomics. Rather, as technology changes, the same principle is applied at a broader level: the work system should be designed to fit human characteristics. What has changed is the scope of both the 'work system' and 'human characteristics.' Today's work system includes not only tables, chairs, machines, and the physical environment, but also algorithms, robots, decision-support systems, data flows, and organizational policies. Likewise, human characteristics are no longer defined solely by anthropometric measurements; they include cognitive state, experience, skill, fatigue, health, individual differences, and trust in technology.

3. THE INTERSECTION OF INDUSTRIAL ENGINEERING AND ERGONOMICS: THE HUMAN DIMENSION OF SYSTEM PERFORMANCE

Although ergonomics and industrial engineering have historically addressed many of the same problems, their relationship is often not sufficiently visible. Industrial engineering problems such as production planning, work measurement, line balancing, facility design, scheduling, quality management, and optimization directly or indirectly affect human performance. Likewise, many ergonomic decisions have consequences for production capacity, cost, cycle time, and resource utilization. Treating human factors and operational decisions independently therefore fails to represent the structure of real work systems adequately.

Traditional industrial engineering models often represent the worker as a resource with relatively fixed capacity. A worker's task time, skill level, or eligibility may be included as a parameter, but fatigue, accumulated physical loading, or the effect of previous tasks on subsequent performance is rarely represented explicitly. Although such simplification is understandable from a mathematical modeling standpoint, it excludes a substantial part of ergonomic reality.

For example, allocating assembly tasks among workers solely to balance cycle time may appear operationally efficient. Yet if the same worker is repeatedly assigned tasks requiring overhead work throughout the day, physical workload may become highly unbalanced. Conversely, a task allocation focused only on reducing ergonomic risk may produce unacceptable losses in production rate or skill compatibility. The real decision problem is therefore multidimensional rather than single-objective.

This is where the complementarity between ergonomics and industrial engineering becomes clear. Ergonomics introduces variables related to human capabilities and limitations into system design, while industrial engineering provides modeling and optimization tools for considering those variables together with production, cost, resource utilization, and service-level objectives. Ergonomic assembly-line balancing is a concrete example of such integration. Incorporating ergonomic risk directly into task-allocation decisions demonstrates that operational performance and worker exposure can be addressed within the same model (Otto & Scholl, 2011).

A particularly important point is that ergonomic variables should not be treated merely as constraints checked after a plan has already been produced. Asking whether a production plan is 'ergonomically acceptable' only after it has been developed is reactive. Human-centered industrial engineering instead requires ergonomic criteria to be represented in decision variables, objectives, and constraints from the beginning of model development. Neumann and Dul (2010) likewise

emphasize that stronger integration between human factors and operations management is important for both worker outcomes and system performance.

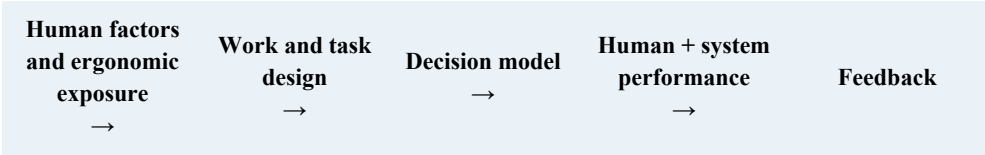


Figure 1. Integrated decision cycle linking ergonomics and industrial engineering

Table 2. Comparison of the traditional operational approach and human-centered industrial engineering

Decision dimension	Traditional approach	Human-centered approach
Worker	Resource with relatively fixed capacity	Person whose physical and cognitive state can change
Workload	Time or production quantity	Physical, cognitive, and psychosocial exposure
Performance	Output, cost, time	Output + human performance + well-being
Task allocation	Skill and capacity	Skill + capacity + ergonomic suitability
Optimization	Operational objectives	Joint optimization of operational and ergonomic objectives
Control	Conformance to the planned system	Feedback-based adaptation to human state

The human-centered approach also challenges the assumption that productivity and ergonomics are necessarily in conflict as seen in Table 2. Appropriate ergonomic design can reduce fatigue, error probability, work-related health problems, and performance variability, thereby supporting long-term system performance. However, this relationship should not be assumed to occur automatically in every context. Ergonomic interventions should not be presumed economically or operationally beneficial without evaluation; their effects should be measured systematically. The integration of ergonomics and industrial engineering therefore means more than simply 'considering the human': it means measuring human and system performance within the same decision framework.

In this chapter, human-centered industrial engineering is treated as a broader perspective than adding human-factor constraints to otherwise conventional operational models. The human is not a passive element outside the optimized system that must merely be protected, but a dynamic component that actively contributes to system performance. Such a perspective shifts the dominant question from 'How can a given

production target be achieved at the lowest human cost?' to 'How should a work system be designed so that human performance and operational performance can be sustained together?'

4. THE SOCIOTECHNICAL SYSTEMS PERSPECTIVE: JOINT DESIGN OF PEOPLE, TECHNOLOGY, AND ORGANIZATION

For human-centered industrial engineering to rest on a sound theoretical foundation, production systems must be recognized as more than collections of technical subsystems. The sociotechnical systems perspective provides one of the strongest conceptual foundations for this requirement. Its origins can be traced to early studies of how technological change affects work organization and worker behavior. The classic study by Trist and Bamforth (1951) in coal mining showed that an arrangement that appeared technically rational could fail to deliver expected performance when it conflicted with the social system. This observation later became foundational to the idea of joint optimization.

The essence of joint optimization is that improving technical and social subsystems independently may not be sufficient for the performance of the overall system. An automation investment may reduce machine cycle time, yet if it turns the operator into a passive observer who intervenes only during failures, it can create new problems such as vigilance loss, skill degradation, or delayed intervention. Similarly, an initiative intended to increase worker autonomy may raise cognitive load if adequate information flow and decision support are not provided. Solutions that are technically 'good' and humanly 'good' therefore cannot be designed separately and combined afterward; they must be considered together from the outset.

The importance of the sociotechnical perspective for ergonomics lies in its expansion of the boundaries of the work system. Ergonomic design is concerned not only with the worker's chair, hand tool, or lifted load, but also with task allocation, team structure, shift systems, performance indicators, software interfaces, maintenance policies, learning processes, and managerial decisions. Carayon (2006) emphasizes that human factors in complex sociotechnical systems must be considered at multiple levels, while Clegg (2000) argues that human and organizational dimensions cannot be separated from technological design.

This perspective has gained renewed importance in contemporary digital production environments. Industrial Internet of Things technologies, manufacturing execution systems, AI-based decision-support tools, and autonomous robots create hybrid systems in which decisions are no longer made exclusively by humans. In such systems, 'technology' is not limited to physical equipment; it also includes the algorithm that selects data, the form in which warnings are presented to operators, the conditions under which decision authority is transferred to automation, and the performance criterion

optimized by the algorithm. Ergonomic design therefore expands from the human-machine interface toward human-algorithm-organization interaction (Soori et al.,2024).

Another important principle of sociotechnical thinking is that local optimization may generate undesirable system-level consequences. In a warehouse order-picking system, for example, optimizing routes solely to minimize walking distance may concentrate repetitive bending or reaching exposure on particular workers. Likewise, managing call-center performance solely through average handling time may increase cognitive and emotional load. The issue is not that these indicators are inherently wrong; rather, the indicators used to manage a system shape human behavior and patterns of exposure.

From an industrial engineering perspective, the sociotechnical approach has an important modeling implication: objective functions and constraints cannot represent technical performance alone. System design should consider ergonomic risk, workload balance, learnability, decision autonomy, trust, and resilience alongside productivity, quality, and cost. Even when all of these variables cannot be quantified with equal precision, omitting them from a model is not a neutral choice; it is an implicit design decision about which outcomes are considered important as seen in table 3.

The sociotechnical perspective therefore moves ergonomics beyond an end-of-process compliance check and makes it one of the principles of system architecture. When technology selection, task allocation, decision authority, performance indicators, and worker participation are considered jointly, ergonomics is no longer an external corrective mechanism added to the technical system. This perspective also provides a conceptual foundation for the human-centric orientation of Industry 5.0.

Table 3. Dimensions that should be jointly considered in ergonomic sociotechnical system design

Dimension	Example design variables	Ergonomic outcomes
Human	Skill, experience, anthropometry, capacity, fatigue	Physical and cognitive fit; error; well-being
Task	Work content, sequence, repetition, autonomy, duration	Exposure, monotony, mental workload
Technology	Automation level, interface, robot, decision algorithm	Trust, usability, physical load, situation awareness
Organization	Team structure, shifts, performance targets, training	Psychosocial load, learning, resilience
Environment	Noise, lighting, thermal conditions, spatial layout	Comfort, attention, safety, performance
Decision system	Objective functions, KPIs, feedback	Behavioral incentives, risk distribution, adaptability

5. FROM INDUSTRY 4.0 TO INDUSTRY 5.0: FROM TECHNOLOGY-CENTERED EFFICIENCY TO HUMAN-CENTERED VALUE CREATION

Industry 4.0 became widely used as a framework describing the integration of digital connectivity, cyber-physical systems, data analytics, cloud computing, advanced robotics, and automation in manufacturing. This transformation has made production systems more visible, connected, and flexible and has enabled maintenance, quality, planning, and logistics decisions to use data more intensively. In early Industry 4.0 discourse, however, technological capabilities were often more visible than the role of the human. Smart-factory success was frequently discussed in terms of connected equipment or levels of automation, while questions about how people would work in such systems, what skills they would require, and what kind of relationship they would develop with technology could remain secondary.

Industry 5.0 is not a single technical standard designed to fill this gap, but rather a policy and research framework that proposes rebalancing the goals of industry. The European Commission (2021) emphasizes three principles in particular: human-centricity, sustainability, and resilience. These principles do not reject technological progress; instead, they redefine the purposes technology should serve. Xu et al. (2021) interpret the relationship between Industry 4.0 and Industry 5.0 as an evolution rather than a rupture and show how Industry 5.0 places human and societal values more explicitly at the center of technological development. Ergonomic comparison of Industry 4.0 and Industry 5.0 perspectives can be seen in table 4.

From a human-centric perspective, the key change is to view workers not as cost elements competing with automation, but as value creators whose capabilities can complement technology. Nahavandi (2019) discusses Industry 5.0 as a human-centered orientation that combines human creativity with the strengths of intelligent systems. Similarly, Longo et al. (2020) argue that technological design in the factory of the future should be considered together with ethical and human-oriented values. This perspective is important for ergonomics because system performance is evaluated not only through production output but also through worker health, safety, learning, competence, and the ability to perform work sustainably (Arshi et al., 2026).

Nevertheless, it would be misleading to interpret Industry 5.0 simply as 'bringing people back into the factory.' The central issue is the qualitative redesign of the human role within technological systems. Human-centricity does not mean assigning people only those physical tasks that robots cannot perform. Human-centered design requires decisions about whether tasks should be assigned to people or automation to consider human capabilities, limitations, preferences, and learning potential. Automation level, task allocation, and the distribution of decision authority therefore become ergonomic design decisions.

The sustainability dimension is also directly related to ergonomics. Sustainable production is often measured in terms of energy consumption, emissions, material efficiency, and waste, but social sustainability requires people to be able to work in healthy and productive ways over the long term. A production system dependent on chronic overtime, high repetition, or excessive cognitive load may be energy-efficient but not sustainable from the worker's perspective. Social sustainability therefore brings ergonomics into the same decision framework as environmental and economic sustainability.

Resilience concerns the capacity of a system to maintain functioning and adapt in the face of disturbances. The resilience-engineering literature treats safety not only as the prevention of failure but also as the capacity to sustain successful performance under variable conditions (Hollnagel et al., 2006; Woods, 2015). Humans are important resources for resilient systems because they can interpret unexpected situations, fill information gaps, create novel solutions, and balance conflicting objectives. Yet this capacity depends on people not being overloaded, having access to adequate information, and retaining sufficient decision latitude.

The three central principles of Industry 5.0 are therefore not independent objectives. Human-centricity requires not only protecting workers but also making meaningful use of their capabilities; sustainability requires this relationship to remain viable over time; and resilience requires the system to reconfigure human and technological resources as conditions change. Ergonomics is one of the disciplines capable of translating these three principles into concrete work-system design.

Table 4. Ergonomic comparison of Industry 4.0 and Industry 5.0 perspectives

Dimension	Dominant emphasis in Industry 4.0	Broader emphasis in Industry 5.0	Ergonomic implication
Technology	Connectivity, automation, data	Technology that augments human capabilities	Human-technology fit
Performance	Efficiency, speed, flexibility	Human + system + societal value	Multidimensional performance
Human role	Operator/user	Collaborator, decision maker, value creator	Competence and well-being
Sustainability	Resource/energy efficiency	Economic + environmental + social sustainability	Long-term workability
Resilience	Technical redundancy and automation	Joint human-technology adaptive capacity	Flexibility, situation awareness, recovery

6.HUMAN-CENTERED PRODUCTION SYSTEMS: MOVING ERGONOMICS TO THE BEGINNING OF DESIGN

Human-centered production requires ergonomic requirements to be incorporated at the beginning of system design rather than addressed primarily through corrections after implementation. This distinction is practically important. Once a workstation is operational, reach distances can often be reduced or assistive devices added; however, if the task structure, product architecture, level of automation, or cycle-time pressure is ergonomically problematic, local corrections made afterward may have only limited impact. Decisions taken early in design define the range of ergonomic options that remain available later.

Ergonomic standardization also supports this systems view. ISO 6385:2016 calls for human characteristics to be considered in work-system design and for interactions among the human, task, equipment, workspace, and organization to be addressed holistically. This perspective is broader than the isolated application of individual ergonomic assessment tools. Methods such as RULA, REBA, or OWAS can be useful for evaluating specific exposures, and their integration with digital technologies can extend the way such assessments are performed. For example, image-processing techniques have been used to support RULA-based upper-extremity assessment, illustrating the transition from conventional observational evaluation toward computer-assisted ergonomic assessment (Can & Fırlalı, 2017). However, the goal of human-centered design is not simply to produce an acceptable risk score.

Task design is particularly critical in human-centered production. Task duration, repetition, force requirements, attentional demands, decision autonomy, and learning content jointly shape the worker experience. The same physical load may have different consequences under different forms of work organization because recovery opportunities, rotation, social support, and control can modify exposure. Task design is therefore a key point at which physical and cognitive ergonomics intersect with organizational ergonomics.

Another central issue is human-automation task allocation. When the purpose of automation is defined only as eliminating human labor, allocation decisions are driven largely by technical feasibility and economic return. A human-centered approach also considers the long-term consequences of assigning a task to a person or to automation. Full automation may reduce physical exposure in the short term, yet it can also erode operator process knowledge, leave workers unprepared for rare but critical interventions, or create under-arousal through prolonged monitoring. Rather than 'automating everything that can be automated,' a more appropriate design principle is to match the complementary strengths of people and technology.

Participatory ergonomics also becomes important in this context. Workers are not merely objects of ergonomic measurement; they are sources of knowledge about day-to-day variability and practical constraints in the work. In the framework presented by Noro and Imada (1991), participatory ergonomics emphasizes active worker involvement in ergonomic improvement processes. This principle is even more important in contemporary digital production because algorithmic decision systems and automation can widen the knowledge gap between those who design work and those who perform it. User participation can help prevent technically impressive but operationally unusable solutions.

Human-centered production also includes skill and learning. New technologies may reduce some physical tasks while creating demands for data interpretation, robot programming, fault diagnosis, or multi-system monitoring. This transformation requires more than simply retraining workers; jobs themselves should be designed to support learning. A system that reduces the worker to a passive executor of algorithmic instructions may deliver short-term standardization but weaken problem-solving capacity and the system's ability to respond to unexpected situations over the longer term.

Human-centricity should therefore be considered at three levels as seen in table 5. The first is protective: work should remain within acceptable health and safety limits. The second is supportive: technology should strengthen human performance, decision quality, and competence. The third is developmental: work design should create opportunities for learning, autonomy, mastery, and meaningful contribution. A system that satisfies only the first level may meet minimum ergonomic requirements, but it does not fully realize the human-centered value-creation vision associated with Industry 5.0.

Table 5. Three levels of human-centered production

Level	Primary objective	Example design question	Expected outcome
Protective	Prevent harm and excessive load	Is the task within acceptable physical/cognitive limits?	Health and safety
Supportive	Strengthen human capabilities	How does technology support decisions and performance?	Performance, usability, trust
Developmental	Increase competence and autonomy	Does the job create space for learning and problem solving?	Engagement, learning, resilience

7. THE ROLE OF ERGONOMICS IN SUSTAINABLE AND RESILIENT WORK SYSTEMS

The relationship between sustainability and ergonomics is incomplete if it is treated only under the heading of 'worker well-being.' Ergonomics can serve as a bridge that connects social sustainability to production-system design variables. A work system that rapidly exhausts workers, creates a high probability of injury, or depends on continuous employee turnover is not sustainable over the long term even if its economic output is strong. Likewise, a system that protects worker health but cannot meet production requirements may lose practical viability. Sustainable ergonomics therefore requires human, economic, and environmental objectives to be considered together.

In industrial engineering, this integration can be viewed as a multi-objective decision problem. A job-rotation problem, for example, can address not only the reduction of total ergonomic risk but also production loss, skill compatibility, workload balance, and shift feasibility. Similarly, facility layout can be evaluated not only in terms of material flow and space utilization but also walking load, accessibility, noise, and worker safety. Ergonomics thus moves from being an abstract 'social' component of sustainability reporting to a set of measurable and optimizable design criteria.

The human role is even more evident from a resilience perspective. Under normal conditions, automation provides efficiency and consistency; during unexpected demand changes, equipment failures, information gaps, or supply disruptions, however, people often keep systems functioning by acting beyond predefined rules. Woods (2015) treats resilience not simply as the capacity to bounce back, but as the management of adaptive capacity under changing conditions. This has an important implication for ergonomic design: human adaptability should not be treated as an unlimited buffer.

A production system that repeatedly compensates for planning errors through overtime, understaffing through faster work, or incomplete automation through manual workarounds may appear resilient while actually consuming human reserves. Such adaptations can preserve performance in the short term but increase fatigue, error, absence, and burnout over the long term. A resilient work system must therefore manage not only how much additional load workers can absorb but also when that load should be reduced.

Ergonomics can contribute here by monitoring and protecting adaptive capacity. Indicators of physical fatigue, cognitive workload, task history, shift patterns, and performance variability can reveal how heavily a system is relying on human reserves. Such data can be used not only for health monitoring but also to update production-planning and resource-allocation decisions. This perspective is directly

related to the real-time ergonomic monitoring and dynamic job-rotation approaches discussed later in the book.

Considering sustainability and resilience together also changes the time scale of ergonomic design. Traditional assessment often measures exposure at a particular moment or within a specific task. Sustainable work design, however, requires understanding how exposure accumulates across hours, shifts, weeks, and working lives. This is one of the main reasons ergonomics is moving from cross-sectional measurement toward longitudinal data and predictive models.

8. INCLUSIVE ERGONOMICS AND HUMAN DIVERSITY: MOVING BEYOND THE "AVERAGE WORKER" ASSUMPTION

One of the oldest principles of ergonomics is to fit the job to the person; however, the way 'the person' is represented is critical. For many years, design decisions commonly relied on anthropometric users represented through averages or selected percentiles. This approach remains useful for many physical design problems, but it cannot by itself represent the diversity of real workforces. People differ not only in stature, body mass, or limb length, but also in strength, range of motion, visual capacity, cognitive strategy, experience, age, health status, and patterns of technology use.

Inclusive ergonomics requires design to consider the broadest feasible range of users. It recognizes that systems optimized around a particular 'standard worker' can systematically disadvantage others. A fixed-height workstation may suit one body size while increasing postural risk for shorter or taller workers. Likewise, an interface with small text and dense information may appear functional for young, experienced users while increasing error probability in groups affected by age-related changes in visual or cognitive function.

An aging workforce makes this issue particularly important. Although average changes in some physical and sensory capacities occur with age, the effects of aging vary greatly among individuals. Age should therefore not be used as a stand-alone proxy for capacity. A more appropriate approach is to match job demands to individual capacities and to use adjustable design, assistive technologies, flexible work organization, and skill-based task allocation. The purpose of ergonomics is not to exclude workers on the basis of age or other demographic characteristics, but to increase the ability of systems to accommodate different capacity profiles.

Inclusiveness also requires methodological care in the use of anthropometric data. Population body dimensions can change over time, and the sampling structure, measurement protocol, and historical period of a dataset can affect design outcomes. Percentiles taken from older anthropometric tables should therefore not be assumed to represent a current workforce automatically. Three-dimensional body scanning, large anthropometric datasets, and parametric digital human models offer more detailed

representations of diversity. Yet more data do not automatically produce more inclusive design; the population represented by the data and the way those data are translated into design decisions must remain explicit.

Digitalization creates both opportunities and risks for inclusive ergonomics. Adjustable interfaces, personalized levels of assistance, cobot support, and adaptive workstations can make it possible to alter systems according to individual needs. Conversely, AI-based systems may perform less accurately for user groups underrepresented in training data. Human-centered design must therefore include not only physical accessibility but also algorithmic and digital accessibility.

A key implication of inclusive ergonomics for industrial engineering is that workforce heterogeneity should be treated not as a deviation but as a natural feature of the planning problem. Scheduling, task-allocation, or capacity-planning models become mathematically simpler when workers are assumed to have equal and constant capacity, but they may then represent the real system less faithfully. Incorporating individual differences can support personalized, or at least group-sensitive, decisions. Dimensions of diversity and corresponding design responses in inclusive ergonomics can be seen in table 6.

An ethical balance is also required. Personalized ergonomic systems may support more appropriate task allocation, but health, performance, or fatigue data may be used against workers. Data-driven ergonomics should therefore develop together with governance principles such as data minimization, purpose limitation, transparency, explainability, and worker participation. Human-centricity means not only that the task recommended by an algorithm has lower ergonomic risk, but also that the decision process is compatible with worker rights and autonomy.

Table 6. Dimensions of diversity and corresponding design responses in inclusive ergonomics

Diversity dimension	Potential design implication	Example human-centered response
Anthropometric	Reach, clearance, working height	Adjustable workstation and equipment
Physical capacity	Strength, endurance, range of motion	Assistive equipment, task redesign
Sensory	Vision, hearing, tactile perception	Multimodal and scalable interface
Cognitive/experience	Information processing, learning, error patterns	Adaptive support and training
Life course/age	Changes in capacity and experience profiles	Flexible task and pace design
Digital representation	How well the algorithmic model represents the user	Data diversity, validation, explainability

9. A NEW ERGONOMICS PARADIGM: FROM ASSESSMENT TO ADAPTIVE ERGONOMICS

Taken together, the historical development, sociotechnical perspective, Industry 5.0, human-centered production, sustainability, resilience, and inclusiveness discussed thus far indicate a clear expansion in the scope of ergonomics. Traditional ergonomic practice often aims to determine the current risk level of a particular job. This remains indispensable because systematic improvement is difficult without making risk visible. Digital production environments and new analytical capabilities, however, are turning assessment into only the first stage of a broader decision process.

The conceptual framework proposed in this book describes ergonomic transformation in four stages: assessment, prediction, optimization, and adaptation. These stages are not historical periods that replace one another. New capabilities build on earlier ones. Prediction requires reliable assessment data; optimization requires models of both ergonomic risk and operational outcomes; and an adaptive system requires those models to be updated using real-time data.

The first stage, assessment, determines the worker's current exposure or the current ergonomic state of the system. Observational methods, biomechanical calculations, surveys, performance measures, and physiological sensors can all be used at this stage. Technology-supported approaches have also extended established observational methods; for example, image-processing techniques have been integrated with OWAS to support the automated identification and classification of working postures (Fırlalı et al., 2015). The central question is, 'What is happening now?' Much of traditional ergonomics has been devoted to answering this question and will continue to do so.

The second stage, prediction, uses current and historical data to estimate how risk may evolve. The question becomes, 'What will happen if current conditions continue?' Predictive models can address how physical load accumulates across successive tasks, how error probability changes later in a shift, or which worker profiles face higher risk under a particular work arrangement. Machine learning can be useful at this stage, but data quality, generalizability, and explainability are critical.

The third stage, optimization, goes beyond predicting what will happen and seeks the decision likely to produce better outcomes. The central question is, 'What should we do?' Decisions about how tasks should be distributed among workers, how frequently job rotation should occur, where cobot assistance should be used, or how ergonomic risk should be balanced against production objectives are optimization problems. The transition from assessment to action can also be supported by knowledge-based decision systems; for example, expert-system approaches have

been used to prioritize preventive actions for shift work by combining worker- and organization-related information (Esen et al., 2019). Such approaches illustrate how ergonomic information can move beyond identifying a problem toward supporting the selection and prioritization of interventions.

The fourth stage, adaptation, means that the system does not remain tied to a fixed decision made at the planning stage but updates itself as new data become available. The question is, 'What should change when conditions change?' If fatigue increases faster than expected, the task sequence may be altered; if a production-line failure occurs, new assignments may prevent physically demanding tasks from accumulating on the same worker; or in human-robot collaboration, robot assistance may change according to operator performance. Ergonomics thus expands from static conformity assessment toward feedback-based management of the work system.

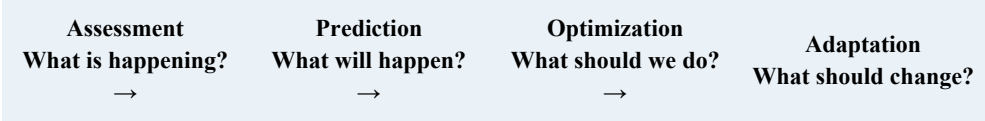


Figure 2. Core conceptual framework of the book: assessment-prediction-optimization-adaptation

Each of these four stages requires different data, methods, and governance. Assessment depends on valid and reliable measurement; prediction on external validation and uncertainty management; optimization on correct specification of objectives and constraints; and adaptation on safety boundaries, decision authority, and human oversight. A technologically advanced system is therefore not automatically more ergonomic. Predicting a poorly measured risk with artificial intelligence, or optimizing a flawed objective function in real time, may simply make the underlying error faster and more systematic.

Within this framework, human-centricity is not a final checklist but a design principle that should apply at every stage of the decision chain. Decisions about what data are genuinely necessary, which worker groups are represented in a model, which objectives remain visible or invisible during optimization, and how far final authority is delegated to automation during adaptation must all be examined together. Ergonomic performance thus becomes more than a score; it becomes a property of how the system measures, predicts, decides, and learns.

In this book, the term 'adaptive ergonomics' does not refer to an unrestricted technological vision in which workers are continuously monitored and automatically managed. On the contrary, it denotes an approach that acknowledges human variability and designs systems to respond to that variability in a safe, transparent, and proportionate manner. The goal of adaptation is not to fit the person to the

objectives of an algorithm, but to make the work system sensitive to changes in human capacities and conditions.

Conceptually, this perspective redefines the contribution of ergonomics at three levels. The first is a protective function: reducing harmful exposure. The second is a performance function: improving human and system performance together. The third is an adaptability function: enabling the work system to sustain safe performance under changing human and environmental conditions. When these functions are combined, ergonomics can be positioned not merely as a specialty concerned with risk assessment but as a science of designing and managing human-centered operations.

Table 7. Four stages of the new ergonomics paradigm

Stage	Central question	Typical data/method	Industrial engineering counterpart	Primary risk
Assessment	What is happening?	Observation, survey, sensors, biomechanical measurement	Performance measurement and state analysis	Measurement validity
Prediction	What will happen?	Statistical models, machine learning, time series	Forecasting and prediction	Generalizability, uncertainty
Optimization	What should we do?	MIP, multi-objective optimization, heuristics	Planning, scheduling, task assignment	Incorrect/incomplete objective function
Adaptation	What should change?	Real-time data, feedback, online decisions	Dynamic replanning and control	Over-automation, governance

10. CHAPTER CONCLUSION AND TRANSITION TO THE REST OF THE BOOK

The historical development of ergonomics has progressed in parallel with changes in the human role within production systems. Human factors, initially considered mainly in relation to physical capacity and work methods, gradually expanded into a systems perspective encompassing cognitive, organizational, and sociotechnical dimensions. Today, digitalization, artificial intelligence, and advanced automation are moving this transformation into a new stage. Ergonomics is no longer concerned only with the physical fit between humans and machines, but with the integrated relationships people form with algorithms, robots, data systems, and organizational decision mechanisms.

The Industry 5.0 principles of human-centricity, sustainability, and resilience provide an important overarching framework for this transformation. Human-centricity, however, should not be treated as a well-being objective added to technological systems after the fact. Industrial engineering decisions concerning task structure, automation level, performance indicators, work schedules, data-collection policies, and decision authority all shape human outcomes. The integration of ergonomics and industrial engineering is therefore a fundamental design requirement for future production systems.

The central conceptual conclusion of this chapter is that the ergonomic decision process is expanding along an assessment-prediction-optimization-adaptation chain. Assessment makes the current state visible; prediction estimates the future trajectory of risk; optimization selects systematically among possible interventions; and adaptation updates decisions in response to real-time conditions. This chain serves as the common backbone linking the remaining four chapters of the book.

Chapter 2 focuses on the measurement side of this transformation. It examines the strengths and limitations of established physical ergonomics approaches such as RULA, REBA, OWAS, OCRA, and NIOSH together with wearable sensors, computer vision, and AI-based automated risk assessment. In doing so, it explores how the 'assessment' stage defined conceptually here can become more continuous, objective, and data-intensive. Chapter 3 addresses the cognitive dimensions of human-AI and human-robot interaction; Chapter 4 examines ergonomic optimization, work design, and job-rotation problems; and Chapter 5 discusses digital human twins, predictive ergonomics, and adaptive work systems.

In conclusion, the contemporary transformation of ergonomics is moving from viewing the human as a constraint on technological progress toward recognizing people as sources of flexibility, creativity, and resilience within the system. Realizing this perspective requires attention not only to protecting people but also to supporting their capabilities; not only to the average user but to diversity; not only to current exposure but to future risk; and not only to fixed design but to safe and transparent adaptation. In this sense, ergonomics is not merely a complementary subfield of human-centered industrial engineering; it is one of the core disciplines that helps define how human-centered industrial engineering should be designed.

Statement on the Use of Generative AI

In preparing this book, the authors used OpenAI's ChatGPT as an assistive tool for the English translation of the original Turkish manuscript, language editing, consistency checking, and document formatting. The authors reviewed and revised the resulting text and take full responsibility for the accuracy, interpretation, and final content of the book.

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Next-Generation Ergonomic Risk Assessment: From Physical Ergonomics to Intelligent Measurement Systems

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ABSTRACT

Physical ergonomic risk assessment is based on the systematic identification of exposures such as working posture, force, repetition, duration, and manual handling. Established methods such as RULA, REBA, OWAS, OCRA, and the NIOSH lifting equation have provided low-cost, interpretable and practically powerful tools; however, they also have important limitations, including restricted sampling frequency, observer variability, reduction of complex movements to discrete categories, and limited representation of how exposure changes over time. Wearable inertial sensors, surface electromyography, pressure and force measurement, computer vision, and artificial-intelligence-based movement analysis can reduce some of these limitations, allowing ergonomic assessment to expand from one-time observation toward continuous and data-intensive monitoring. Automation alone, however, does not guarantee measurement accuracy or the validity of an ergonomic decision. Sensor errors, occlusion, viewing angle, anthropometric diversity, domain shift, label quality, model explainability, and privacy introduce new sources of error and governance challenges. This chapter treats conventional and next-generation methods not as competing alternatives but as complementary tools operating at different levels of measurement and decision making. The layered framework proposed at the end of the chapter defines ergonomic assessment through five connected layers: data acquisition, feature extraction, ergonomic interpretation, uncertainty assessment, and intervention decision. Within this framework, the central aim of next-generation ergonomic risk assessment is not to “measure instead of the human,” but to transform reliable data into ergonomic knowledge and ergonomic knowledge into timely, verifiable work-system decisions.

Keywords: physical ergonomics, ergonomic risk assessment, RULA, REBA, OWAS, wearable sensors, computer vision, artificial intelligence, real-time ergonomics

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1. INTRODUCTION

The assessment of physical ergonomic risks is one of the most visible and widely applied areas of ergonomics. Questions such as how far a worker bends, how long the shoulders remain elevated, how often force is exerted, how heavy a lifted load is, or how frequently the same movement is repeated provide fundamental inputs for understanding mechanical loading on the musculoskeletal system and improving work design. This need has encouraged the development of observational and semi-quantitative methods for decades, and tools such as RULA, REBA, OWAS, OCRA, and the NIOSH lifting equation have become an important part of the common language of field ergonomics (Karhu et al., 1977; McAtamney & Corlett, 1993; Waters et al., 1993; Occhipinti, 1998; Hignett & McAtamney, 2000).

An important reason for the enduring use of these methods is not merely their scientific history. Most can be applied with limited equipment, produce results that specialists and managers can understand, are relatively rapid for field screening, and generate classifications that help translate risk into action. These characteristics have helped ergonomic assessment evolve from an academic measurement exercise into an organizational decision tool. Nevertheless, observational methods summarize dynamic exposure in real work through a limited number of observations or representative postures. Particularly in highly variable tasks, movement patterns that change over a shift, or work involving short-duration but high loading, a single score may not fully represent the temporal structure of exposure (David, 2005; Takala et al., 2010).

In recent years, the decreasing cost of wearable sensors, the spread of wireless data transmission, and advances in computer-vision methods have offered new solutions to this limitation. Inertial measurement units can record joint and segment movement over long periods; electromyography can reveal changes in muscle activity over time; pressure and force sensors can quantify the magnitude of physical interaction; and camera-based human pose estimation can generate information on movement kinematics without markers or wearable devices. When machine learning is added to these technologies, raw signals can be used for task classification, recognition of risk states, or identification of patterns associated with fatigue.

Greater technological detail, however, does not automatically make ergonomic assessment more valid. Measuring a joint angle at a high sampling rate and producing a meaningful ergonomic risk estimate for a worker are different problems. If measurement accuracy, biomechanical relevance, exposure duration, individual differences, and task context are not considered together, high-resolution data may simply produce high-resolution uncertainty. Sensor placement, calibration, camera angle, clothing, lighting, occlusion, missing data, and the application of a model to a workplace that differs from its training data also create new sources of error.

The central question of next-generation ergonomic risk assessment should therefore not be “Which technology is newer?” but “Which data are sufficient for which decision?” An observational method may be appropriate for rapid screening on a production line, whereas wearable sensors may be more useful for understanding the distribution of long-term exposure. Detailed biomechanical measurement may be needed in workstation design, whereas camera-based automation may be more scalable for daily monitoring of many stations. Technology selection should therefore consider the risk factor, required accuracy, degree of interference with workflow, privacy, cost, and frequency of decision making together.

This chapter examines the transformation of physical ergonomic risk assessment from this decision-oriented perspective. It first explains the fundamental characteristics that make risk difficult to measure and then compares established observational methods within a common framework. Wearable sensors, computer vision, and AI-supported systems are subsequently examined, with particular emphasis on the distinction between real-time assessment and feedback-driven intervention. The final section proposes a layered approach for integrating conventional and automated methods.

2. THE STRUCTURE OF PHYSICAL ERGONOMIC RISK: FROM POSTURE TO EXPOSURE PATTERN

Physical ergonomic risk is more complex than labeling a single posture as “good” or “bad.” The same joint angle may be of little concern when it occurs briefly and infrequently, yet it may create meaningful biomechanical loading when maintained for a long period or combined with high force. Similarly, a moderate force can generate a different risk profile when combined with high repetition and insufficient recovery. Physical exposure should therefore be considered through at least five interacting components: posture magnitude, applied force, repetition frequency, exposure duration, and recovery structure.

The relationship among these components is often nonlinear. For example, a trunk posture far from neutral may contribute little to total shift exposure if it occurs for only a very small fraction of task time, but instantaneous risk may increase substantially if a heavy load is lifted in the same posture. Conversely, low-force but sustained static muscle activity may be important for long-term discomfort and fatigue. Ergonomic assessment should therefore consider not only “maximum values” but also the distribution and temporal sequence of exposure.

The multi-task nature of work makes this problem even more evident. If a worker alternates among assembly, transport, quality inspection, and material supply during a shift, one representative posture may not describe the entire shift. Risk depends not

only on the characteristics of individual tasks but also on their sequence, whether recovery opportunities occur between them, and whether the same anatomical region is loaded repeatedly. This characteristic also explains why exposure needs to be treated as a time-dependent variable in ergonomic job-rotation and scheduling problems.

Measurement of physical risk is also affected by inter-individual differences. The same workstation may create different joint angles for workers with different stature and arm length. Strength capacity, experience, movement strategy, and current fatigue can also change the biomechanical effect of the same task. A workstation being suitable for an “average worker” therefore does not guarantee that it is suitable for all workers. From an inclusive-ergonomics perspective, risk assessment should consider population distributions and extreme values.

Another critical distinction in measurement is between external exposure and internal loading. The lifted load, hand location, trunk angle, or movement frequency describe external exposure, whereas muscle activation, joint moment, or mechanical tissue loading represent internal responses. Observational methods generally begin with indicators of external exposure. Sensor-based and biomechanical modeling systems attempt to link these two levels more directly. More complex measurement, however, does not always imply better decisions; repeatability, field applicability, and interpretability of the measurement are equally important.

Table 1 illustrates why next-generation assessment systems should not rely on a single sensor or a single score. Not every measurable variable has the same ergonomic meaning. A camera system, for example, may estimate shoulder angle with high precision, but if it does not know how long that angle is maintained or the magnitude of the load in the hand, it observes only one part of the risk. Similarly, EMG provides detailed information on muscle activity but does not directly explain the work context of the movement. For this reason, a “combination of data required for the decision” is more useful than simply pursuing “more data.” The main factors of physical ergonomic stress and their measurement tools are presented in the Table 1.

Table 1. Core dimensions of physical ergonomic exposure and measurement options

Dimension	Core question	Observational indicator	Technological measurement	Main interpretation risk
Posture	How far are body segments from neutral?	Angle categories, posture codes	IMU, camera, goniometer	Confusing instantaneous angle with long-term risk
Force	How much external or internal force does the worker exert?	Load class, grip estimate	Force sensor, EMG, dynamometer	Treating muscle activity and force as directly equivalent
Repetition	How frequently is the movement repeated?	Task or movement count	Movement-event recognition, video/sensor signal	Incorrect event segmentation
Duration	How long does the risky state persist?	Proportion of time within observation	Continuous time series	Measurement period not representing the shift
Recovery	How much recovery does the same structure receive?	Breaks and task changes	Task history, EMG recovery pattern	Equating formal breaks with actual physiological recovery
Individual fit	How does the same task affect different workers?	Anthropometric fit check	Personal calibration, digital human model	Generalizing one model to all workers

2.1. Established Observational Methods: Common Logic, Different Decision Domains

Observational ergonomic assessment methods transform complex biomechanical exposures into a limited number of categories that can be applied in the field. This simplification can be viewed as a limitation, but it is also one of their most important practical strengths. The success of a method depends not only on measurement precision but also on whether an ergonomist or occupational-safety professional can produce the result consistently and translate it into an intervention priority. RULA, REBA, OWAS, OCRA, and the NIOSH lifting equation therefore provide different levels of resolution for different problems and should not be treated as directly interchangeable.

OWAS is one of the early and influential approaches developed for the systematic observation and classification of industrial working postures (Karhu et al., 1977). It creates categorical codes for the back, arms, legs, and external load and converts the observed posture into an action category. Its main advantage is relatively simple coding

for prolonged observation and work sampling. Its limited detail for the upper extremities and broad categorization of joint angles, however, can reduce resolution in precise hand-arm tasks.

RULA was developed as a rapid screening method, particularly for work involving the upper extremities (McAtamney & Corlett, 1993). It combines upper-arm, forearm, wrist, neck, and trunk postures with muscle-use and force factors to generate an action level. It is a powerful screening tool for office work, assembly, and repetitive upper-extremity tasks. A high RULA score, however, should not be interpreted as a quantitative estimate of a specific probability of tissue injury; the score primarily supports prioritization for investigation and intervention.

REBA was developed for a more comprehensive assessment of whole-body posture and is particularly applicable to work involving variable and unpredictable postures (Hignett & McAtamney, 2000). It evaluates the trunk, neck, legs, upper arm, forearm, and wrist together with force, coupling, and activity components. Its ability to classify the whole body relatively quickly explains its use across healthcare, maintenance, logistics, and manufacturing. Selecting a single “worst posture” to represent an entire shift, however, can oversimplify the temporal distribution of exposure.

The OCRA approach focuses on exposure to repetitive upper-extremity movements and considers repetition, force, posture, additional factors, and recovery together (Occhipinti, 1998). This is important because it evaluates not only instantaneous posture but also the temporal and repetitive structure of the task. Its data requirements and implementation complexity, however, are greater than those of rapid screening methods.

The NIOSH lifting equation evaluates manual lifting tasks through the Recommended Weight Limit and Lifting Index. By considering horizontal distance, vertical location, travel distance, asymmetry, lifting frequency, and coupling, the method makes the relationship between task-design parameters and ergonomic risk explicit (Waters et al., 1993). The equation is nevertheless based on defined task assumptions and may not be directly applicable to conditions such as one-handed lifting, seated lifting, very rapid lifting, or unstable loads.

A common feature of these methods is that they transform continuously varying characteristics of the real world into a limited number of scores or categories. This transformation is a deliberate compression of information. Shoulder flexion, for example, is a continuous angle, whereas RULA or REBA divides it into categories using defined thresholds. Technological measurement systems can record the continuous value directly, but an ergonomic decision still requires that value to be related to thresholds, duration, force, and context. Automation therefore does not eliminate the logic of observational methods; in many cases, it automates the measurement layer while retaining the same ergonomic rules in the interpretation layer.

A comparison of commonly used physical ergonomics methods is summarized in Table 2.

Table 2. Comparison of commonly used physical ergonomics methods

Method	Primary focus	Appropriate use	Strength	Main limitation
OWAS	Whole-body working postures	Long-term posture sampling, field screening	Simple coding and action categories	Limited upper-extremity and angular detail
RULA	Upper extremity and neck-trunk	Office work, assembly, repetitive upper-extremity work	Rapid and interpretable screening	Limited representation of exposure distribution over time
REBA	Dynamic whole-body posture	Maintenance, logistics, manufacturing, variable tasks	Rapid applicability to the whole body	Risk of overdependence on one or a few postures
OCRA	Repetitive upper-extremity loading	Repetitive work, cyclical production	Considers repetition, force, and recovery together	Higher data requirements and implementation time
NIOSH RNLE	Manual lifting	Defined two-handed lifting tasks	Explicit link to design variables	Applicability limits and task assumptions

In their systematic evaluation of observational methods for biomechanical exposure, Takala et al. (2010) showed substantial differences among methods in purpose, validity, and repeatability. This finding suggests that searching for the “best ergonomic method” in the field may be the wrong starting point. A more appropriate question is which method is sufficient for the risk factor being assessed, the structure of the work, and the precision required by the decision.

2.2. Strengths and Limitations of Observational Assessment: Why Is Automation Needed?

When criticizing observational methods, it is important not to overlook why they have been used for decades. Their first major strength is economic and operational accessibility. A trained assessor can screen many workstations without expensive laboratory equipment. Their second strength is interpretability. The formation of a REBA or RULA score can be traced, and the posture or force component responsible for increasing the score can be identified. This makes it easier to explain the rationale for an intervention to workers and managers.

A third strength is the standardized common language they provide. Evaluating different jobs with the same method offers a practical framework for prioritization and intervention planning. In large organizations, detailed biomechanical measurement at hundreds of stations may not be realistic during an initial survey. Observational methods can therefore function as a “risk-screening filter,” identifying jobs that require more detailed measurement.

One of the principal limitations of observational methods, however, is sampling. An assessor sees and codes only a selected part of the work. If the chosen observation is not typical, the result may be misleading. Selecting the worst posture is conservative for intervention purposes but may overestimate total shift exposure; selecting an average or frequent posture may miss short-duration, high-risk events. David (2005) emphasized that ergonomic exposure measurements are sensitive to methodological choices and that the measurement strategy directly influences interpretation of the results.

A second limitation is observer variability. Assessors may differ in deciding which joint-angle category applies, how force should be classified, or at which instant the posture should be coded. Particularly near category thresholds, small visual differences can change the score. Video recording, training, and dual-assessor procedures can reduce this problem but do not eliminate it completely.

A third limitation is temporal resolution. Ergonomic risk often depends not only on “which posture?” but also on “for how long, how often, and in what sequence?” Classical work-sampling approaches can provide information on proportions of time, but manually coding movement histories at second-level resolution is labor intensive. Wearable sensors and video analytics provide a major advantage here because the same variable can be tracked over long periods at high sampling frequencies.

A fourth limitation concerns simultaneous measurement of multiple risk factors. Posture, force, repetition, and recovery may all change at the same time. Observational methods combine some of these factors categorically, but internal biomechanical responses or fatigue cannot be observed directly. EMG, force sensors, and physiological measurements can provide additional information on these otherwise hidden components.

New problems arise, however, when the purpose of automation is defined as eliminating the observer entirely. If an automated system estimates posture incorrectly and no expert is present to detect the error, that error can scale across many observations. Intervention design also becomes difficult when the reason for an algorithmic score is not explainable. Explainability, actionability, and sensitivity to work context—the strengths of observational methods—should therefore be retained as design principles in new systems.

Table 3 presents a comparison of the core differences between observational and continuous measurement approaches.

Table 3. Fundamental differences between observational and continuous measurement approaches

Dimension	Observational method	Continuous/sensor-based method	Managerial implication
Sampling	Selected moments or work cycles	High-frequency time series	Continuous measurement may better represent the exposure distribution
Cost	Low equipment cost; expert time	Equipment, setup, data infrastructure	The cost balance can change as scale increases
Explainability	Generally high	Varies with the algorithm	Decision logic should remain visible to users
Error source	Observer, sampling, category selection	Calibration, sensor drift, occlusion, model domain shift	Both approaches require a QA protocol
Context information	Strong through expert observation	May be limited in automated systems	Technology should be supported by work-context data
Scalability	Limited by expert time	Potentially high once infrastructure is established	Initial screening and continuous monitoring may require different designs

2.3. Wearable Sensors: Continuous Measurement of Exposure

Wearable sensors have created one of the most important transformations in physical ergonomics by enabling quantitative monitoring of worker movement outside the laboratory and over extended periods. Inertial measurement units (IMUs), in particular, combine accelerometer, gyroscope, and in some systems magnetometer information to estimate segment orientation and movement dynamics. One or more sensors can be attached to the trunk, upper arm, forearm, or leg to generate time series of joint angles and posture duration. Lim and D’Souza (2020) noted that the use of inertial sensing in occupational ergonomics has expanded from posture assessment to activity recognition and long-term exposure monitoring.

The main advantage of IMU systems is that they are not dependent on a camera field of view. Workers can move across areas, pass behind objects, and change orientation during a task. This is important in logistics, maintenance, warehousing, and large production areas. A high sampling rate also makes it possible to examine not only the presence of a risky posture but also its duration, repetition, and transitions. For example, the percentage of a shift during which shoulder elevation remains above a given threshold, or the number and duration of trunk-flexion events, can be calculated directly from the time series.

IMU measurement, however, is not as simple as “attach and measure.” Misalignment of a sensor relative to the body segment, sensor displacement, magnetic disturbances, and calibration errors can affect joint-angle estimates. Even movement of the sensor over clothing during a prolonged recording can create systematic error. Calibration protocols, standardized sensor placement, and data-quality checks are therefore as important as the ergonomic analysis itself.

Surface electromyography (sEMG) measures the electrical activity of muscle and provides information on muscular loading that cannot be observed externally. Indicators such as sustained low-level muscle activity, differences in muscle use across tasks, and fatigue-related frequency changes may be useful in ergonomic assessment. EMG signals, however, are affected by electrode placement, skin preparation, movement artifacts, and inter-individual physiological differences. Direct comparison of raw amplitude values across workers is therefore generally inappropriate; normalization is required in many applications.

Pressure-based systems can be used to examine sitting, gripping, plantar loading, or the distribution of load across contact surfaces. Force sensors contribute to direct measurement of external force in pushing, pulling, gripping, and manual-material-handling tasks. Combining pressure or force measurements with posture data enables more meaningful biomechanical interpretation than simply knowing that “the worker bent forward.”

Physiological signals such as heart rate, heart-rate variability, skin conductance, and skin temperature can also be collected with wearable systems. These signals, however, are influenced by many factors, including physical workload, mental workload, temperature, stress, caffeine, and individual characteristics. Inferring “ergonomic risk” directly from physiological data therefore requires caution. Physiological signals are generally more meaningful when interpreted together with posture and task context.

The workflow for translating wearable sensor data into ergonomic information is illustrated in Figure 1.



Figure 1. Transforming wearable-sensor data into ergonomic information

The second and fifth steps in the chain shown in Figure 1 are particularly critical. Calibration error can create a systematic bias that affects all subsequent calculations. Ergonomic interpretation connects the technical signal to the decision. A sensor measures movement; risk is constructed by considering the magnitude, duration, force, repetitive structure, and task context of that movement.

The key determinant of the ergonomic value of wearable technology is not the number of sensors used, but the degree to which the system disrupts the work process. A detailed full-body sensor system may provide high accuracy, yet have limited field value if workers cannot use it throughout a shift. Measurement-system design should therefore balance accuracy against intrusiveness. One or two IMUs may be sufficient for screening, whereas detailed biomechanical studies may justify a larger sensor set.

An overview of the leading wearable and contact-based measurement technologies in ergonomics is provided in Table 4.

Table 4. Main wearable and contact-based measurement technologies in ergonomics

Technology	Measured signal	Ergonomic use	Strength	Points requiring attention
IMU	Acceleration, angular velocity, orientation	Posture, movement, repetition, duration	Mobile and continuous measurement	Calibration, sensor drift, magnetic disturbance
sEMG	Electrical muscle activity	Muscle loading, static activity, fatigue indicators	Information close to internal loading	Electrode placement, normalization, artifacts
Force sensor	External force	Push-pull, grip, lifting	Direct measurement of force	Contact arrangement and device-induced task changes
Pressure sensor	Contact pressure and distribution	Sitting, plantar loading, grip	Regional load distribution	Calibration and surface characteristics
HR/HRV/EDA	Cardiovascular/autonomic response	Supporting indicators of load and stress	Long-duration, portable monitoring	Multiple causation; risk of interpretation without context

2.4. Automated Posture and Movement Analysis with Computer Vision

Camera-based movement analysis has strong scalability potential in industrial ergonomics because it can produce posture and movement data without requiring workers to wear sensors. Conventional optical motion-capture systems offer high accuracy but are limited in routine field applications because they require markers, a calibrated capture volume, and controlled environments. Deep-learning-based

markerless human pose estimation has substantially reduced this barrier by estimating body keypoints from RGB or depth-camera images.

A camera-based ergonomic assessment pipeline consists of several steps. First, an image or video is acquired. Human detection and body-keypoint estimation are then performed. These keypoints represent anatomical references such as the shoulder, elbow, hip, knee, and ankle. Segment angles and posture features are subsequently calculated from the keypoints. Finally, these features are mapped to RULA, REBA, or task-specific risk-classification rules. Work that enabled real-time multi-person 2D pose estimation represented an important milestone in the development of open-source human-pose methods (Cao et al., 2017). The spread of markerless deep-learning systems in movement science has similarly reduced the cost of data acquisition (Mathis et al., 2018).

From an ergonomics perspective, the most apparent advantage of camera systems is the reduced burden on the worker. Many work cycles can be analyzed using existing camera infrastructure without requiring sensors to be worn, charged, or calibrated. Historical video recordings can also be reanalyzed. This is particularly valuable for quantitatively extracting posture patterns in short-cycle production.

Diego-Mas and Alcaide-Marzal (2014) presented one of the pioneering field studies showing that skeletal data from depth sensors such as Kinect could be used in observational ergonomic methods. This approach made it possible to derive measurements from sensor data rather than relying on a human assessor to estimate joint angles visually. Related studies also demonstrated that established observational methods could be enhanced through image-processing-based automation. For example, Can and Fiğlalı (2017) developed an image-processing-supported extension of RULA (ARULA) to obtain objective angular measurements and reduce limitations associated with observation-based assessment, including subjectivity and analysis time. Similarly, image-processing techniques were integrated with OWAS to automate the identification and classification of working postures (Fiğlalı et al., 2015). Later deep-learning approaches reduced the need for specialized depth sensors by enabling posture estimation from ordinary RGB images

Errors in computer-vision systems, however, may become much more apparent outside laboratory conditions. Occlusion of the arm by the torso, a handled object hiding a joint, poor lighting, protective clothing, camera angle, motion blur, and overlap among multiple workers can affect keypoint estimation. In systems where ergonomic scores depend on category thresholds, even a few degrees of angular error may alter the final score. The system should therefore be evaluated not only for average joint error but also for its ability to produce the correct ergonomic category.

Two-dimensional pose estimation is also sensitive to perspective. Movements that are not parallel to the camera plane may appear to have a different joint angle from the true angle. Multiple cameras, depth information, or 3D pose estimation can reduce this

problem, but they increase infrastructure cost and system complexity. In single-camera systems, camera placement should be designed around the critical movements of the task; it is as important as model selection.

Domain shift is another important issue. A model may perform well on general internet images or a controlled movement dataset but lose accuracy in production environments because of hard hats, safety vests, gloves, workwear, machine occlusion, and unusual body postures. A ready-made pose-estimation model should therefore not be treated as a reliable ergonomic instrument in industrial use without local validation.

The sources of error and their respective control measures in camera-based ergonomic analysis are outlined in Table 5.

Table 5. Sources of error and control measures in camera-based ergonomic analysis

Error source	Effect	Possible effect on risk score	Control approach
Occlusion	Missing or misplaced keypoint	Joint-angle and posture-code error	Camera placement, multiple cameras, confidence threshold
Perspective	Distortion of 2D angles	Misclassification near category thresholds	3D estimation, depth, or task-specific camera angle
Lighting/motion blur	Detection instability	Spikes in the time series	Exposure settings, frame rate, filtering
PPE/clothing	Reduced joint visibility	Systematic localization error	Validation/fine-tuning with local data
Domain shift	Reduced model performance in a new workplace	Biased risk estimate	Field validation, error monitoring, retraining
Multiple workers	Identity confusion	Exposure assigned to the wrong worker	Tracking algorithm and identity-quality control

2.5. AI-Supported Ergonomic Risk Classification

The term artificial intelligence can refer to different techniques in ergonomic risk assessment, and these should be distinguished. The simplest form of automation applies existing ergonomic rules to angles measured by sensors or cameras. Shoulder and trunk angles, for example, can be calculated automatically and converted into REBA categories. This approach can provide automated ergonomic scoring even without “AI,” while retaining a highly explainable decision logic.

At a second level, machine learning can classify a task or risk state from sensor features. A model may recognize events such as “lifting,” “reaching,” “bending,” or “neutral work” from an IMU time series. These events can then be used to calculate exposure duration and repetition count. Here, AI does not directly produce an ergonomic risk score; instead, it automatically extracts the work events required for risk calculation.

At a third level, a model can directly estimate an ergonomic class or score. Producing a “low, medium, high risk” class from camera images or multimodal sensor data is one example. This approach is fast in use, but the quality of training labels becomes critical. If the model is trained on RULA or REBA scores, it is essentially learning to reproduce expert labels from those methods. The validity of its prediction is therefore constrained by both the validity of the reference method and the quality of labeling.

A fourth and more ambitious approach attempts to predict future outcomes such as discomfort, fatigue, or performance loss rather than imitate conventional scores. The problem then becomes one of causality and long-term outcome modeling rather than classification alone. Strong longitudinal data are required because confounding variables such as physical activity outside work, age, prior health status, psychosocial factors, and individual capacity can influence outcomes. Predicting “injury risk” directly from short-term sensor data may be overly ambitious without adequate external validation.

Accuracy alone is not sufficient for evaluating model performance. In ergonomic screening, missing a high-risk condition may be more costly than producing a false alarm. Sensitivity, specificity, positive predictive value, and class imbalance should therefore be considered. Performance should also be tested across different groups of workers and different workstations. Good average performance does not guarantee the same accuracy for shorter workers, different body sizes, or workers wearing protective equipment.

Explainability has particular importance in ergonomic decision support. A model that produces a high-risk label should also indicate which component should be targeted by the intervention. A result of “high risk” alone does not explain how a workstation should be redesigned. In contrast, an output such as “shoulder elevation exceeds the threshold during 18% of the shift; trunk flexion increases while carrying loads” can be linked directly to design action. Good AI in ergonomics should therefore provide not only accurate classification but also actionable explanation.

Model calibration and uncertainty reporting are also important. Rather than presenting every prediction as certain, a safer system may flag low-confidence observations for human review. In this way, a human-in-the-loop approach does not eliminate the ergonomist; it directs expert attention toward uncertain and high-impact cases.

An AI-assisted ergonomic assessment workflow with human oversight is presented in Figure 2.

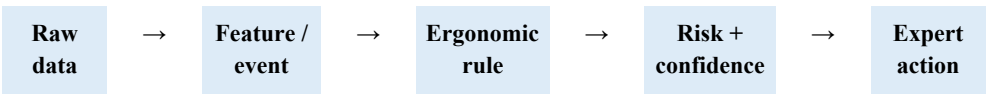


Figure 2. Human-supervised AI-supported ergonomic assessment chain

Ergonomic assessment systems can be categorized into distinct levels, including rule-based automation, event/activity recognition, risk classification, and outcome prediction. Table 6 summarizes the four distinct levels of ergonomic assessment systems, ranging from simple to advanced, by comparing their functions, exemplary outputs, advantages, and primary risks.

Table 6. Four levels of automation and artificial-intelligence use in ergonomics

Level	What does the system do?	Example output	Advantage	Main risk
1. Rule-based automation	Applies measured angles to existing ergonomic rules	Automated REBA/RULA	High explainability	Measurement error transfers directly into the score
2. Event/activity recognition	Extracts task or movement events from time series	Number of bends, lifting duration	Automation of duration and repetition	Incorrect segmentation
3. Risk classification	Directly estimates a risk class/score from data	Low-medium-high risk	Speed and scalability	Label dependence, domain shift
4. Outcome prediction	Predicts future outcomes such as fatigue/discomfort	Probability of high fatigue	Potential for proactive intervention	Need for causal reasoning, longitudinal data, and external validation

2.6. Real-Time Ergonomic Monitoring: From Measurement to Intervention

Real-time measurement is one of the most attractive features of next-generation ergonomic systems; however, real-time data and real-time ergonomic intervention are not the same thing. A system may display shoulder angle every second, but deciding when and how that information should trigger feedback is a separate design problem. A system that generates continuous alarms may quickly be ignored by workers, disrupt production flow, or encourage avoidance of normal movement variability.

A five-stage closed-loop logic for real-time ergonomic intervention is illustrated in Figure 3.

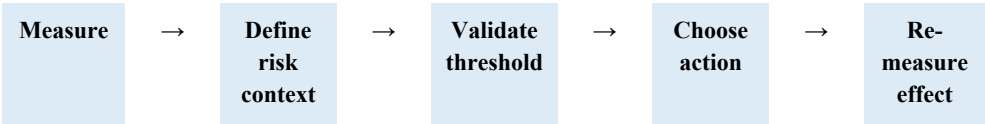


Figure 3. Closed-loop logic for real-time ergonomic intervention

The simplest form of real-time feedback is a vibration, auditory, or visual alert when a risky posture persists beyond a specified duration. This can be useful for training and behavioral awareness. Not all ergonomic risks, however, originate from worker behavior. If the problem is a high shelf, inadequate reach distance, or poor tool placement, warning the worker may shift responsibility for a design problem onto the individual. Feedback should therefore target not only the person but also work-system design.

A more advanced approach combines continuous exposure data with task planning. If accumulated loading in a particular anatomical region increases, the system can select the next assigned task from work with a different loading profile. This converts ergonomic job rotation from a fixed schedule into dynamic scheduling. More generally, workforce-scheduling research has demonstrated that ergonomic considerations can be incorporated alongside operational and synchronization constraints, providing a basis for linking ergonomic information with task-allocation decisions (Shahmaleki & Fırlalı, 2021). Such a decision, however, requires not only reliable sensor data but also prior characterization of the ergonomic profiles of tasks and integration of production constraints into the model.

Another application is adaptation of workstation or robot parameters. An adjustable workstation can be automatically configured according to a worker's anthropometric and posture data; a cobot can alter its speed or task allocation according to the person's current movement space and workload. Such applications connect physical ergonomic assessment directly to a control system and provide a concrete example of the assessment-prediction-optimization-adaptation chain defined in Chapter 1.

The costs of false alarms and missed alarms should be defined explicitly in real-time systems. An overly sensitive threshold may repeatedly label brief normal movements as risky, whereas an overly permissive threshold may miss meaningful exposures. The solution is not simply a better classifier; duration thresholds, context, task type, and the worker's right to control the system should be designed together.

The effect of feedback on worker experience should also not be overlooked. Continuous monitoring can create a perception of surveillance. Concern that data could be used for performance appraisal or disciplinary purposes may reduce acceptance of an ergonomic system. Data governance should therefore be part of the technical architecture: what data are collected, how long they are stored, who can access them, whether they are linked to individual identity, and for which decisions they may be used should be specified from the outset.

The success of an ergonomic monitoring system should therefore be evaluated in three dimensions: technical accuracy, ergonomic benefit, and organizational acceptance. A technically accurate system that workers reject is not sustainable. Likewise, an acceptable system that does not reduce risk is ergonomically unsuccessful. Real-time

ergonomics should be viewed as a sociotechnical-system design problem rather than merely a sensor project.

Table 7 outlines a multi-tiered framework for ergonomic interventions in real-time systems, classifying them into five distinct levels based on their feedback targets, operational advantages, and inherent design challenges. At the individual level, interventions focus on worker movement via posture alerts, providing immediate awareness but risking the unfair displacement of systemic responsibility onto the worker. The task level modulates work sequences or durations to manage exposure distribution, though it must remain compatible with production constraints. On a structural level, workstation interventions modify the physical environment—such as automatic height adjustments—to achieve ergonomic improvement at the source, which requires clear boundaries regarding safety and control authority. Furthermore, the human-robot system level dynamically adapts task sharing and cobot behaviors to enable dynamic collaboration, though this hinges heavily on algorithmic trust and predictability. Finally, the management level leverages risk dashboards for macro-level work-system planning, offering long-term decision support while raising critical ethical concerns regarding the potential misuse of individual worker data. Ultimately, as interventions transition from individual behavioral feedback to systemic management planning, the design focus shifts from immediate physical adjustment to complex challenges in collaborative robotics, operational control, and data privacy governance.

Table 7. Intervention levels in real-time ergonomic systems

Level	Feedback target	Example	Advantage	Risk / design question
Individual	Worker movement	Posture alert through vibration	Immediate awareness	Risk of shifting responsibility for the source of the problem to the worker
Task	Work sequence or task duration	Task change when accumulated load rises	Manages exposure distribution	Must be compatible with production constraints
Workstation	Physical work environment	Automatic height adjustment	Ergonomic improvement at the source	Safety and control authority
Human-robot system	Task sharing and robot behavior	Adaptation of cobot speed/role	Dynamic collaboration	Algorithmic trust and predictability
Management	Work-system planning	Shift/station risk dashboard	Long-term decision support	Use of individual data beyond the intended purpose

2.7. Validation, Reliability, and Field Validity

One of the most common mistakes when developing a new ergonomic technology is to treat technical measurement accuracy as equivalent to ergonomic validity. In fact, there are several levels of validation. An IMU system accurately measuring segment angle relative to an optical motion-capture system is sensor validation. Those angles correctly producing REBA categories is method-level validation. Agreement between the generated risk category and expert assessment in the real workplace is field validation. A reduction in risky exposure or symptoms after implementation of the system represents intervention effectiveness. These four levels are not interchangeable.

Laboratory accuracy is generally measured under controlled movements, unobstructed visibility, and standardized sensor placement. Field conditions add rapid movement, different body sizes, clothing, equipment, and production-environment complexity, all of which may increase error. Systems should therefore be evaluated not only through mean error but also through the error distribution and performance in critical cases. Boundary analysis is particularly important near ergonomic category thresholds, where a small error can change the decision class.

Test-retest performance and consistency across devices should also be examined as aspects of reliability. The same worker performing the same task on different days will naturally show variation. The system should distinguish this biological and task-related variability from measurement error. Whether the calibration procedure yields consistent results when performed by different users should also be assessed.

For AI models, the data-splitting strategy is a critical methodological issue. If consecutive video frames from the same worker appear in both training and test sets, model performance can be artificially inflated because the frames are highly similar. Stronger evaluation requires splits by worker, day, or workplace. If true generalization is the goal, the test set should contain workers not previously seen by the model and, where possible, different work conditions.

External validation is particularly important. A system trained in one factory cannot be assumed to retain the same accuracy in another. Camera height, clothing, workstation geometry, and task repertoire may change. “Model accuracy” should therefore be treated not as a single permanent number but as performance measured for a defined domain of use.

Validation of ergonomic systems also requires comparison with human experts, but an expert score is not absolute ground truth. Because observational methods contain inter-rater variability, reference labels should, where possible, be produced through consensus among multiple trained assessors, and disagreement should be reported. Algorithm performance can then be interpreted together with measurement uncertainty rather than against the supposedly error-free judgment of a single person.

Table 8 outlines a four-tier framework of recommended validation layers for next-generation ergonomic systems to systematically evaluate their technical and operational utility. The structure advances from baseline instrumental precision (Measurement accuracy) and expert-coded categorization (Ergonomic-method agreement) to real-world performance tracking across diverse environments (Field generalizability). Finally, it addresses systemic impact (Intervention effectiveness) by measuring actual exposure reduction and operational acceptance. Ultimately, this paradigm ensures that emerging ergonomic technologies are both methodologically robust and practically viable for workplace deployment.

Table 8. Recommended validation layers for next-generation ergonomic systems

Validation layer	Core question	Example reference	Recommended output
1. Measurement accuracy	Does the sensor/camera measure the physical variable accurately?	Optical motion capture, goniometer, calibrated force sensor	MAE/RMSE, bias, confidence interval
2. Ergonomic-method agreement	Does the measurement produce the correct ergonomic category/score?	Expert-coded RULA/REBA/OWAS	Classification accuracy, sensitivity, weighted kappa
3. Field generalizability	Is performance maintained across different workers and jobs?	Unseen worker/station/workplace	Worker-based and external-test performance
4. Intervention effectiveness	Does use of the system reduce actual exposure?	Pre-post or controlled field design	Exposure change, acceptance, production effect

These four layers make the statement “the technology works” more disciplined. A prototype may succeed at the first two layers yet fail to generalize across workers. Likewise, a technically excellent system may fail to reduce risk in the workplace because feedback has been designed poorly. Clearly reporting which validation layer has been completed in scientific publications and industrial applications helps prevent overinterpretation of results.

2.8. Integrating Conventional and Intelligent Ergonomics Systems

Positioning conventional and next-generation ergonomics tools as opposing approaches is practically unproductive. Observational methods provide strong work-context knowledge, explainability, and decision classification, whereas sensor and camera systems provide continuous measurement, temporal resolution, and

scalability. The strongest approach combines the complementary properties of both classes within the same assessment architecture.

The first form of integration is “automated scoring.” A camera or IMU measures joint angles, and an algorithm maps those angles to RULA, REBA, or OWAS categories. Manual estimation of angles is reduced while the method logic is retained. This is particularly valuable when analyzing large numbers of video frames. Expert input may still be required when force, coupling, or task context cannot be measured automatically.

The second form is a “hybrid exposure profile.” A camera may provide posture duration, a force sensor external load, the production system task identity, and an ergonomist contextual information and exceptions. Rather than forcing these data sources into one risk score, they can be displayed as parallel indicators. The decision maker can then see both the magnitude and the cause of risk.

The third form is “two-stage screening.” Many workstations are first screened using low-cost automated or observational methods; stations with high or uncertain risk are then selected for more detailed sensor, EMG, or biomechanical analysis. This structure allocates measurement resources according to risk and is consistent with the staged decision logic of industrial engineering.

The fourth form is “human-supervised learning.” The automated system routes low-confidence cases to an ergonomist. As the expert labels these cases, the database becomes richer and the model can be adapted to the local work environment. Expert effort is thereby directed toward the observations with the greatest decision value instead of manual review of all data.

This integration also makes data quality more visible. Rather than presenting a single risk score, the system can display measurement confidence, missing data, and model uncertainty. An output such as “REBA = 8; camera visibility is low; trunk angle is reliable; shoulder estimate is low confidence; total category requires expert review” may be safer than reporting “REBA = 8” alone. In ergonomics, making uncertainty visible is more valuable than creating an illusion of certainty.

The integration of conventional and intelligent ergonomics offers a synergistic approach to workplace health and safety. While conventional methods provide the fundamental risk logic, expert contextual interpretation, and standard methodological frameworks, intelligent systems contribute automated, high-volume data processing, continuous real-time monitoring, and precise quantitative comparisons. By combining both approaches, organizations can implement comprehensive two-stage screenings, human-supervised feedback loops, and scalable, data-driven interventions that enhance overall ergonomic assessment and intervention design. Table 9 outlines the complementary features of conventional and intelligent ergonomics.

Table 9. Complementary features of conventional and intelligent ergonomics

Decision need	Contribution of the conventional method	Contribution of the intelligent system	Recommended use
Rapid field screening	Simple, interpretable risk class	Automated pre-screening and high volume	Two-stage screening
Long-term exposure	Work context and risk logic	Duration, repetition, and temporal distribution	Continuous measurement + ergonomic rules
Intervention design	Expert interpretation of the cause of risk	Quantitative before-after comparison	Expert design + sensor validation
Real-time control	Threshold and action logic	Instant measurement and automated alert	Human-supervised feedback
Organizational scaling	Common methodological language	Data automation across many stations	Standard protocol + centralized QA

Author Synthesis: A Five-Layer Intelligent Ergonomic Assessment Architecture

Based on the literature and methodological discussion in this chapter, next-generation ergonomic risk assessment can be conceptualized as a five-layer decision architecture: (1) data acquisition, (2) feature and event extraction, (3) ergonomic interpretation, (4) uncertainty and confidence assessment, and (5) intervention decision. This is not a classification of technologies; it is a proposal for making the chain of responsibility between data and ergonomic decision visible.

The first layer acquires data from sources such as cameras, IMUs, EMG, force measurement, or manual observation. The second extracts features such as joint angle, task event, repetition, duration, and load. The third connects these features to established rules such as RULA/REBA/OWAS, a biomechanical model, or a validated risk model. The fourth evaluates measurement confidence and model uncertainty. The fifth selects an action such as an alert, workstation modification, task rotation, or more detailed assessment.

The most important aspect of this architecture is that it treats the ergonomic risk score as an intermediate output rather than the end of the data chain. The ultimate goal is not to generate a score but to improve the work system. A good intelligent ergonomics system should therefore answer not only “What is the risk?” but also “How reliable is this result?”, “Which component dominates the risk?”, and “Which intervention is feasible?” The five-layer intelligent ergonomic assessment architecture provides a structured framework for evaluating human work conditions by turning raw inputs into actionable insights. It systematically processes information through five stages: acquiring raw metrics (Data acquisition), identifying relevant patterns (Feature / event extraction), interpreting these patterns within a human-factors context (Ergonomic

meaning), assessing data reliability (Confidence / uncertainty), and executing optimal interventions (Action decision), as presented in Figure 4.

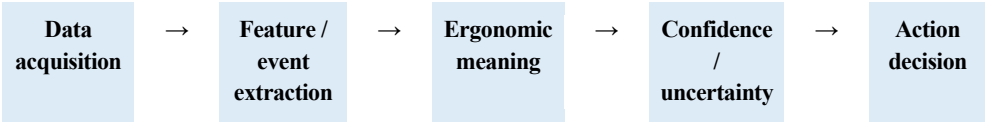


Figure 4. Five-layer intelligent ergonomic assessment architecture

2.9. Implementation Strategy: A Staged Transition for Organizations

Implementation of next-generation ergonomic technologies does not have to begin by building a comprehensive system that continuously monitors all workers. A safer and more economical approach is a staged transition based on decision needs. In the first stage, the organization standardizes its existing ergonomic risk-assessment process. Adding technology before clarifying which methods are used for which jobs, inter-rater consistency, data-storage practices, and intervention tracking may simply digitize existing uncertainty.

In the second stage, a repetitive, high-volume, or observationally difficult problem can be selected for a pilot application. A single assembly station with many cycles, for example, may be used for camera-based posture-duration analysis, or one IMU may monitor trunk flexion in warehouse work. The purpose of the pilot is not merely to show that the algorithm runs; it is to measure data quality, worker acceptance, setup time, and whether the ergonomic decision actually changes.

In the third stage, the automated system should operate in parallel with the existing expert method. For a defined period, it should be used not “instead of” expert assessment but “alongside” it. This enables identification of systematic errors, category boundaries, and site-specific problem cases. The period also provides an opportunity to give workers transparent information about the purpose of the system and its data-governance practices.

In the fourth stage, the system may automatically process high-confidence routine cases while routing low-confidence, high-risk, or novel tasks to an expert. This division of labor improves both safety and scalability. It is important not to treat the automation rate as a success metric. The objective is not to reduce human review to zero, but to direct expert time toward the highest-value decisions.

The fifth stage is closed-loop decision support. The system no longer merely reports risk; it can generate recommendations for task rotation, workstation adjustment, or engineering intervention. This transition from assessment to recommendation is not limited to physical-risk monitoring. Knowledge-based systems can similarly combine worker- and organization-related information to support the prioritization of preventive

actions; for example, the Shift Expert system was developed to generate and prioritize recommendations aimed at reducing adverse effects associated with shift work (Esen et al., 2019). Ergonomic objectives at this stage should be considered together with production, quality, and safety objectives. In this way, physical risk assessment connects to the ergonomic optimization and decision-support systems discussed in Chapter 4.

Table 10 presents a structured, five-stage framework for integrating intelligent ergonomics into organizations, focusing on a gradual transition from manual methods to automated systems.

A concise summary of the progression outlined in Table 10 is provided below:

- Stage 1 (Standardization): Establishes data integrity and reliable manual processes as a foundation.
- Stage 2 (Pilot measurement): Tests automated tools on a small scale to ensure technical quality and worker acceptance.
- Stage 3 (Parallel validation): Compares automated results with expert assessments to identify and control errors.
- Stage 4 (Human-supervised scaling): Automates routine cases while routing complex data to human experts for quality assurance.
- Stage 5 (Closed-loop decision): Integrates automated risk data directly into operational and workstation design decisions.

Table 10. Proposed staged roadmap for implementing intelligent ergonomics in organizations

Stage	Main activity	Success criterion	Condition for moving to the next stage
1. Standardization	Standardize the existing observational process, labels, and intervention records	Inter-rater consistency and data integrity	Core process is reliable and traceable
2. Pilot measurement	Run a sensor/camera pilot in a limited task	Technical data quality and worker acceptance	Measurement is stable under field conditions
3. Parallel validation	Use the automated system and expert method together	Agreement, error types, boundary cases	Errors are understood and control mechanisms are in place
4. Human-supervised scaling	Automate routine high-confidence cases and send uncertain ones to experts	Quality is maintained while expert time decreases	Confidence thresholds and QA processes are stable
5. Closed-loop decision	Connect risk data to task/workstation decisions	Exposure reduction + production effect + acceptance	Effectiveness has been validated through field design

2.10. Ethics, Privacy, and Data Governance

While intelligent ergonomic systems make physical risks more visible, they also generate detailed and continuous data about workers. Video, location, movement patterns, physiological signals, and task history are privacy-sensitive even when collected solely for ergonomic purposes. Data governance should therefore be a starting condition of system design rather than a legal control added afterward.

The first principle is data minimization. Data that are not necessary for the ergonomic decision should not be collected. If anonymized skeletal coordinates are sufficient for posture analysis, for example, long-term storage of facial images may be unnecessary. Likewise, if a decision can be made at workstation level, creating a long-term individual performance profile linked to personal identity can introduce avoidable risk.

The second principle is purpose limitation. Using data collected for ergonomic improvement later for discipline, pay decisions, or individual performance ranking can undermine trust and reduce system acceptance. Data-use purposes, access rights, and retention periods should be explicitly defined.

The third principle is algorithmic fairness. A model may produce different error rates across body sizes, sexes, age groups, or clothing/PPE conditions. If these differences are not tested, an automated system may systematically under- or overestimate risk for some workers. Field validation should therefore evaluate not only overall accuracy but also subgroup performance.

The fourth principle is contestability and human control. When an automated system generates a decision about a worker or a job, the worker and ergonomist should be able to see the rationale, flag erroneous measurements, and invoke human assessment when necessary. This design principle is important for organizational legitimacy as well as technical reliability.

2.11. Conclusion: From Measurement to Ergonomic Decision

Physical ergonomic risk assessment is undergoing a substantial transformation from observational methods developed to evaluate the fit between work and the human toward intelligent systems using continuous, multi-source data. Established methods such as RULA, REBA, OWAS, OCRA, and the NIOSH lifting equation are not losing their relevance in this transformation. On the contrary, they continue to provide a common ergonomic language and decision logic for interpreting the high-resolution data produced by new technologies.

Wearable sensors make the duration, repetition, and transition patterns of exposure visible, while computer vision provides scalable, contact-free posture analysis. Artificial intelligence extends capabilities for event recognition, classification, and prediction. These advantages, however, come with new sources of error: sensor displacement,

camera occlusion, domain shift, labeling error, uncertainty, algorithmic bias, and privacy concerns. System success should therefore not be measured solely by technical accuracy.

The five-layer architecture proposed in this chapter structures next-generation ergonomic assessment into data acquisition, feature extraction, ergonomic interpretation, confidence-uncertainty assessment, and intervention decision. This approach makes the connection between measurement technology and ergonomic decision explicit and facilitates identification of the layer at which an error occurs.

Within this framework, the central direction of next-generation physical ergonomics is not “automatic score generation.” The more fundamental transformation is a shift from one-time assessment to long-term exposure profiles, from general risk classes to cause-oriented explanation, and from static reports to timely intervention. The next chapter extends this transformation beyond physical measurement to cognitive ergonomics, human-AI interaction, and human-robot collaboration.

Statement on the Use of Generative AI

In preparing this book, the authors used OpenAI’s ChatGPT as an assistive tool for the English translation of the original Turkish manuscript, language editing, consistency checking, and document formatting. The authors reviewed and revised the resulting text and take full responsibility for the accuracy, interpretation, and final content of the book.

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Chapter 3

Cognitive Ergonomics, Human–AI Interaction, and Human–Robot Collaboration

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ABSTRACT

Digitalization and automation are transforming not only the physical tasks performed by workers but also the ways in which they perceive, attend, decide, monitor, and coordinate. Consequently, ergonomic design in modern work systems cannot be limited to reducing physical load; it must also systematically consider how technology redistributes cognitive workload, how it affects human situation awareness, and when people should rely on automation. This chapter treats cognitive ergonomics as the common foundation of human–artificial intelligence and human–robot collaboration. After explaining mental workload, situation awareness, attention, decision making, and error mechanisms, subjective, performance-based, and psychophysiological measurement approaches are compared. Neuroergonomics is discussed together with the practical contributions and limitations of EEG, eye tracking, heart rate variability, and electrodermal activity for field decisions. The second half of the chapter examines the ironies of automation, automation bias, overtrust and undertrust, explainable artificial intelligence, human oversight, and appropriate trust calibration. Human–robot collaboration is considered in a framework broader than physical safety, including cognitive workload, predictability, role clarity, pace, psychological safety, and task allocation. The Human–AI–Robot Task Allocation Framework proposed at the end of the chapter evaluates each task along six dimensions—human capability, AI capability, robotic capability, ergonomic cost, uncertainty, and error consequence—and links these dimensions to four fundamental work-design options: retain with the human, support with AI, collaborate with a robot, and conditional automation. Cognitive ergonomics therefore shifts the central question away from how closely technology resembles a human and toward how safely, intelligibly, and sustainably humans and technology can form a joint work system.

Keywords: cognitive ergonomics, mental workload, neuroergonomics, human–AI interaction, trust in automation, explainable artificial intelligence, human–robot collaboration, task allocation

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1. INTRODUCTION

Technological development in industrial systems was long evaluated primarily in terms of reducing physical labor. Mechanization replaced muscular effort, automation assumed repetitive operations, and robots removed heavy and hazardous tasks from workers. Yet the reduction of physical load did not eliminate human-factors problems. In many contemporary jobs, the nature of the load has changed: cognitive activities such as monitoring processes, detecting exceptions, integrating multiple information sources, evaluating automation recommendations, and taking over the system when necessary have become more important than direct physical execution. This shift requires ergonomics to move beyond physical workstation design and to treat decision and information-processing processes as explicit objects of system design.

Cognitive ergonomics examines the relationship between work systems and mental processes such as perception, attention, memory, mental workload, decision making, situation awareness, and human–technology interaction. Its central question is not how to provide workers with more information, but how to present the right information at the right time and in the right form. The assumption that decision quality automatically improves as the amount of information increases is incorrect. Excessive alarms, unnecessary displays, frequent task switching, and ambiguous automation behavior can make an apparently light physical job cognitively demanding.

Digitalization makes this problem even more important. AI-based decision-support systems, production-planning software, predictive-maintenance algorithms, automated quality inspection, autonomous mobile robots, and collaborative robots increasingly participate in the same decision loop as the worker. These systems are not merely tools: they select information, generate recommendations, sometimes act autonomously, and thereby alter the distribution of human attention, decision strategies, and perceptions of responsibility. This is where the ergonomic character of human–AI interaction becomes visible: high algorithmic accuracy does not guarantee high system-level performance unless the human uses the system appropriately.

Similarly, safety in human–robot collaboration means more than preventing the robot from striking the worker. Ergonomic safety also requires that the worker can anticipate what the robot will do, understand their own role, avoid being forced to keep pace with the robot, know when control can or should be transferred, and understand how the system behaves when an error occurs. Villani et al. (2018) emphasize that industrial human–robot collaboration requires safety, intuitive interfaces, and application design to be considered together. This illustrates why

physical and cognitive ergonomics are becoming increasingly inseparable in smart manufacturing systems.

The purpose of this chapter is not to present human–AI and human–robot interaction as a catalogue of technologies. Rather, it is to show how emerging technologies reorganize the human cognitive role and how industrial engineering decisions can account for this change. The chapter first addresses the core components and measurement approaches of cognitive performance, then turns to automation and trust, human–AI collaboration, and human–robot work systems. In the final sections, task allocation is framed not as the binary question of “human or machine?” but as a multidimensional design problem that jointly evaluates the complementary capabilities of humans, AI, and robots together with their ergonomic costs.

2. THE BASIC STRUCTURE OF COGNITIVE ERGONOMICS: FROM PERCEPTION TO ACTION

Cognitive ergonomics does not treat the human as a decision maker with unlimited information-processing capacity. Instead, it views the human as a system component with limited attention and working memory but strong capabilities for experience-based reasoning, pattern recognition, and contextual judgment. Within this perspective, performance is not simply the product of individual ability. Task structure, interface design, time pressure, level of automation, alarm configuration, organizational procedures, and team communication jointly shape cognitive performance. Error therefore cannot usually be explained only as “worker inattention”; the information architecture and work design that place the worker in particular decision conditions must also be examined.

Perception is the first stage through which information from the system is selected and transformed into meaningful patterns. In industrial work, a worker may simultaneously monitor screen values, colors, auditory alarms, machine motion, product appearance, and the behavior of coworkers. Yet not all visible information has equal perceptual importance. A critical alarm may be lost among many low-priority alarms, or an important indicator may be displayed in a form that is difficult to read. In such cases, human performance may deteriorate even though the information is technically available.

Attention is a limited resource, and the allocation of that resource is an important design problem in modern work systems. If an operator is monitoring machine status while checking a production order, evaluating a quality alert, and tracking robot movement, the tasks compete for attention. Task switching causes more than a few seconds of time loss; it also requires reconstruction of the context held in working memory. From the standpoint of cognitive ergonomics, therefore,

“adding more information to a screen” and “providing better support to an operator” are not equivalent.

Working memory refers to the limited capacity for holding information temporarily during decision making. Designs that require operators to remember numerous codes, temporary targets, or processing steps can increase the likelihood of error. External memory aids, appropriate visual grouping, visible process steps, and context-sensitive assistance can reduce this burden. Excessive automation, by contrast, may remove workers from the information-processing loop and make it more difficult for them to understand the system when intervention becomes necessary.

Decision making should not be understood merely as choosing among alternatives; it includes recognizing the problem, interpreting information, anticipating possible outcomes, and monitoring the action taken. Under high uncertainty, people may rely on heuristics, while experienced operators can rapidly recognize patterns encountered in the past. AI systems can also provide powerful pattern recognition, but human contextual knowledge and the statistical inference of an AI model are not the same type of knowledge. Effective collaboration requires understanding the conditions under which these two information sources complement one another. These core cognitive processes, their associated work-system questions, common risks, and corresponding ergonomic design principles are summarized in Table 1.

Table 1. Core cognitive processes and their work-design implications

Cognitive process	Work-system question	Common risk	Ergonomic design principle
Perception	Can critical information be distinguished?	Alarm/display clutter, low visibility	Prioritization, differentiation, perceptual compatibility
Attention	How many sources must the worker monitor at the same time?	Divided attention, task interruption	Reduce unnecessary notifications, support focused attention
Working memory	How much information must be kept in mind?	Code and step burden, forgetting	External memory aids, process visibility, effective grouping
Decision making	Are alternatives and consequences understandable?	Time pressure, uncertainty, bias	Decision rationale, comparable alternatives
Situation awareness	Are current state, meaning, and trajectory visible?	Automation surprise, loss of process awareness	Present state + cause + projection together

Situation awareness is a central concept in cognitive performance within dynamic systems. Endsley (1995) conceptualized situation awareness at three levels: perception of elements in the environment, comprehension of their meaning, and projection of their status in the near future. In a production environment, this means not only seeing the current machine temperature but also understanding why it is rising and anticipating what continued increase could imply for production or safety. If automation shows only an outcome while hiding how the process is developing, it may reduce workload in the short term while weakening situation awareness over time. The interaction among perception, interpretation, anticipation, decision making, and subsequent monitoring can be represented as a continuous cognitive work cycle, as illustrated in Figure 1.

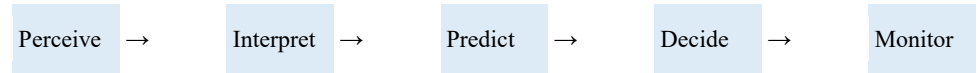


Figure 1. Simplified representation of the cognitive work cycle from an ergonomic design perspective

Figure 1 should not be read as a linear model of human information processing, but as a continuously feedback-driven work cycle. In real work, the outcome of an action generates new information and the worker enters the next perception–decision cycle. AI and automation can enter at any point in this loop: they may filter information, interpret it, predict future conditions, recommend actions, or execute actions directly. From an ergonomic design perspective, the critical question is not only where automation enters the loop, but also what information the human loses when it does so.

3. MENTAL WORKLOAD: MEASUREMENT, INTERPRETATION, AND USE IN DESIGN

Mental workload is a fundamental ergonomic concept used to describe the relationship between the cognitive demands of a task and the mental resources a worker uses to meet those demands. Workload, however, is not a one-dimensional quantity. The same task may be routine for one worker and highly demanding for another; the same worker may also experience different levels of load as fatigue, experience, or time pressure changes. Work organization and temporal factors, including shift-work arrangements, may further influence worker fatigue and performance and therefore form part of the broader context in which workload should be interpreted (Hatipoğlu & Fırlalı, 2025). Mental workload is therefore neither purely a property of the task nor merely a subjective feeling of the

individual; it emerges from the interaction among the person, the task, and the context (Fıǧlalı & Fıǧlalı, 2025).

From an ergonomic perspective, excessively low workload can be as problematic as excessively high workload. Dense decision requirements and alarm traffic may generate errors, delays, and stress, whereas prolonged passive monitoring may reduce vigilance and attention. Bainbridge (1983) showed that one of the ironies of automation is that it can turn the human into a passive monitor when the system is operating normally while demanding the highest level of cognitive performance precisely when abnormal conditions arise. Accordingly, the aim of good design is not to “minimize workload,” but to create a workload range compatible with the task and with human capacity.

Three major approaches are used to measure mental workload: subjective assessment, performance-based measurement, and physiological or psychophysiological measurement. Subjective instruments directly ask workers about their experience and are economical in practice. NASA-TLX is one of the most widely used tools in this area, assessing workload through mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart & Staveland, 1988; Hart, 2006). A key strength of subjective scales is that they do not reduce a complex experience to a single sensor signal. Their results, however, may be influenced by retrospective recall, individual use of rating scales, and social expectations.

Performance measures examine how workload is reflected in task behavior. Reaction time, error rate, production quality, secondary-task performance, and decision delay can all be used for this purpose. Preserved performance does not necessarily imply low workload; a worker may maintain performance by exerting additional effort. Performance data are therefore often more informative when interpreted together with effort or physiological response.

Physiological measures offer the advantage of continuously tracking changes in mental load independently of subjective report. Heart rate and heart rate variability, electrodermal activity, pupil diameter, blink behavior, and EEG indicators have all been used for this purpose. In their systematic review of physiological measures of mental workload, Charles and Nixon (2019) show that no single physiological indicator can serve as a universal workload measure across all tasks and contexts. The sensitivity of each signal to the task, physical activity, and environmental conditions must therefore be considered.

For industrial engineering applications, the value of workload measurement lies not merely in producing a score but in changing system decisions. If two interface designs yield the same production output, the design that generates fewer errors and a more balanced mental workload may be preferable. Similarly, task allocation

can be designed not only around processing time but also to prevent successive accumulation of cognitively intensive tasks. Mental workload thereby moves from being an isolated research outcome to becoming a work-design parameter. The main characteristics, strengths, limitations, and appropriate application contexts of these measurement approaches are compared in Table 2.

Table 2. Comparison of mental workload measurement approaches

Approach	Examples	Strength	Limitation	Appropriate use
Subjective	NASA-TLX, post-task ratings	Low cost; captures direct experience	Affected by recall and subjective scaling	Condition comparison, field assessment
Performance	Errors, time, secondary task	Directly linked to task outcome	Extra effort may mask high workload	Interface and procedure comparison
Eye behavior	Gaze distribution, pupil, blinking	Rich evidence on attention allocation	Affected by lighting and visual-task characteristics	Control rooms, displays, monitoring work
Autonomic physiology	HR/HRV, EDA	Continuous and portable measurement	May be confounded by physical activity and stress	Long-term workload trends
EEG	Band power, event-related indicators	Closer to central nervous system response	Artifacts, equipment, and interpretive complexity	Controlled tasks, research, advanced field studies

4. NEUROERGONOMICS AND PSYCHOPHYSIOLOGICAL MEASUREMENT: FROM BRAIN SIGNAL TO WORK-SYSTEM DECISION

Neuroergonomics has developed as an interdisciplinary approach that links human performance to measurements of the brain and nervous system under real or realistic work conditions. Parasuraman and Rizzo (2006) positioned neuroergonomics as the study of the brain at work, and subsequent research has applied it to cognitive and physical workload, attention, fatigue, and human–automation interaction. Mehta and Parasuraman (2013) emphasize that neuroergonomic methods can complement traditional ergonomic measures of physical and cognitive work.

EEG is among the most frequently used neurophysiological tools for studying cognitive states. Changes in power across different frequency bands can be associated with attention, arousal, or mental workload. These relationships are context-sensitive, however, and simple rules such as “higher theta equals higher workload” should not be transferred directly to field decisions. Head and facial movement, muscle activity, blinking, and electrical interference can all affect EEG

recordings. These artifacts become particularly important in industrial settings where the worker is mobile rather than seated under laboratory conditions.

Eye tracking is a powerful cognitive-ergonomics tool closely related to neuroergonomics, although it does not directly measure brain activity. The location of gaze, time to reach critical information, visual scanning patterns, and fixation duration within specific areas can provide direct evidence about interface and task design. When an operator makes an incorrect decision, for example, eye tracking can go beyond the fact that “the wrong option was selected” and help determine whether the critical information was ever seen.

Autonomic indicators such as heart rate variability and electrodermal activity are well suited to long-duration recording with wearable sensors. Shaffer and Ginsberg (2017) note that heart rate variability includes numerous time- and frequency-domain metrics whose interpretation depends on measurement conditions. A central challenge in industrial ergonomics is that mental workload and physical activity can produce physiological responses simultaneously. Is an increase in heart rate due to decision stress, walking, or a hot environment? A single signal cannot always distinguish these causes.

For this reason, multimodal measurement has become increasingly important in contemporary cognitive ergonomics. Time-synchronizing task records, performance, gaze behavior, and physiological signals can reduce the ambiguity associated with any single indicator. Yet more sensors do not automatically produce a better model. As the number of sensors grows, so do calibration demands, synchronization complexity, worker acceptance issues, data-storage requirements, and privacy concerns.

One of the most valuable contributions of neuroergonomics to industrial engineering is its ability to compare task and technology designs not only through output performance but also through the otherwise invisible cognitive cost imposed on the worker. At the same time, broad conclusions about an individual’s capability, motivation, or reliability should not be inferred casually from brain signals. The ergonomic objective is not to “read” the worker, but to understand the cognitive demands created by the work system and to redesign that system when necessary. Accordingly, the interpretation of neuroergonomic data can be structured as a sequence linking task context, observable behavior, physiological signals, integrated interpretation, and work-system decisions, as shown in Figure 2.

Within this chain, a physiological signal does not produce a decision by itself. It is interpreted together with task context and behavioral performance. Such an approach can reduce false causal inferences and connect ergonomic interventions directly to measurable characteristics of the work system.



Figure 2. Proposed interpretation chain for converting neuroergonomic data into work-system decisions

5. COGNITIVE ERGONOMICS OF AUTOMATION: USE, MISUSE, AND SITUATION AWARENESS

Automation can be broadly defined as technology performing all or part of a function that would otherwise be performed by a human. Yet “level of automation” is not one-dimensional. Parasuraman, Sheridan, and Wickens (2000) showed that automation may occur at different levels across distinct functional stages such as information acquisition, information analysis, decision and action selection, and action implementation. A system may, for example, merely detect abnormal temperature, analyze its cause, recommend an action to the operator, or stop the machine directly. These designs are not equally automated and they alter the human cognitive role in different ways.

The primary ergonomic benefit of automation is the transfer of routine, high-volume information processing away from the human. Algorithms can monitor thousands of sensor values, identify rare patterns, and increase decision speed. At the same time, because automation changes how people interact with the system, it can create new forms of error. Parasuraman and Riley (1997) distinguish appropriate use from misuse, disuse, and abuse of automation, emphasizing that performance depends not on merely possessing technology but on using it appropriately.

Automation bias can occur when users place excessive weight on an automated recommendation or stop searching for a problem when the system does not issue an alert. Parasuraman and Manzey (2010) show that automation-related complacency and bias are closely linked to attention processes. Paradoxically, the problem may become stronger when a system is highly accurate: after long periods without witnessing an error, users may become less likely to question it.

At the opposite extreme is undertrust in automation. If users continually reject recommendations or conduct unnecessary manual verification even when a system is highly reliable, the potential performance advantage of automation is lost. The ergonomic target is therefore not maximum trust, but appropriate or calibrated trust. Lee and See (2004) emphasize that trust should be designed to support appropriate reliance on automation. Hoff and Bashir (2015) likewise show that trust is dynamic, shaped jointly by personal disposition, system characteristics, and experience of use.

Another risk is that automation can distance workers from system dynamics. When the system conducts most operations on its own, workers use their process

knowledge less often, may lose skill in taking over during rare failures, and can experience “automation surprise.” Bainbridge’s (1983) classic irony remains relevant: as automation reduces the human role in routine work, it may require greater expertise in the exceptional situations the automation cannot manage. Keeping the human in the loop therefore means more than adding an approval button; work must be designed so that the worker can understand system status and maintain relevant skills.

Adaptive automation addresses this problem by changing the allocation of functions between human and automation over time and according to system state. Certain functions may shift to automation during high workload, while the human takes a more active role when workload is low. Although this approach can theoretically balance workload, unpredictable or unexplained transitions may create new cognitive costs. If the worker must repeatedly ask, “Am I responsible now, or is the system?”, role ambiguity is already present. The principal cognitive risks associated with automation and the ergonomic measures that can be used to address them are summarized in Table 3.

Table 3. Major cognitive risks in automation design and ergonomic countermeasures

Risk	Typical manifestation	Possible system consequence	Ergonomic countermeasure
Automation bias	Accepting a recommendation without sufficient questioning	Scaling of an incorrect recommendation	Confidence/evidence display, independent checkpoint
Undertrust	Persistent rejection or double checking	Time loss, nonuse of automation	Reliability feedback, understandable error boundaries
Loss of situation awareness	Operator cannot explain how the process is evolving	Late or incorrect takeover	Visibility of process state + cause + projection
Skill degradation	Reduced performance in rare manual operations	High risk during abnormal conditions	Periodic manual practice, simulation, training
Role ambiguity	Responsibility is unclear	Delay, duplicate action, or omission	Clear authority boundaries and transition protocols

6. HUMAN–AI INTERACTION: FROM ACCURACY TO APPROPRIATE TRUST

AI-based systems differ from classical automation in several important ways. Machine-learning models may rely on patterns learned from data rather than explicit rules, generate probabilistic outputs under uncertainty, and lose performance when the domain of use changes. For users, this can make it difficult to understand why a particular recommendation was generated and to anticipate the conditions under which the system may fail. The ergonomic design of human–AI interaction therefore extends beyond interface usability to include trust, explanation, communication of uncertainty, and responsibility for decisions.

Amershi et al. (2019) proposed guidelines for human–AI interaction that include explaining what the system can do and how well it can do it, showing system status in a timely manner, making incorrect behavior easy to correct, and learning from user feedback. The common theme is that an AI system should not be designed as an opaque “smart box,” but as a work partner whose capabilities, limits, and behavior are understandable.

Explainability lies at the center of this discussion, but not every explanation is useful. Miller (2019) shows that people evaluate explanations selectively and comparatively within a social context. A quality-control AI that states “92% probability of defect” provides different decision support from one that says “the texture pattern near the edge differs from the normal class; similar examples were defective.” Yet more detailed explanation is not always better. Under time pressure, lengthy technical explanations can increase cognitive workload.

One reason accuracy alone is insufficient for designing appropriate trust is that the cost of error depends on context. Two AI systems that are both 95% accurate may not have the same ergonomic risk. In one system, the remaining 5% may consist of low-cost recommendations that are easy to detect and reverse; in another, the same error rate may include missed safety-critical conditions. Users therefore need information not only about overall accuracy, but also about uncertainty, the type of case the model is encountering, and the consequence of a potential error.

Human oversight cannot be solved by simply attaching a “human-in-the-loop” label. If a person must approve every AI decision but lacks adequate time or information, oversight becomes merely procedural. The human then serves as a final stamp on the system’s decision and automation bias may persist. Effective oversight requires the user to have the information needed to evaluate the decision, sufficient decision time, authority to select an alternative action, and a meaningful mechanism for objection or override.

From a cognitive-ergonomics perspective, the success of an AI-supported decision system should be evaluated through the combined quality of algorithmic

output and human decision making. An AI system may be 95% accurate and a person 90% accurate when working alone; if the joint system is only 93% accurate, “adding AI” has not improved system performance. Inappropriate trust, poor explanation, time pressure, or unclear responsibility may account for the loss. Human–AI performance is therefore a property of the combined system.

Shneiderman (2020) argues within human-centered AI that high levels of human control and high levels of automation are not necessarily mutually exclusive. This idea is particularly important for industrial ergonomics: the goal is not to reduce automation, but to increase automation capability together with human capacity for oversight, understanding, and intervention. It also supports viewing trust in technology as a designable system property rather than merely a personal attitude.

Another critical factor in human–AI performance is how the recommendation is presented. If users see the AI recommendation before forming their own judgment, the initial recommendation may become a cognitive anchor and influence subsequent reasoning. On the other hand, requiring a fully independent human assessment before every AI-supported decision can increase time and workload. Decision architecture should therefore depend on consequence and AI reliability. Independent initial assessment or a second check may be valuable for safety-critical, uncertain, and irreversible decisions, whereas rapid joint assessment may be preferable for high-volume, low-consequence decisions.

The timing of explanations also matters. Displaying the entire technical rationale of an AI system before every decision can overload the interface, especially in routine work. Layered explanation can provide a more ergonomic alternative: the user first sees the recommendation, level of confidence, and two or three key reasons, with access to more detailed evidence when needed. Explainability then becomes a problem of making the information required for a decision accessible, rather than displaying the maximum possible amount of information.

The visibility of evidence that could contradict the AI recommendation is also important for appropriate trust. If an interface highlights only indicators that support the AI’s conclusion, users may find it difficult to generate alternative hypotheses. In maintenance, quality, and safety decisions in particular, counterevidence or boundary information that helps answer “what observation would weaken this recommendation?” can be useful. This positions AI as a testable decision partner rather than a single authority. Taken together, these considerations provide a practical set of design questions for human–AI decision support, summarized in Table 4.

Table 4. Ergonomic design checklist for human–AI decision support

Design dimension	Question to ask	Risk of inadequate design
Capability boundary	Under which conditions does the AI perform well or poorly?	User may assume universal capability
Uncertainty	Is confidence or ambiguity in the recommendation visible?	Perception of unjustified certainty
Explanation	Is there enough rationale to support user action?	Blind acceptance or unnecessary doubt
Correctability	Can the user correct an incorrect output?	Errors persist and learning is weakened
Authority	Are final decision rights and responsibility clear?	Role ambiguity and delay
Feedback	Are past performance and error types visible?	Trust calibration deteriorates

Appropriate trust can therefore be understood as a dynamic process in which AI output is reviewed, translated into a decision, and continuously recalibrated through feedback, as illustrated in Figure 3.

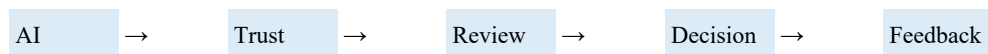


Figure 3. Closed-loop human–AI decision cycle supporting appropriate trust

7. HUMAN–ROBOT COLLABORATION: FROM PHYSICAL PROXIMITY TO JOINT WORK

In traditional industrial robotics, the primary safety strategy was to physically separate people and robots. Protective fencing and access restrictions allowed robots to operate at high speed and force while keeping workers outside the hazard zone. Collaborative robots and advanced sensing systems have enabled new designs in which humans and robots can share the same workspace. Physical proximity, however, is only the beginning of genuine collaboration. Joint work requires robot behavior to be predictable, timing to be understandable, and division of labor to be sustainable from the human perspective.

The human–robot interaction literature considers safety, performance, and trust together. Goodrich and Schultz (2008) define human–robot interaction broadly to include communication and coordination of joint tasks between people and robots. Hancock et al. (2011) show that trust in human–robot interaction is influenced by robot characteristics, environmental conditions, and human factors. Sheridan (2016) likewise emphasizes that human–robot interaction involves not only safety but also control, autonomy, and the role of the human.

Physical risks in industrial human–robot collaboration may include collision, entrapment, unexpected movement, and ergonomically inappropriate joint pace.

Standardization efforts such as ISO/TS 15066:2016 have contributed to defining safety strategies for collaborative robot applications. Ergonomic assessment, however, must go beyond compliance with technical safety conditions. If a robot relieves a worker from heavy lifting but requires the worker to bend repeatedly into the robot workspace or accelerate continuously to keep up with the robot cycle, physical risk may merely have changed form.

From a cognitive perspective, robot predictability is critical. If a person cannot anticipate the robot's next movement, substantial mental workload and tension may occur even within a physically safe system. Visual, auditory, or movement-based cues can make the robot's motion onset, target, and stopping intention more understandable. Too many signals, however, can create warning clutter. The design goal should be to communicate critical intent with the lowest reasonable cognitive burden.

Role clarity is a second foundation of joint work. It should be explicit which assembly step is performed by the human, which by the robot, and who takes over when an error occurs. Constantly changing task allocation that is not explained to the user may make a system appear "smart" while disrupting the worker's mental model. Ajoudani et al. (2018) link the future of human-robot collaboration to integration of physical interaction, perception, and adaptive control, while emphasizing the need to understand human intent and exploit complementary capabilities.

Work pace is also an ergonomic variable. If a robot operates at a fixed cycle and the human must repeatedly accelerate to compensate for small delays, both physical and cognitive pressure can increase. In human-centered collaboration, the robot should not slow down only when a safety sensor is triggered; it should also be designed to accommodate human variability within the task flow and the need for recovery. This issue is directly related to the scheduling and optimization problems addressed in Chapter 4.

Psychological safety and acceptance are also important, though sometimes neglected, dimensions of collaboration. A worker may perceive that the robot is monitoring them or that their performance is being evaluated algorithmically, which can affect acceptance even if the technical system is safe. Similarly, workers concerned that the robot may replace their job require more than technical training. A human-centered implementation should treat workers as sources of knowledge and stakeholders in the design process.

When evaluating collaborative cells, the questions "is the robot safe?" and "is the work safe?" should be separated. A robot may meet technical speed-force limits, yet the operator may repeatedly twist the trunk to reach parts, maintain static posture while waiting for robot movement, or forgo micro-recovery periods to

avoid missing the cycle. Safety validation is therefore necessary but not sufficient for ergonomic adequacy.

Adaptation of robot behavior should also not be reduced to lowering speed. Changing task sequence, presenting parts in a more ergonomically favorable position, switching the robot to another subtasks while the worker’s hand is in a shared zone, or turning micro-waiting periods into recovery opportunities can reduce physical and cognitive load together. Such decisions require robot control and production scheduling to be integrated around ergonomic objectives.

Trust in human–robot team performance also changes with experience. A new user may initially behave very cautiously; as the robot demonstrates predictable and reliable behavior, working distance and pace may change. Conversely, a single unexpected movement can rapidly reduce trust. Acceptance should therefore not be measured only on the installation day; trust, behavior, and ergonomic exposure should be observed over time. These physical, cognitive, organizational, and acceptance-related dimensions of human–robot collaboration are brought together in Table 5.

Table 5. Ergonomic assessment dimensions in human–robot collaboration

Dimension	Assessment question	Possible indicator	Design target
Physical safety	Are collision and entrapment risks controlled?	Distance, speed, force, stopping behavior	Safe shared workspace
Physical ergonomics	Does the robot truly reduce demanding human load?	Posture, force, repetition, static load	Net exposure reduction
Cognitive workload	How much effort is required to monitor robot behavior?	NASA-TLX, error, attention distribution	Balanced monitoring load
Predictability	Can the human understand the robot’s next movement?	Prediction accuracy, hesitation, takeover	Transparent motion and intent
Role clarity	Are task and responsibility boundaries clear?	Role error, duplication, waiting	Explicit task sharing
Pace and control	Is the human forced to adapt to robot speed?	Micro-waiting, rushing, recovery	Human-adaptive pace
Acceptance and trust	Does the worker want to use and appropriately trust the system?	Trust/acceptance scales, use behavior	Appropriate trust and participation

8. TASK ALLOCATION: BEYOND THE QUESTION “HUMAN OR MACHINE?”

Allocation of functions between people and technology is one of the oldest questions in automation design. Traditional approaches assume that humans are comparatively strong in flexible perception, judgment, and dealing with uncertainty, whereas machines are strong in speed, force, repeatability, and computation. This distinction remains a useful starting point, but it is insufficient

for modern AI and robotic systems. Technological capabilities now change rapidly from task to task, while human performance also varies with experience, fatigue, and context.

Designing task allocation simply by “assigning the task to whoever performs it best” can create system-level problems. An AI system may detect defects more accurately than a human, yet fully automating all quality decisions may weaken human process knowledge and reduce intervention skill for rare defect classes. Likewise, a robot may execute a fastening operation faster, but in a high-variety product environment frequent reprogramming and exception handling may reduce overall system performance.

Ergonomic task allocation should consider short-term process performance together with long-term human capability. Assigning a task to a robot may reduce physical load but leave the human with only monotonous monitoring and high-stress exception handling. Such a design may lower muscular load while weakening mental well-being and skill variety. The ergonomic effect of an automation decision should therefore be assessed across the entire portfolio of tasks.

It is also important to distinguish AI from robotics. AI often performs information processing, prediction, classification, and recommendation, whereas a robot can execute physical actions. A production problem may combine the two sequentially: AI detects a defect, a human validates the recommendation, and a robot removes the defective part. Performance in such a system depends not only on the accuracy of an individual component but also on the design of information and authority transitions.

Task allocation must also consider the consequence of error. High automation may be acceptable for low-risk, easily reversible decisions, while safety-critical and irreversible decisions may require human verification. Human verification, however, has value only when the person retains the capacity to conduct an independent assessment. Otherwise, a formal approval step merely increases process time. The complementary strengths, limitations, and potential roles of humans, artificial intelligence, robots, and combined human–technology arrangements are summarized in Table 6.

Table 6. Typical complementary capabilities of humans, artificial intelligence, and robots

Actor	Relative strengths	Typical limitations	Example suitable roles
Human	Context, intuition, value judgment, flexibility, rare events	Fatigue, attention limits, physical capacity	Exception handling, final judgment, creative problem solving
Artificial intelligence	Large datasets, pattern recognition, rapid prediction and classification	Domain shift, limitations in explanation and causality	Decision support, prediction, prioritization, anomaly screening
Robot	Force, precise repetition, high pace, hazardous environments	Limited flexible physical skill; cost of perception and reconfiguration	Handling, repetitive assembly, precise physical execution
Human + AI	Contextual judgment + data patterns	Inappropriate trust and role ambiguity	Assisted diagnosis, quality decisions, planning
Human + robot	Flexibility + physical support	Pace, trust, and coordination burden	Joint assembly, material handling, physical assistance

Task allocation is therefore a multi-criteria design problem from an industrial engineering perspective. In addition to processing time, quality, capacity, and cost, relevant criteria include physical load, mental workload, skill use, learning, uncertainty, error consequence, explainability, and worker acceptance. This perspective provides a conceptual bridge to the multiobjective ergonomic optimization discussed in Chapter 4.

9. AUTHOR SYNTHESIS: HUMAN–AI–ROBOT TASK ALLOCATION FRAMEWORK

Drawing on the literature reviewed in this chapter, task allocation is proposed as a system-centered rather than technology-centered process. The framework below is not an established standard or a single validated scale; it is a conceptual synthesis intended to translate findings from human factors, trust in automation, and human–robot collaboration into industrial engineering decisions. Its purpose is to replace the question “which technology should be used?” with the question “which task structure and human–technology role distribution produce the most sustainable overall performance?”

The first step is to define the task unit appropriately. “Quality inspection” may appear to be a single task, yet it can consist of collecting an image, detecting a defect, classifying the defect, evaluating confidence in the decision, removing the part, and investigating root cause. These subtasks do not need to be assigned to the same actor. If automation decisions are made without such decomposition, the

meaningful role of the human and the flow of information through the system may become invisible.

The second step is to evaluate each subtask along six dimensions: human capability, AI capability, robotic capability, ergonomic cost, uncertainty, and error consequence. Human capability reflects the need for contextual judgment, flexibility, and experience; AI capability reflects the learnability of the data pattern; robotic capability reflects the repeatability of physical execution. Ergonomic cost includes both physical and cognitive load. Uncertainty captures task predictability, while error consequence reflects the effect of an incorrect decision on safety, quality, and the wider system.

The third step is to select among four basic design options: retain the task with the human, support the human with AI, create human–robot collaboration, or use conditional automation. The word “conditional” is important: routine, high-confidence cases may be automated while uncertain or high-consequence cases are routed to a human. Automation thereby becomes more than a binary on/off choice.

The fourth step is to re-evaluate the complete task portfolio. Even if each subtask is allocated well in isolation, the overall design is not ergonomic if the remaining human work consists only of tedious monitoring, high-stress exceptions, or physically monotonous tasks. The final assessment should therefore consider physical load, mental workload, skill variety, learning opportunities, and sense of control across the entire shift and role.

The resulting task-allocation process can be represented as a five-step sequence—Split, Skill, Load, Role, and Validate—as illustrated in Figure 4.

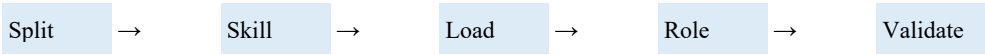


Figure 4. Five-step decision process of the Human–AI–Robot Task Allocation Framework

The six decision dimensions underlying this allocation process and the implications of high values on each dimension are detailed in Table 7.

Table 7. Decision dimensions of the Human–AI–Robot Task Allocation Framework

Decision dimension	Core question	What does a high value suggest?
Human capability	Does the task require context, judgment, empathy, flexibility, or rare-event knowledge?	Preserve an active human role
AI capability	Can the pattern be learned reliably from sufficient data?	AI support or automated information processing
Robotic capability	Is the physical action structured and repeatable?	Robotic execution or physical collaboration
Ergonomic cost	Is physical or cognitive load high when the task remains with the human?	Prioritize support, redesign, or automation
Uncertainty	Do conditions change frequently or out-of-distribution cases occur?	Human supervision and flexible roles
Error consequence	Would an incorrect decision be irreversible or safety-critical?	Independent verification and controlled authority

Based on these considerations, four fundamental role configurations and their associated ergonomic risks are presented in Table 8.

Table 8. Four basic role designs within the framework

Role design	When is it appropriate?	Human role	Primary ergonomic risk
Retain with human	High context, rare events, value judgment; manageable ergonomic load	Primary decision/action owner	Excessive cognitive or physical load
Support with AI	Strong data pattern; contextual evaluation of the decision is still needed	Evaluates recommendation and decides	Overtrust or unnecessary double checking
Collaborate with robot	High physical load; task requires flexibility and joint work	Performs flexible/fine work while robot provides physical support	Pace, predictability, proximity stress
Conditional automation	Routine cases can be automated with high confidence and uncertain cases can be identified	Manages exceptions and high-consequence cases	Skill degradation and rare-event takeover

An important implication of the framework is that it does not equate “the highest level of automation” with “the most advanced work system.” An effective design may combine high automation for some tasks, AI-supported human judgment for others, and direct human control for still others. The criterion of

success is not technology intensity but the joint preservation of overall system performance and sustainable human performance.

Application Example: AI-Supported and Robot-Collaborative Assembly Cell

To illustrate how the framework can be used, consider a hypothetical high-mix assembly cell. The worker positions a part, prepares fasteners, visually inspects critical surfaces, and makes the final assembly decision. The redesigned cell includes an AI system that estimates defect probability from camera images and a collaborative robot that positions a heavy part. At first glance, the objective may appear to be automation of as many tasks as possible. Once the work is decomposed into subtasks, however, a more balanced design emerges.

Heavy lifting of the part has a high physical ergonomic cost and requires relatively little contextual judgment. If the physical movement is structured, robotic capability is high; lifting and coarse positioning are therefore strong candidates for robotic execution. If final millimeter-level alignment depends on product variation and tactile assembly cues, the human's fine motor control can be retained. The robot then removes much of the physical load while the worker does not lose all control over the process.

Visual defect screening has a different structure. Large numbers of images and repeated patterns are well suited to AI, whereas rare defects and production context may still require human judgment. AI can conduct initial screening and automatically classify low-risk, high-confidence examples as normal. For medium-confidence cases or safety-critical defects, the image and the most important reasons are shown to the worker. The interface should allow the worker to access information that is independent of the AI recommendation. In this way, AI directs human attention toward the most valuable cases while the worker contributes exception handling and contextual knowledge.

Preparation of fasteners may be physically light yet repetitive and monotonous. If robotic handling of the small components creates high reconfiguration cost, automation may not be economically attractive. The ergonomic improvement may instead come from redesigning feeder placement, reducing reach distance, and introducing task rotation. The importance of the framework in this example is that it does not equate an ergonomic problem with an automation problem; sometimes the best solution is to redesign the task rather than add technology.

Final validation of the cell should not rely on cycle time alone. Trunk and shoulder exposure, changes in NASA-TLX across the shift, rates at which workers reject AI recommendations, decision time for low-confidence cases, waiting behavior near the robot, and success in taking over during rare error scenarios should all be evaluated. If cycle time improves while the worker is continually

rushing to keep pace with the robot or begins accepting AI recommendations without question, the design should be revised.

This example shows that human–AI–robot design is not a one-time technology selection but a sequential systems-engineering process. Tasks are first decomposed, then capability and ergonomic cost are assessed, role allocation is designed, and finally the system is validated through actual user behavior. Feedback may lead to changes in task boundaries—for example, raising the AI confidence threshold, replanning robot motion sequence, or keeping the worker more active in selected operations. The resulting allocation of the principal subtasks, together with their dominant design issues and proposed validation indicators, is summarized in Table 9.

Table 9. Example task allocation in a hypothetical assembly cell

Subtask	Dominant issue	Recommended role	Validation indicator
Lift heavy part	High physical load	Robot execution + human supervision	Shoulder/trunk load, cycle time, waiting
Final alignment	Product variation and fine motor skill	Retain with human / robot-assisted positioning	Error, time, perceived control
Visual defect screening	High image volume	AI prescreening + human exception decision	False negatives, trust calibration
Fastener preparation	Repetition and reach	Workstation redesign or limited automation	Repetition, reach, cost
Rare fault management	Uncertainty and high consequence	Human-led verification	Takeover time and decision accuracy

10. IMPLEMENTATION AND VALIDATION: HOW SHOULD HUMAN FACTORS BE MEASURED IN INTELLIGENT WORK SYSTEMS?

Technical performance alone is insufficient to demonstrate that a human–AI or human–robot system is ergonomically successful. After deployment, cycle time, production quantity, or model accuracy may improve while mental workload, trust, error detection, or perceived control deteriorates. Evaluation should therefore be multi-criteria and, wherever possible, compare pre-implementation and post-implementation conditions.

The first measurement layer is task performance. Error rate, decision time, cycle time, missed alarms, rework, and takeover success indicate functional performance.

The second layer is human state and experience. NASA-TLX, trust scales, acceptance, perceived control, and role clarity belong here. The third layer is behavioral process: eye tracking, acceptance or rejection of AI recommendations, withdrawal behavior near a robot, waiting, and task-switching patterns reveal how the system is actually being used.

The fourth layer concerns long-term outcomes. A new system may appear engaging and easy to use during the first weeks, yet skill degradation, overtrust, monotony, or new forms of physical load may emerge over months. Strong conclusions about field sustainability should therefore not be drawn from short laboratory experiments alone. If an AI system is updated over time, human–AI interaction should also be reassessed.

The fifth layer is exception performance. Automation may perform extremely well during normal conditions, but its real safety value often becomes visible during failure, uncertainty, or unusual events. Can the worker take over? What information is needed? Does the AI correctly route low-confidence cases? Does the robot stop in an understandable way when unexpected conditions occur? These questions may remain invisible in average performance metrics.

A pragmatic implementation strategy for organizations is to establish a human-factors baseline on a limited task, compare a technology pilot against the same indicators, and then validate exception handling and long-term performance. This converts technology selection from a one-time investment decision into a learning process for work-system design.

Learning effects should receive particular attention in comparative designs. If workers first use a manual system and then an AI- or robot-supported system, part of the improvement in the second condition may reflect experience rather than the technology itself. Where possible, balancing the order of conditions, using comparable tasks, and providing sufficient practice can reduce this confounding. In field studies where full experimental control is impossible, variables such as task complexity, production volume, and worker experience should at least be recorded across pre- and post-implementation periods.

The measurement time window also affects conclusions. A five-minute trial of robot collaboration cannot reveal attention fatigue or static waiting load that develops across a shift. Conversely, an end-of-shift questionnaire alone may miss brief but critical takeover problems. A more balanced assessment therefore combines event-level measurement, cycle-level performance, and shift- or week-level experience data.

Interpretation should consider operational and ergonomic meaning in addition to statistical difference. A small reduction in NASA-TLX may be statistically significant without being large enough to justify redesign, whereas eliminating a rare but safety-critical takeover error may have little effect on average measures but major practical importance. The purpose of human-factors evaluation is not to compress the system into one composite score, but to explain under which conditions and for what reasons the system performs well or poorly. A multilayer evaluation structure combining system performance, human performance,

cognitive and physical ergonomics, trust, acceptance, and long-term or exceptional-condition outcomes is summarized in Table 10.

Table 10. Proposed multilayer evaluation set for human–AI/robot systems

Layer	Example measures	Core question
System performance	Cycle time, quality, error, downtime	Does the technology meet the operational objective?
Human performance	Decision accuracy, takeover, error detection	Does the human–technology system perform better as a whole?
Cognitive ergonomics	NASA-TLX, attention distribution, situation awareness	Does the new system keep cognitive load at an appropriate level?
Trust and acceptance	Trust, use, rejection, perceived control	Does the user trust the system appropriately and accept it?
Physical ergonomics	Posture, force, repetition, pace	Has the robot/automation genuinely reduced physical load?
Long-term/exception	Skill retention, rare-event takeover, change over time	Is the system sustainable over time and under unusual conditions?

11. ETHICS, PRIVACY, AND HUMAN AUTONOMY

When cognitive ergonomics is combined with artificial intelligence and neuroergonomic measurement, ethical concerns extend beyond data security. Gaze patterns, physiological signals, estimated attention levels, and decisions to reject an AI recommendation may be collected for work-design purposes yet later become individual performance profiles. It should therefore be explicit which data are collected, why they are collected, who may access them, and how long they will be retained.

“Cognitive-state estimation” carries a particularly high risk of overinterpretation. If an EEG or HRV model estimates high workload, this does not automatically mean that the worker is incapable, stressed, or prone to error. The model classifies particular signals within a particular task context; it does not establish the individual’s character or general capability. Preserving this distinction is essential both for scientific validity and for worker rights.

Human autonomy is an important design value in decision-support systems. In an environment where acceptance of AI recommendations is tied continuously to performance scoring, a worker may formally have the right to reject the recommendation while feeling unable to do so in practice. Similarly, if robot pace is centrally determined and workers hesitate to use their stop authority, technical control and experienced control are not the same. Ergonomic assessment should therefore include perceived control.

Transparency means more than providing a mathematical explanation of the algorithm. Workers should understand the purpose for which the system is used, which decisions it affects, what data it uses, and what they can do when the system

fails. This organizational transparency is an important component of appropriate trust alongside technical explainability.

A core ethical principle of human-centered technology implementation is that improved technical performance should not transform the worker into a more intensely monitored, less autonomous, or more easily replaceable system component. Ergonomics contributes here not only by reducing risk but also by defending work that remains meaningful, understandable, and sustainable for the human.

12. CONCLUSION: THE EMERGING ROLE OF COGNITIVE ERGONOMICS IN INTELLIGENT SYSTEMS

Cognitive ergonomics is not a secondary field beside physical ergonomics in modern industrial systems; it is a fundamental design layer of human–technology integration. As AI and robotic systems extend physical and information-processing capabilities, they also reorganize human attention, situation awareness, decision making, trust, and the experience of control. The ergonomic success of new technology should therefore be evaluated not only by how quickly or accurately it performs a task, but also by how well people can understand the system, question it when necessary, and work with it sustainably.

Assessment of mental workload requires complementary use of subjective, behavioral, and psychophysiological measures. Neuroergonomic tools can reveal important information about otherwise invisible cognitive processes, but they are easily overinterpreted when separated from task context. Likewise, AI explainability and trust in robots cannot be solved through a single interface feature; system behavior, user experience, and organizational conditions must be considered together.

The Human–AI–Robot Task Allocation Framework developed in this chapter reframes task distribution as a design problem across human capability, AI capability, robotic capability, ergonomic cost, uncertainty, and error consequence rather than as a competition of technical capacities. The objective of automation is therefore not to remove the human from the process, but to combine human strengths in judgment, context, and flexibility with the data-processing capability of AI and the physical execution capacity of robots in a balanced way.

This perspective leads directly to the next chapter. Once it has been determined how tasks should be distributed among people, AI, and robots, an operational question remains: how should those tasks be planned and optimized across workers, time periods, and resources? Chapter 4 addresses this question through ergonomic work design, job rotation, scheduling, and multiobjective decision-support systems.

Statement on the Use of Generative AI

In preparing this book, the authors used OpenAI's ChatGPT as an assistive tool for the English translation of the original Turkish manuscript, language editing, consistency checking, and document formatting. The authors reviewed and revised the resulting text and take full responsibility for the accuracy, interpretation, and final content of the book.

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Chapter 4

Optimization Of Ergonomic Work Systems: Work Design, Job Rotation, and Decision Support

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ABSTRACT

Ergonomic assessment makes the physical and cognitive demands of a work system visible, but measuring risk does not by itself determine how work should be redesigned. From an industrial engineering perspective, the central decision problem is how workers, tasks, workstations, and time periods should be matched so that production objectives, human health, and performance are protected simultaneously. This chapter treats ergonomic work design as an operational decision problem and examines how ergonomic risk indicators can be translated into job-rotation, workforce-scheduling, assembly-line-balancing, and resource-allocation models. It first argues that ergonomic exposure should not be represented only by a single risk score, but should also account for duration, sequence, cumulative dose, body region, recovery opportunity, individual health restrictions, and worker competence. It then discusses the transformation of job rotation from simple task switching into controlled exposure management within mathematical programming and multiobjective optimization. The distinct roles of exact solution methods, goal and lexicographic programming, Pareto-based approaches, genetic algorithms, and multicriteria decision-making methods are differentiated across decision levels. The later sections address dynamic ergonomic decision-support systems by combining wearable sensors, real-time ergonomic measurement, production data, and rolling-horizon replanning. The Ergonomic Work-System Optimization Cycle proposed at the end of the chapter integrates measurement, modeling, optimization, implementation, validation, and adaptation within a single decision architecture. Ergonomics is thus repositioned from a post hoc compliance check to a human-centered optimization component embedded at the outset of production-system decisions.

Keywords: ergonomic work design, job rotation, scheduling, mathematical programming, multiobjective optimization, decision support, human-centered manufacturing, dynamic ergonomics

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1. INTRODUCTION

There is an important methodological distance between identifying an ergonomic problem and solving it within a production system. Determining that a workstation has a high REBA score, measuring high loading in specific muscle groups, or showing that mental workload exceeds an acceptable level provides information needed for intervention; however, it does not automatically determine which task should be performed by whom, in what sequence, for how long, and with which resources. This second question brings ergonomics directly into the planning, scheduling, and optimization domains of industrial engineering.

Traditional production-planning models often focus on variables such as cycle time, capacity, cost, machine eligibility, and due dates. The worker may be represented as a resource with fixed and interchangeable production capacity. In real work systems, however, exposing two workers to the same task may not produce the same ergonomic outcome. Anthropometry, experience, health restrictions, skill, previous assignments, fatigue, and recovery time can change both the feasibility and the risk of an assignment. Human-centered production planning therefore requires the worker to be represented not only through an eligible/ineligible distinction but also through a state that may change over time.

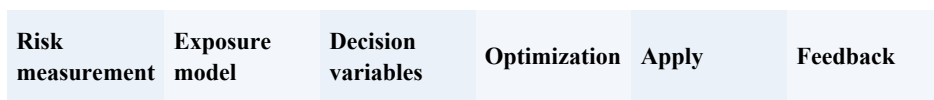
The primary purpose of ergonomic optimization is not to circulate high-risk work among workers. The first priority is to reduce risk at its source through engineering controls and work-design improvements. Job rotation, scheduling, and task allocation are complementary organizational tools for managing residual exposure that cannot be completely eliminated in a more balanced and health-sensitive manner. The fact that evidence on the effectiveness of job rotation for preventing musculoskeletal disorders is not uniformly consistent reinforces this distinction: successful rotation depends not only on changing tasks but also on task exposure profiles, sequence, duration, and worker characteristics (Padula et al., 2017; Otto & Battaia, 2017).

In this chapter, ergonomic work-system design is moved from a logic of “assess and then correct” to one of “measure, translate into a model, generate options, optimize, implement, and reassess.” This is the operational counterpart of the Assessment-Prediction-Optimization-Adaptation chain introduced in Chapter 1. Sensor and computer-vision systems discussed in Chapter 2 provide inputs to decision variables here, while the human-AI-robot task allocation discussed in Chapter 3 is carried to the production-planning level by asking which actor should perform which task. The progression from ergonomic assessment to modeling, optimization, implementation, and adaptation is summarized in Table 1.

Table 1. From ergonomic assessment to optimization

Level	Core question	Typical data	Decision output
Assessment	Where is risk and how high is it?	REBA/RULA/OCRA, force, repetition, sensor data	Risk profile
Modeling	How should risk be represented in the decision model?	Duration, sequence, dose, body region, worker characteristics	Objectives and constraints
Optimization	Who should do what, and when?	Production and ergonomic parameters	Assignment/rotation/schedule
Implementation	Can the plan be implemented in the field?	Skill, shift, transition, acceptance, operational constraints	Implementable plan
Adaptation	How should the plan be updated when conditions change?	Real-time exposure and production state	Replanning

The transformation of ergonomic information into operational decisions through measurement, modeling, optimization, implementation, and feedback is illustrated in Figure 1.

**Figure 1.** From ergonomic information to operational decision

2. RETHINKING ERGONOMIC WORK DESIGN AS A DECISION PROBLEM

In ergonomics, work design is often discussed in terms of the physical layout of the workstation, reach distances, work height, tool placement, or task content. From an industrial engineering perspective, another decision network is added: how work should be decomposed into subtasks, which tasks should be assigned to which stations, which worker should perform which task, in what sequence tasks should be performed across the shift, and where automation should enter the process. Ergonomic work design is therefore not a single design variable but a set of interdependent allocation and sequencing decisions.

An important consequence of this perspective is that ergonomic risk no longer remains a “compliance criterion” checked after the production plan has been created. When ergonomic variables are placed in the objective function,

constraints, or eligibility sets at the beginning of planning, the model can exclude solutions that are infeasible from a human perspective before they are generated. Botti et al. (2017) showed that lean-manufacturing and ergonomic requirements can be addressed jointly in assembly-system design, while Polat et al. (2018) and Kahya and Yetkin (2019) demonstrated that physical workload can be integrated directly into assembly-line-balancing decisions. Their common contribution is to treat ergonomics not as an external inspection activity but as an endogenous component of the decision model.

Not every ergonomic indicator, however, is suitable for direct transfer into an optimization model. Using a score produced by an observational method from a single instantaneous posture as the “workload” of an entire shift can obscure time and movement variability. Likewise, it is not always defensible to assume that scores from different risk methods are linear and additive. During modeling, it must be made explicit what the measurement represents, at what time scale it is valid, and which decision it is intended to support.

A second fundamental distinction in ergonomic work design is between preventive engineering control and exposure distribution. If a workstation is structurally high risk, even the best rotation plan cannot eliminate that risk; it only changes who accumulates the exposure and when. An optimization model should therefore not become locked into “fairly distributing high risk.” Where possible, redesign of hazardous stations should also be treated as a decision option. In the long term, the best system is not merely one that schedules work better, but one that systematically reduces tasks that generate high ergonomic demands.

A third distinction is between feasibility and optimality. A plan may be mathematically optimal but impossible to implement because of workers’ skills, health restrictions, or workplace rules. Conversely, a feasible plan that satisfies all constraints may still be ergonomically unbalanced. Human-centered optimization must address both properties together: solutions that are invalid in terms of health, safety, or operations should first be excluded, and performance-ergonomics trade-offs should then be sought among the remaining solutions. The main variable groups involved in ergonomic work-system decisions, together with their modeling roles and potential risks of misrepresentation, are presented in Table 2.

Table 2. Main variable groups in ergonomic work-system decisions

Variable group	Examples	Role in the model	Risk of poor representation
Task demand	Posture, force, repetition, duration, cognitive load	Risk parameter / objective	Oversimplification through one score
Worker characteristic	Skill, anthropometry, health restriction, experience	Eligibility / capacity	Assuming workers are homogeneous
Time	Period, shift, sequence, recovery	Scheduling dimension	Missing cumulative exposure
Production	Cycle time, demand, capacity, transition	Operational constraint / objective	Making ergonomics operationally infeasible
Technology	Machine, cobot, assistive device	Alternative resource / control	Assuming technology is automatically beneficial

3. MODELING ERGONOMIC EXPOSURE AND WORKLOAD

The quality of an optimization model depends not only on the algorithm but also on the variables used to represent the problem. One of the most critical modeling questions in ergonomic planning is how “workload” should be defined. The same term may refer to a total REBA score, a force-time integral, a repetition count, or subjective fatigue. These indicators do not measure the same phenomenon. The modeling process should therefore begin by identifying the exposure mechanism that the decision is intended to manage.

The first dimension of exposure is intensity. High shoulder flexion, heavy lifting, or high-force hand use can create substantial mechanical demand even over a short period. The second dimension is duration; moderate load can produce a high total dose when sustained for long periods. The third dimension is repetition. The fourth is sequence: the same total exposure may not have the same physiological effect when high-load tasks occur consecutively versus when they are separated by low-load work or opportunities for recovery. Dickhout et al. (2018) showed that task order and differences in the muscle groups used can change the effect of job rotation on fatigue.

Reducing ergonomic workload to a single score may be practical, but multidimensional exposure representation is preferable at least for critical problems. Body-region-based representation is one option. A workstation may have a moderate overall REBA score while creating high local loading for the neck or wrist. This distinction is especially important for workers with health restrictions affecting particular body regions. Yoon et al. (2016) and later

REBA-based rotation studies indicate that managing consecutive high loads by body region is a different decision problem from merely balancing total scores.

Cumulative exposure can be represented by summing loads over the planning horizon or combining them through an appropriate dose function. A pure total, however, loses sequence information. Total exposure can therefore be combined with constraints on consecutive high-load tasks. A worker may end the day with a total risk score similar to that of colleagues but may have performed four tasks stressing the same body region in succession during the first half of the shift. Equality of totals makes the ergonomic character of that sequence invisible.

Recovery can also be an active component of the model. Periods of low load, tasks that use different muscle groups, or planned micro-breaks can be treated as recovery opportunities. Methods such as OCRA, which consider repetition, force, and recovery together, show that ergonomic risk reflects not only the amount of load but also its load-time structure. For optimization, this means consecutive tasks should be evaluated not only in terms of production transition cost but also in terms of biological recovery.

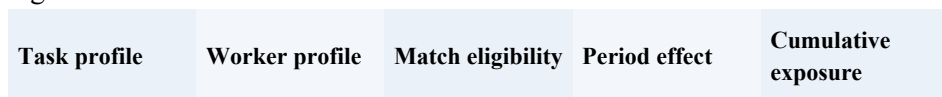
Individual differences are another important consideration. Workers' technical competence, physical capacity, health restrictions, or temporary conditions can change allocation decisions. Asensio-Cuesta et al. (2012) demonstrated that ergonomic and competence criteria can be combined in job-rotation planning, while Rinaldi et al. (2022) showed that skill and ergonomic constraints can be considered within the same workforce-scheduling model. These studies suggest that the assumption "same job = same load for everyone" is often invalid in real work systems.

A practical modeling approach is to define an ergonomic exposure vector for each task or workstation. The vector may contain components for the neck, trunk, upper extremity, wrist, and lower extremity. On the worker side, skill, health eligibility, and, when appropriate, individual capacity are represented. The ergonomic cost of an assignment is then derived from the interaction between the task profile and worker profile. Risk becomes a property not only of the workstation but of the worker-task match. Alternative approaches to representing ergonomic exposure in decision models, including their respective advantages and limitations, are compared in Table 3.

Table 3. Options for representing ergonomic exposure in decision models

Representation	What does it capture?	Advantage	Limitation
Single overall score	General station risk level	Simple and fast modeling	Body-region and time information are lost
Body-region vector	Anatomical distribution of load	Can be matched with health restrictions	Requires more data and parameters
Cumulative dose	Total exposure across the planning horizon	Supports long-term balancing	Does not capture sequence by itself
Sequence constraints	Consecutive high loads	Indirectly protects recovery	Sensitive to threshold selection
Dynamic state variable	Change in fatigue/recovery	Suitable for real-time adaptation	Calibration and validation are difficult

The conceptual relationship among task characteristics, worker profiles, assignment eligibility, period effects, and cumulative exposure is illustrated in Figure 2.

**Figure 2.** Conceptual structure of assignment-based ergonomic cost

4. JOB ROTATION: FROM TASK VARIETY TO CONTROLLED EXPOSURE MANAGEMENT

Job rotation refers to moving workers among tasks or workstations according to a defined time plan. Its purposes vary: reducing monotony, developing multiskilling, increasing resilience to absenteeism, distributing repetitive loading across muscle groups, or balancing total ergonomic exposure. These objectives do not necessarily produce the same rotation schedule. A plan that maximizes skill variety, for example, may rotate workers among tasks with very similar body-region exposure profiles.

Systematic reviews show that job rotation should not be viewed as an automatic solution for reducing musculoskeletal risk (Padula et al., 2017). This does not mean that rotation lacks value; rather, its effectiveness depends on design details. Rotation period, task sequence, muscle-group exposure profiles, workers' health status and skills, and production requirements must be considered together. Diego-Mas et al. (2009) showed that a multicriteria genetic-algorithm approach can generate rotation schedules using multiple criteria such as task variety and worker constraints. Assunção et al. (2022)

developed a genetic-algorithm approach in the automotive context that jointly considers homogeneity of exposure and task diversity.

An important ergonomic design principle is more detailed than a simple “high-to-low” transition rule. Two tasks can have different total risk scores yet intensively use the same body region. Rotation should therefore seek meaningful diversification of exposure profiles rather than merely different total scores. Moving from a task involving heavy trunk flexion to repetitive work at shoulder height may provide trunk recovery while creating a new upper-extremity load. The suitability of such a transition should be evaluated by asking which risk is reduced and which is increased, not by looking only at one score.

Worker-station competence is a fundamental feasibility constraint in rotation planning. In real factories, the assumption that every worker can perform every job is rarely valid. Specific quality checks, equipment use, certifications, or experience levels may determine task eligibility. Hochdörffer et al. (2018) demonstrated this requirement through a personnel-scheduling approach that combines skill preservation and ergonomic criteria in job-rotation environments. An ergonomically attractive rotation plan that ignores competence requirements may become infeasible because of training cost or quality risk.

Health eligibility must be evaluated separately from technical competence. A worker may have the skill to perform a job at a station but may be unsuitable for that station because of a health restriction involving the back, neck, or upper extremity. Rotation models may therefore require two different eligibility matrices: technical assignability and health-based assignability. From a human-centered planning perspective, a health restriction is not a penalty term to be considered later; in many cases it is a hard constraint.

Fairness is another dimension of the rotation plan. “The same total risk for everyone” may appear fair, but equal exposure is not necessarily equitable when workers differ in health restrictions and capacity. Fairness can instead be interpreted as ensuring that no worker is loaded beyond their tolerance or health eligibility and that residual exposure is distributed in a justifiable manner. This transforms ergonomic optimization from a simple balancing problem into a problem of inclusive work design. The principal criteria that should be considered jointly when designing ergonomic job-rotation schedules are summarized in Table 4.

Table 4. Design criteria to consider jointly in ergonomic job rotation

Criterion	Example decision rule	Purpose
Total exposure	Limit differences in cumulative load among workers	Prevent load from accumulating on selected workers
Body region	Do not assign consecutive high loads to the same region	Create recovery opportunities
Health eligibility	Do not assign a worker to a station that heavily loads a restricted region	Protect vulnerable workers
Skill/competence	Assign workers only to stations for which they are qualified	Preserve quality and feasibility
Task variety	Limit long repetition of the same task	Reduce monotony and uniformity
Production continuity	Guarantee coverage of critical stations	Preserve operational performance

5.ERGONOMIC WORK-SYSTEM DESIGN THROUGH MATHEMATICAL PROGRAMMING

Ergonomic job rotation and task-allocation problems naturally have assignment and scheduling structures. The most basic decision variable is binary, indicating whether a particular worker is assigned to a particular workstation in a particular period. This structure represents the worker-station-period triplet in the same model and allows production constraints to be incorporated alongside ergonomic rules. Similar integration has been demonstrated in workforce-scheduling models in which ergonomic considerations are incorporated together with operational and synchronization constraints (Shahmaleki & Fırlalı, 2021).

Hard constraints represent conditions that may not be violated. Typical examples include assigning each worker to at most one station in each period, ensuring that each critical station is covered by the required number of workers, preventing technically unqualified workers from being assigned to a task, and prohibiting worker-station matches that violate health restrictions. More generally, mathematical programming provides a structured way to translate operational requirements and resource limitations into explicit decision variables, objectives, and constraints. Applications in other industrial-engineering domains illustrate the same modeling principle; for example, Ekiz Bozdemir and Fırlalı (2025) formulated a coverage-path-planning problem for multiple disjoint areas as a mathematical model that accounts for routing decisions and UAV battery-capacity constraints. In ergonomic work-system

models, the specific constraints differ, but the underlying modeling principle is similar: operational requirements define the feasible decision space. In contrast, preferences such as exposure imbalance, task variety, or number of station changes may be represented as penalties in the objective function.

The objective function determines what the model regards as a “good plan.” A single-objective model may minimize the maximum worker risk or reduce differences in total load among workers. Ergonomic planning, however, usually involves several partially conflicting objectives: preserving productivity, ensuring adequate station coverage, reducing high exposure, improving fairness, and limiting unnecessary transitions. Goal programming, lexicographic optimization, and multiobjective programming are therefore natural tools in this domain.

A lexicographic approach is especially appropriate when trade-offs among objectives should not be permitted. For example, accepting a health-ineligible assignment in order to slightly reduce the overall REBA imbalance is ethically and operationally unacceptable. In such a problem, the highest valid coverage under health and technical eligibility can first be guaranteed; exposure balance can then be improved without reducing that coverage. This reduces the risk of sacrificing fundamental safety for a slightly better average result. Solving objectives in order of priority makes the decision maker’s value structure explicit within the model (Ignizio, 1976; Romero, 2004).

The weighted-sum approach is more flexible because different objectives can be normalized and combined within a single objective function. However, the selected weights can strongly influence results, and even a small weight can make some safety objectives compensable. Weighted models should therefore preserve the distinction between hard safety constraints and performance preferences. The epsilon-constraint approach optimizes one objective while limiting other objectives through specified thresholds, making it suitable for systematic examination of different trade-off levels.

Uncertainty must also be considered. Ergonomic risk scores may contain observational error, sensor uncertainty, or task-to-task variability; demand and worker attendance can also deviate from planned values. A deterministic model may perform well in one scenario but become infeasible after small changes. Robust optimization, scenario analysis, or replanning policies can reduce this problem. In a human-centered model, not only the optimal value but also the resilience of the solution to reasonable changes in conditions is important.

The concept of “balance” used in ergonomic objective functions must also be selected carefully. Minimizing total exposure does not guarantee low exposure for every worker; a model may reduce the total by concentrating high

load on a few people. Conversely, minimizing only the maximum individual exposure ignores the distribution among workers with low and moderate loads.

Measures such as the maximum-minimum range, variance, mean absolute deviation, or risk measures that jointly track the highest-load workers represent different notions of fairness. The objective function should therefore be chosen not only for mathematical convenience but also according to the organization's principle of ergonomic fairness.

Another option is to manage exposure through classified thresholds. Rules such as "total time at a high-risk station may not exceed two periods" or "two high exposures to the same body region may not occur consecutively" preserve field-expert interpretation explicitly within the model. This can be more understandable than optimizing a continuous risk score. The thresholds, however, must be justified by data and method; otherwise, the model converts measurement uncertainty into a sharp decision boundary.

Infeasibility, meaning that no feasible solution exists, is itself an important signal in model design. If many health restrictions, a narrow skill matrix, and high station-coverage requirements are imposed simultaneously, no schedule may satisfy all requirements. In that case, an "infeasible" result from the solver should not be read as a technical failure but as managerial information indicating a capacity or design problem in the work system. Identifying which combinations of constraints destroy feasibility can reveal needs for additional training, workstation redesign, assistive equipment, or alternative staffing.

The output of an ergonomic optimization model should therefore not be limited to the final assignment schedule. The model can also report how binding constraints are, which worker-station matches restrict the system, which stations repeatedly generate high ergonomic cost, and which additional skill would most increase system flexibility. Used this way, optimization becomes a work-system diagnostic tool rather than merely a schedule generator.

The distinction between assembly-line balancing and job rotation is also important. Line balancing intervenes in the structural design of work by deciding how tasks are distributed among stations, whereas rotation determines how workers move over time within a given task-station structure. Otto and Battaia (2017) emphasize that physical ergonomic risks can be reduced through both line balancing and job rotation. In human-centered design, the station structure should, where possible, first be improved ergonomically and residual exposure should then be managed by rotation. Reversing these stages risks using increasingly complex rotation merely to cope with a poorly designed line.

Finally, whether there is an absolute priority among model objectives should be discussed explicitly. Some conditions, such as health eligibility, are

noncompensable and should remain hard constraints. Real trade-offs may exist among task variety, transition frequency, and small production losses. The decision architecture can therefore be divided into three layers: inviolable safety and health rules, minimum operational requirements, and optimizable preference criteria. This layering also makes model results easier for practitioners to understand. The main components of an ergonomic optimization model and their corresponding modeling interpretations are presented in Table 5.

Table 5. Main components of an ergonomic optimization model

Component	Example	Modeling interpretation
Decision variable	Assignment of worker i to station j in period t	Binary 0-1 assignment variable
Hard eligibility	Skill or health restriction	Inviolable constraint
Exposure	REBA, RULA, OCRA, force/duration profile	Parameter or state variable
Sequence	No two high loads to the same region in succession	Transition constraint
Balance	Difference in total load among workers	Objective function
Operational performance	Coverage, cycle, number of changes	Objective or constraint
Uncertainty	Demand, absenteeism, measurement error	Scenario/robustness layer

Simplified model logic. A binary variable x_{ijt} can represent whether worker i is assigned to station j in period t . Ergonomic exposure is calculated by accumulating these assignments across periods after combining them with station risk profiles. Health and competence matrices force some x_{ijt} values directly to zero; sequence constraints prevent selected hazardous transitions; and the objective function improves load balance, coverage, or other performance criteria among the remaining feasible solutions. Although this structure appears simple, it grows combinatorially as the numbers of workers, periods, tasks, skills, and risk dimensions increase.

6. MULTIOBJECTIVE OPTIMIZATION AND METAHEURISTIC SOLUTION APPROACHES

Objectives in ergonomic work-system design often do not move in the same direction. Improving load balance among workers may require more station changes; increasing task variety may reduce quality or speed at specialized

stations; and keeping the highest-risk stations away from selected workers may increase the load borne by others. Multiobjective optimization makes these conflicts visible instead of hiding them in a single “best” value. More generally, multiobjective combinatorial models provide a structured means of representing competing decision criteria within a common optimization framework across different resource-allocation and selection problems (Hülagü & Fırlalı, 2024).

Under the Pareto concept, a solution is efficient if one objective cannot be improved without worsening at least one other objective. This is valuable for ergonomic decision making because it can show, for example, how much ergonomic balance deteriorates when a given production loss is reduced, or how many additional rotations are required for a given exposure reduction. Alternatives can therefore be compared more transparently when objective weights are not known precisely in advance (Ehrgott, 2005).

Small and medium-sized linear or mixed-integer models can often be solved to optimality, or within proven bounds, using commercial or open-source solvers. The major advantage is that solution quality can be evaluated mathematically. As the numbers of workers, stations, periods, skill classes, and risk dimensions increase, however, model size can grow rapidly. In applications such as real-time replanning, where decisions are required within seconds or minutes, searching for a fully optimal solution may be impractical.

Metaheuristics become important at this point. Genetic algorithms, tabu search, simulated annealing, variable-neighborhood search, and evolutionary multiobjective algorithms can search large solution spaces for high-quality solutions within shorter times. Diego-Mas et al. (2009), Asensio-Cuesta et al. (2012), and Assunção et al. (2022) showed that genetic algorithms can combine different criteria in ergonomic job-rotation planning. Dalle Mura and Dini (2019) incorporated ergonomic criteria into assembly-line optimization using a multiobjective genetic algorithm. Beyond conventional metaheuristic search, recent work in scheduling also illustrates how structural information learned from previously generated solutions can be used to guide subsequent heuristic search, providing an example of the broader integration of data-driven learning and optimization (Fırlalı et al., 2026). Recent manufacturing applications further demonstrate the potential of hybrid metaheuristic frameworks for workforce scheduling under uncertainty. Denizhan et al. (2026) integrated a genetic algorithm with Monte Carlo simulation and Taguchi-based parameter tuning to address multi-skilled workforce assignment while accounting for variability in task duration and worker performance. Selected deterministic instances were also benchmarked against exact MILP solutions to assess solution quality.

Two issues are especially important when metaheuristics are used. First, leaving hard constraints such as health and safety entirely to a penalty function requires caution. Even if the algorithm is allowed to generate prohibited solutions temporarily, the final solution must be guaranteed to satisfy every hard constraint. Second, algorithm performance should not be reported from a single run. Stochastic methods require repeated runs with different random seeds, reporting of the solution-quality distribution and computation time, and, where possible, validation against exact solutions on small instances.

Hybrid approaches are powerful for many real problems. A metaheuristic can generate a feasible high-quality starting solution, after which mathematical programming can improve it within a selected neighborhood. Conversely, an exact model may solve a small core set of decisions while more flexible surrounding decisions are updated heuristically. Such combinations can balance reliable enforcement of ergonomic constraints with computational speed on larger problems. The suitability, strengths, and principal considerations associated with different solution approaches for ergonomic optimization are compared in Table 6.

Table 6. Selecting a solution approach for ergonomic optimization

Approach	Suitable problem	Strength	Points to consider
MILP / exact solution	Small-medium, linear structure	Optimality and bound information	Computation time on large instances
Goal/lexicographic programming	Prioritized, noncompensable objectives	Makes decision hierarchy explicit	Priority order must be justified
Pareto multiobjective method	Conflicting objectives	Makes trade-offs visible	Final selection still requires a decision maker
Genetic/evolutionary algorithm	Large and complex search space	Flexible encoding, multiple objectives	Repeated experiments and parameter sensitivity
Hybrid method	Large but structured problem	Balance of speed and quality	Implementation complexity

The decision process from the feasible solution region to the Pareto set, threshold evaluation, operational comparison, and final choice is depicted in Figure 3.

Feasible region	Pareto set	Thresholds	Ops. comparison	Final choice
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Figure 3. Decision flow in multiobjective ergonomic optimization

7. MULTICRITERIA DECISION MAKING AND ERGONOMIC DECISION-SUPPORT SYSTEMS

Optimization and multicriteria decision making belong to related problem families but do not perform the same function. Optimization generates solutions from many combinations of decision variables according to objectives and constraints. Multicriteria decision making generally evaluates or ranks a set of already defined alternatives against several criteria. In ergonomic work-system design, the two approaches can complement one another.

For example, a mathematical model may generate ten Pareto-efficient plans from hundreds of possible rotation schedules. Selection among these ten may involve criteria such as worker acceptance, training requirements, ease of implementation, or managerial preference that are difficult to quantify within the optimization model. AHP, TOPSIS, or similar multicriteria methods can support this final selection stage. Uncertainty in the weights and judgments supplied by decision makers should not be ignored; sensitivity of the ranking to alternative weight scenarios should be examined.

The concept of a decision-support system is broader. A good ergonomic decision-support system should not consist only of an “optimize” button. It should integrate data input, ergonomic risk profiles, worker eligibility, the rationale for constraints, outcomes of alternative schedules, sensitivity analysis, and post-implementation feedback within the same interface. Knowledge-based systems can complement optimization in this process by translating worker- and organization-related information into actionable recommendations. For example, the Shift Expert system combines individual and organizational factors to support the prioritization of preventive actions for reducing the adverse effects of shift work (Esen et al., 2019). Users should be able to see why a worker was not assigned to a particular station or what fundamentally distinguishes two candidate solutions.

Explainability is not a technical luxury here but a condition of implementation. If a schedule directly changes workers’ daily assignments,

being mathematically strong is not enough. Production managers, occupational-safety professionals, and worker representatives should be able to understand the main decision logic. “The algorithm recommended it” is a weak governance position, especially in systems containing health-related constraints. Risks of constraint violation, missing data, and model uncertainty should be visible.

Decision-support systems should also support scenario analysis. If the system can show how a plan changes under worker absence, temporary station closure, increased demand, or a new health restriction, users are not tied to a single ideal schedule. This transforms ergonomic planning from a static report into an operational management tool. The distinct yet complementary roles of optimization and multicriteria decision making within an ergonomic decision-support system are summarized in Table 7.

Table 7. Roles of optimization and multicriteria decision making in an ergonomic decision system

Dimension	Optimization	Multicriteria decision making
Input	Decision variables, objectives, constraints	Defined alternatives and criteria
Primary function	Generate a new solution/schedule	Evaluate/rank alternatives
Strong area	Large combinatorial search space	Combining qualitative and quantitative criteria
Typical use	Assignment, rotation, scheduling	Selection of final schedule or design
Combined use	Generates Pareto/feasible plans	Supports preference among plans

8. DYNAMIC AND REAL-TIME ERGONOMIC REPLANNING

A conventional ergonomic rotation plan is created before a shift begins and remains unchanged throughout the shift. This is simple in terms of data requirements and management, but real production systems are not static. Worker fatigue, production pace, station failure, absenteeism, quality problems, or unexpected demand changes may invalidate the initial assumptions. Wearable sensors and real-time posture analysis discussed in Chapter 2 make part of this variability measurable.

The defining feature of dynamic ergonomic scheduling is that exposure is updated from realized data rather than only from preassigned task profiles. If, for example, a worker exhibits more shoulder elevation or a longer static posture than expected during a period, the next task can be selected from alternatives with lower upper-extremity demands. Rotation then ceases to be a

fixed equal-time cycle and becomes a feedback system that responds to worker state.

Rolling-horizon planning is one suitable control structure for this approach. At defined intervals, the system observes the current state, reoptimizes the plan for the remaining shift, and implements only the nearest decisions. As new data arrive, the horizon moves forward. This provides controlled adaptation rather than changing the full-day plan every second. Replanning frequency should be chosen to balance production stability against ergonomic responsiveness.

Not every measurement change should trigger replanning. If sensor noise or normal movement variability leads to frequent schedule changes, role ambiguity and cognitive workload may increase. Threshold, duration, confidence level, and event importance should therefore be considered together. A trigger might be defined as cumulative load above a duration threshold, repeated high risk across several periods, or worker-reported fatigue rather than a single high-angle sample.

Another critical feature of real-time systems is the simultaneity of production and ergonomic constraints. When a worker is moved to another task, the vacated station must still be covered. The new task must match the worker's skills, quality requirements must remain satisfied, and the transition must occur at a time that does not disrupt workflow. Dynamic ergonomics is therefore not simply a rule of "move the worker when risk rises"; it is a multi-resource, event-triggered rescheduling problem.

Dynamic planning expands further in human-robot systems. Robot speed may be changed, selected subtasks may be transferred to the robot, the part may be presented in a more ergonomic position, or the robot may take over another operation while the worker obtains a recovery opportunity. The task allocation discussed in Chapter 3 thus gains a time dimension: the question becomes not only "who should perform this task?" but "given the current human state and production condition, who should perform it now?"

Privacy and worker autonomy are fundamental design requirements in such systems. Worker acceptance may quickly decline if real-time ergonomic data begin to be used for performance surveillance. What data are collected, who can view them, how long they are stored, and what consequences algorithmic decisions may have for workers should be defined in advance. An ergonomic decision-support system must maintain a clear boundary between health protection and performance monitoring.

The "cost of replanning" should also be modeled explicitly. Mathematically, each new data point may permit a better schedule, but frequent changes in worker assignments can create training needs, walking, tool changes, quality

risk, and psychological uncertainty. The amount by which the new plan differs from the previous plan can therefore be included as a decision criterion. The number of changed assignments, distance between consecutive schedules, or number of plan changes experienced by a worker during a day can be limited. The system then seeks a “sufficiently good and stable plan” rather than the “best instantaneous plan.”

Data latency is also important in real-time decision systems. Processing a sensor-measured movement, converting it into an ergonomic feature, and transferring it to the decision engine all take time. If the system treats delayed data as the current state, it may generate unnecessary interventions. Timestamps, confidence in the data, and age of the latest valid measurement should therefore be retained in the decision engine. Behavior under missing data should be predefined, and a low-confidence signal should not by itself trigger a major health-related reassignment.

Human approval is another design option. Low-impact task changes may be applied automatically, whereas major reassignments based on health restrictions or decisions that substantially alter a worker’s shift plan may require expert approval. A human-supervised decision architecture can thus use the speed of automation without disconnecting it from field knowledge. The decision-support system presents the recommendation, rationale, and expected ergonomic benefit, while the authorized person accepts or rejects it. Rejected recommendations can also provide valuable feedback for subsequent system calibration.

Dynamic ergonomic planning is therefore not only a problem of algorithmic speed. A successful system must jointly design data reliability, decision stability, worker communication, human approval, and operational rollback mechanisms. Otherwise, a system may be technically fast but organizationally unacceptable. Illustrative trigger-action relationships for dynamic ergonomic replanning, together with the operational conditions that must be preserved, are presented in Table 8.

Table 8. Example trigger-action mappings for dynamic ergonomic replanning

Trigger	Possible data	Decision	What must be preserved
Increase in cumulative regional load	IMU/REBA time series	Move to a task with low load on the affected region	Skill and station coverage
Unexpected absence	Shift/personnel data	Re-solve the rotation plan	Health eligibility
Station failure	Production-system event	Assign alternative task/station	Cycle and safety
High subjective fatigue	Brief worker report	Recovery opportunity / task change	Worker autonomy
Robot workload transfer	HRC state data	Reallocate a subtask between human and robot	Physical and cognitive load

The closed-loop structure of dynamic ergonomic replanning, from measurement and state updating to reoptimization, implementation, and outcome validation, is illustrated in Figure 4.



Figure 4. Closed-loop ergonomic replanning

9. IMPLEMENTATION AND VALIDATION: FROM A GOOD MODEL TO A GOOD INTERVENTION

A low objective-function value does not by itself show that an ergonomic intervention is successful. The schedule proposed by the model must be implemented in the field, realized exposure and production performance must be measured, and worker experience must be evaluated. Validation of ergonomic optimization should therefore be conducted at three levels: computational correctness, ergonomic effect, and operational feasibility.

Computational correctness concerns whether the model applies its constraints and objectives correctly. Is the assignment matrix valid for every worker and period? Does any health-prohibited match occur? When total exposure is recomputed independently from the raw data, is the same result obtained? If a metaheuristic is used, reproducibility under controlled conditions and comparison with exact solutions on small instances are important.

Ergonomic validation asks whether the indicator optimized in the model produces the expected change in realized exposure or worker outcomes. Balancing total REBA scores may not be sufficient; additional measures such as body-region exposure, time spent at high risk, subjective fatigue, or muscle activity may be needed. Where appropriate, pre-post comparisons, control conditions, and sufficient follow-up duration should be used. The adaptation period to a new rotation should be distinguished from its persistent effect.

Operational validation evaluates whether production-system performance is preserved. Cycle time, quality, task transitions, learning requirements, station coverage, overtime, and schedule stability can be monitored. An ergonomically superior plan that changes tasks too frequently may be rejected because of implementation cost or cognitive confusion. Solution quality should therefore be assessed together with the total burden of implementation, not only by the reduction in an ergonomic score.

Worker acceptance should also be measured. Whether rotation is perceived as fair, understandable, and predictable is important for long-term sustainability. Workers' health restrictions must be handled confidentially, and allocation decisions should not create stigma. Health-sensitive optimization should be able to operate without visibly labeling workers as "risky" or "restricted."

Sensitivity analysis shows which parameters make the decision model fragile. If the solution changes completely when a high-risk threshold changes by one point, that threshold requires careful calibration in field use. Similarly, if one worker's absence reshapes the entire schedule, the solution may be structurally fragile. Good decision support should report not only the optimum solution but also how stable it is.

The comparison benchmark used in validation must also be chosen correctly. Comparing a new plan only with the current shift schedule provides limited information when the current practice is already poor. Where feasible, three references are useful: current practice, an operational optimum without ergonomic criteria, and an ergonomics-integrated optimum. This three-way comparison shows the production cost at which ergonomic improvement is achieved and the extent to which ergonomic criteria change model behavior.

Short-term and long-term indicators should be separated in field experiments. Posture distribution or time spent at high risk may change within a few shifts, whereas musculoskeletal symptoms, skill development, and worker acceptance may require longer follow-up. A new rotation may initially increase learning load and become more fluent after several weeks. A single pre-post measurement can therefore misrepresent the dynamic effect of the intervention.

The success of ergonomic optimization also depends on intervention fidelity. Whether the plan was actually implemented in the field as proposed should be recorded. Changes made by shift supervisors for production reasons, worker task swaps, or equipment failures may cause planned exposure and realized exposure to differ. Analysis should therefore use the realized schedule as well as the schedule generated by the algorithm. This distinction is critical for the scientific validity of field studies. The computational, ergonomic, operational, human-organizational, and robustness dimensions used to validate ergonomic optimization interventions are summarized in Table 9.

Table 9. Validation matrix for ergonomic optimization interventions

Level	Possible indicators	Core question
Computational	Constraint violations, objective value, optimality gap, reproducibility	Is the model working correctly?
Ergonomic	Regional exposure, high-risk duration, fatigue, discomfort	Did human load actually decrease?
Operational	Cycle, quality, coverage, transition, training	Did the production system remain feasible?
Human/organizational	Acceptance, fairness, understandability, privacy	Do workers find the system sustainable?
Robustness	Absence/scenario sensitivity, solution stability	Is the plan robust to small changes?

10. AUTHOR SYNTHESIS: THE ERGONOMIC WORK-SYSTEM OPTIMIZATION CYCLE

The literature reviewed in this chapter indicates that ergonomic work-system decisions cannot be treated adequately as a one-stage optimization problem. Accuracy of risk measurement, selection of decision variables, health and skill eligibility, priorities among objectives, scalability of the solution method, field implementation, and feedback are parts of the same chain. The Ergonomic Work-System Optimization Cycle is therefore proposed here as the operational counterpart of the book’s overall Assessment-Prediction-Optimization-Adaptation framework.

The first step of the cycle is MEASURE. Physical and, where needed, cognitive exposure profiles of tasks, worker characteristics, and production conditions are described using reliable data. The second step is MODEL. Measurements are translated into objectives and constraints, distinguishing information that defines hard eligibility from indicators to be optimized. The

third step is OPTIMIZE. Feasible plans are generated using exact, multiobjective, or metaheuristic methods, and trade-offs are made visible.

The fourth step is IMPLEMENT. The mathematical plan is transferred to the field while accounting for actual shift structure, training, workplace rules, and worker acceptance. The fifth step is VALIDATE. Realized ergonomic exposure and production performance are compared with planned values. The sixth step is ADAPT. When risk profiles, worker state, or production conditions change, the model is updated and, when necessary, the plan is recalculated. This final step closes the loop and turns ergonomic optimization from a one-time project into a learning work-system mechanism.

A key property of this framework is that it does not place optimization at the center. Optimizing poor or misrepresented data extremely well does not produce good ergonomics. Likewise, a theoretically superior solution that cannot be implemented in the field is a system failure. The framework therefore treats data quality, model quality, solution quality, and implementation quality as equally important.

A second property is that it separates risk reduction from risk distribution. The model should first encourage feasible engineering and design improvements and should use rotation and scheduling only for residual exposure. Optimization should not become a tool for mathematically “fair” distribution of poor work design.

A third property is that worker differences are treated as a normal part of the decision model. Skill, health eligibility, temporary restrictions, experience, and even fatigue that changes over time distinguish human resources from homogeneous capacity units. These differences should be used to create safe and feasible worker-task matches, not to produce discrimination. Data governance and privacy are therefore as important as the technical model.

A fourth property is that static and dynamic decisions are combined within the same architecture. A daily or weekly base rotation can be optimized statically, while real-time data trigger replanning only when a meaningful deviation occurs. This layered structure provides a planning approach that remains stable but can adapt when necessary, rather than a continuously changing system that leaves workers uncertain. The proposed Ergonomic Work-System Optimization Cycle, consisting of measurement, modeling, optimization, implementation, validation, and adaptation, is illustrated in Figure 5.

Measure	Model	Optimize	Implement	Validate	Adapt
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Figure 5. The Ergonomic Work-System Optimization Cycle

The progression of ergonomic optimization from reactive assessment to adaptive, exposure-driven replanning is structured into five maturity levels in Table 10.

Table 10. Maturity levels in ergonomic optimization

Level	Characteristic	Typical decision
1 - Reactive	Risk is checked after the production plan is created	Correct an unsuitable workstation afterward
2 - Constraint integration	Ergonomic thresholds are added as model constraints	Prevent high-risk assignments
3 - Multiobjective	Ergonomics and operational performance are optimized jointly	Pareto/prioritized rotation
4 - Individualized	Skill and health eligibility are modeled by worker	Person-task fit
5 - Adaptive	Plan is updated with realized exposure	Event-triggered rescheduling

11. RESEARCH AND PRACTICE AGENDA

The first major direction in ergonomic optimization research is better exposure models before better objective functions. Linearly accumulating risk scores over time is convenient, but biological loading and recovery are often nonlinear. Dynamic state models that combine sensor data, muscle activity, posture distributions, and subjective fatigue can strengthen the connection between scheduling and physiological processes. Model complexity, however, should not exceed what can be validated; an extremely detailed model that cannot be calibrated in the field may create numerical realism with little practical value.

The second direction concerns uncertainty and robustness. Worker attendance, demand, processing times, and ergonomic measurements are variable. Future studies should move beyond optimizing a single nominal dataset and evaluate schedules that remain reliable across scenarios, together with replanning cost and plan stability. Reassigning a worker after every small change may be mathematically flexible but humanly exhausting. Stability can therefore be treated as an additional objective dimension.

The third direction is joint optimization of physical and cognitive ergonomics. Robot or AI support can reduce physical load while increasing monitoring, decision-making, or coordination demands. A model based only on REBA or RULA cannot detect such load transfer. In future human-robot

production systems, task allocation should evaluate physical exposure and cognitive workload within a common multiobjective framework. Human-centered robotic assembly studies such as Ghorbani et al. (2024) indicate that adaptive workload management is an expanding research direction.

The fourth direction is fairness and inclusion. The aim of ergonomic optimization is not only to reduce average risk but also to prevent high risk from accumulating in particular worker groups. When health restrictions and individual capacities are included in models, data privacy, explainability, and discrimination risk must be considered together. An algorithmic decision that a worker is “not health-eligible” should not become a permanent label that unnecessarily narrows career or task access.

The fifth direction is field evaluation of decision-support systems. The literature contains a growing number of algorithms, while long-term studies in real workplaces remain more limited. Future research should evaluate not only objective-function improvement but also worker acceptance, learning effects, maintenance needs, data quality, and whether ergonomic benefits persist over months. For practitioners, the most valuable system is not necessarily the most theoretically advanced one, but the one that works with reliable data, explains its decision logic, and can be used without disrupting production rhythm. The priority research themes, associated research questions, and expected contributions for future ergonomic optimization studies are summarized in Table 11.

Table 11. Priority research questions for ergonomic optimization

Theme	Research question	Expected contribution
Dynamic exposure	How should fatigue and recovery be represented in scheduling?	More realistic temporal models
Uncertainty	Which plans remain robust under sensor and demand variability?	More reliable field implementation
Physical + cognitive load	Does one type of load fall while another rises?	Holistic human performance
Fairness	On whom does risk accumulate?	Inclusive decision policy
Human-robot system	When should task allocation change dynamically?	Adaptive collaboration
Field validation	Are optimization benefits sustained over time?	Evidence-based implementation

12. CONCLUSION

Measuring ergonomic risk is the beginning of human-centered work-system design, not its end. If risk information is not translated into decisions about how workers and tasks should be matched over time, ergonomics remains outside production planning. This chapter has treated ergonomic work design as an operational decision problem defined by worker-task-station-period relationships and has integrated the roles of job rotation, scheduling, mathematical programming, multiobjective optimization, and decision-support systems in that transformation.

Job rotation is not an engineering control that removes ergonomic risk at its source, and simple task switching does not always reduce risk. Effective rotation should jointly consider exposure intensity and duration, task sequence, body-region profile, recovery opportunity, worker skill, and health eligibility. Modern ergonomic rotation is therefore developing from an approach in which “everyone does every job in turn” toward health-sensitive, data-driven worker-station-period scheduling.

Mathematical programming can represent health and production constraints explicitly; multiobjective methods make trade-offs between ergonomics and operational performance visible; metaheuristics increase search capacity on large problem instances; and multicriteria decision making brings management and human factors that are difficult to quantify into the final selection stage. No algorithm, however, can compensate for a weak definition of exposure or a model disconnected from field reality.

The Ergonomic Work-System Optimization Cycle proposed in this chapter links measurement, modeling, optimization, implementation, validation, and adaptation. Ergonomic decision support thereby evolves from a static report into a learning system that can replan when necessary. The next chapter advances this transformation through digital human modeling, digital human twins, predictive ergonomics, and adaptive work systems, completing the book’s Assessment-Prediction-Optimization-Adaptation framework.

Statement on the Use of Generative AI

In preparing this book, the authors used OpenAI’s ChatGPT as an assistive tool for the English translation of the original Turkish manuscript, language editing, consistency checking, and document formatting. The authors reviewed and revised the resulting text and take full responsibility for the accuracy, interpretation, and final content of the book.

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The Future Of Ergonomics: Digital Human Twins, Predictive Ergonomics, and Adaptive Work Systems

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ABSTRACT

The digital transformation of ergonomics is not simply a matter of introducing new measurement tools. Wearable sensors, computer vision, artificial intelligence, three-dimensional anthropometry, digital human modeling, and digital twin technologies are changing when and how ergonomic decisions are made within production systems. Traditional ergonomics often observes existing work, classifies risk, and then recommends improvement. The emerging approach seeks to simulate scenarios before work is implemented, predict future exposure from worker and task data, compare alternative interventions, and allow the system to adapt to changes in the human state. This chapter distinguishes digital human modeling from the digital human twin and discusses three-dimensional anthropometry and personalized design, data science and predictive models in ergonomics, prescriptive ergonomics, closed-loop adaptive systems, and the validation of these systems. Its central argument is that ergonomics is evolving from a static risk-assessment discipline toward a continuously learning decision system. This transformation is synthesized through the Adaptive Ergonomic Intelligence framework, which integrates the assessment, human-technology interaction, and optimization approaches developed in the preceding chapters within a single loop. The framework combines observing, measuring, assessing, predicting, selecting interventions, adapting, and learning with human oversight, data governance, and field validation.

Keywords: digital ergonomics, digital human modeling, digital human twin, predictive ergonomics, prescriptive ergonomics, adaptive work systems, artificial intelligence, human-centered manufacturing

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1. INTRODUCTION

Ergonomic decision making has long followed a logic of “observe, assess, and correct.” Working posture, force demand, repetition frequency, or mental workload is measured; risk is classified using an appropriate method; and the workstation, work method, or task allocation is subsequently redesigned. This approach remains necessary and has strong practical value, particularly in field ergonomics. In contemporary production systems, however, work, workers, and technology do not change at the same rate. When product variants, task durations, levels of automation, robot behavior, and workers’ momentary physical or cognitive states vary during the day, a one-time assessment represents only a particular moment in the system.

This situation introduces a new temporal dimension into ergonomic decision making. The relevant questions are no longer limited to “Is there a risk?” They also include “Under what conditions will risk increase?”, “For whom and when will it become critical?”, “Which intervention can reduce risk at the lowest acceptable operational cost?”, and “How should the system change its plan when it detects a change in the human state?” Answering these questions requires measurement, modeling, prediction, optimization, and feedback to be integrated within the same decision chain.

Digitalization provides powerful tools for this integration (Figure1). Digital human models can represent different body profiles and task scenarios during design, whereas the digital twin concept seeks to establish a continuous or periodic data connection between the physical system and its digital representation (Grieves & Vickers, 2017; Jones et al., 2020). Three-dimensional body scanning increases the detail of anthropometric representation; wearable sensors and computer vision facilitate the monitoring of exposure over time; and artificial intelligence can identify patterns and generate predictions from high-dimensional data (Table 1). Yet the presence of technology does not guarantee ergonomically sound decisions. If data quality, model validity, human variability, explainability, privacy, and worker autonomy are not addressed, more data may simply create more complex errors.

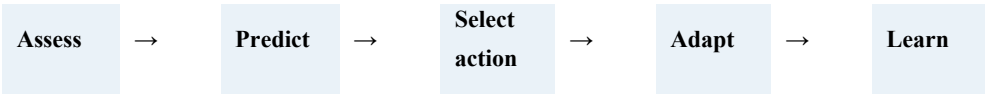


Figure 1. From static assessment to adaptive ergonomics

This chapter therefore treats the future of ergonomics not as a technology-centered list of tools but as a human-centered decision architecture. The central idea is that ergonomics is expanding from an assessment function that classifies the current state to a predictive function that anticipates future exposure; from there to a

prescriptive decision system that selects among intervention alternatives; and ultimately to a closed-loop structure that adapts to changing human-work conditions. This transformation does not change the human factors and ergonomics objective of improving both overall system performance and human well-being; it expands the time horizon and decision tools used to pursue that objective (Dul et al., 2012).

Table 1. Four levels in the digital transformation of ergonomic decision making

Level	Core question	Primary output	Decision character
Assessment ergonomics	What is the current risk?	Risk class / exposure profile	Reactive or diagnostic
Predictive ergonomics	When and for whom will risk increase?	Probability / expected exposure	Proactive
Prescriptive ergonomics	Which intervention should be selected?	Action / task / design recommendation	Decision-oriented
Adaptive ergonomics	How should the system respond to the new state?	Dynamic reconfiguration	Closed-loop and learning

2. DIGITAL ERGONOMICS AND DIGITAL HUMAN MODELING

Digital ergonomics is a broad concept referring to the representation of ergonomic knowledge within numerical models, simulation environments, and data flows. One of its most established components is digital human modeling. Digital human models represent dimensional, kinematic, biomechanical, or cognitive properties of the human body in a virtual environment, enabling design decisions to be examined before a physical prototype is built (Table 2). Chaffin (2005) emphasized the value of digital human modeling for proactive ergonomics, arguing that evaluating reach, vision, posture, and biomechanical loading early in the design process can reduce costly corrections later.

The main advantage of digital human modeling is that design alternatives can be compared without requiring a real worker to physically experience every scenario. Workstation height, reach distance, line of sight, equipment location, assembly sequence, or maintenance accessibility can be varied virtually and their effects on different anthropometric profiles examined. In this sense, the digital human model moves ergonomics from a post-prototype verification activity to an engineering input used early in the design process.

A digital human model, however, should not be interpreted as a “digital copy of the person.” A model represents selected properties under explicit assumptions. Anthropometric data may describe a population distribution; joint ranges of motion may define certain limits; and a biomechanical model may estimate internal loading under external forces. Real workers nevertheless differ in movement strategies, fatigue, experience, pain, learning, and task preferences. Model validity therefore

depends not only on geometric detail but also on the ergonomic question the model was built to answer.

This distinction is particularly important from an industrial engineering perspective. If ergonomic indicators generated by a digital human model are transferred into an optimization or decision-support system, model uncertainty should become part of the decision architecture. For example, a workstation height that is reachable for a particular percentile group does not guarantee the same performance and loading for all workers. Likewise, a design optimized around an “average person” may produce substantial mismatches at the tails of the population distribution. The strongest use of digital human modeling is therefore not the optimization of a single representative avatar, but scenario analysis across population diversity and task variability.

Digital human modeling can also be integrated with virtual reality, motion capture, and production simulation. Allowing designers, operators, and ergonomists to evaluate alternative scenarios in the same virtual environment supports the joint use of quantitative scores and expert judgment. Human factors can thus remain visible throughout the design cycle rather than appearing only as a checklist at the end. The digital human modeling literature compiled by Duffy (2009) likewise emphasizes the field’s role at the interface of ergonomics, design, and engineering.

Table 2. Major representation levels in digital human modeling

Representation level	Example data	Typical ergonomic question	Main limitation
Anthropometric	Dimensions, percentiles, body proportions	How do reach and fit change?	Does not capture individual movement strategy
Kinematic	Joint angles, trajectories	Which postures does the task require?	Force/load may not be represented directly
Biomechanical	Moment, force, compression	What is the internal loading?	Sensitive to model assumptions
Visual/perceptual	Line of sight, visibility	Are information and controls accessible?	Represents actual attention only partially
Task-based	Sequence, duration, motion class	How do alternative methods compare?	May simplify field variability

3. FROM THE DIGITAL HUMAN MODEL TO THE DIGITAL HUMAN TWIN

The digital twin concept is based on establishing a data connection throughout the life cycle between a physical entity or system and its digital representation. Although the concept is used differently across domains and no single absolute definition exists, the nature of the data flow between the digital model and the

physical system is a distinguishing feature (Kritzinger et al., 2018; Jones et al., 2020). In manufacturing, a digital twin is treated not merely as a simulation model but as a digital representation updated from the physical process and, where appropriate, capable of returning decision information to that process (Tao et al., 2019).

When this logic is applied to a person, the concept of the “digital human twin” emerges. Considerable conceptual caution is needed, however. A human being is not a fully observable and deterministic system like a machine component. Physical capacity, fatigue, pain experience, cognitive strategy, motivation, and behavior are variable, and some of these states cannot be measured directly. A digital human twin should therefore be understood not as a complete digital replica of a person but as a functional representation that is updated for a defined ergonomic purpose and explicitly acknowledges uncertainty. This emerging approach positions the Digital Human Twin as a model that integrates human-task-technology-environment interaction; in this model, ergonomic risk, employee well-being, production performance, energy consumption, and resource efficiency are monitored together, guiding the dynamic restructuring of work systems (Rathore and Gupta, 2025). Berti et al. (2023) demonstrate that monitoring the real-time status of employees through ergonomic data and dynamically replanning tasks based on emerging risks is possible within the Human Digital Twin approach. Bolis et al. (2025) highlight the need for research focusing on the combined consideration of human-centeredness, sustainability, and digital technologies in production systems. Therefore, extending the Digital Human Twin approach towards a sustainability-sensitive adaptive decision-making mechanism that takes into account energy consumption, resource use, environmental impacts, and production performance, in addition to ergonomic risks and employee well-being, can be considered a natural area for development within the Adaptive Ergonomic Intelligence framework.

At least four layers can be distinguished within a digital human twin. The first contains relatively stable characteristics such as anthropometry, age group, experience, skill, and relevant health or eligibility restrictions. The second includes task and environmental data such as work sequence, cycle time, load, tools, working height, and automation state. The third captures the dynamic human state through posture, movement, muscle activity, heart-rate-derived variables, fatigue indicators, or self-report data. The fourth is the decision layer, which may contain risk prediction, task changes, break recommendations, robot-speed adjustments, or rescheduling actions.

Using these layers together separates a digital human twin from a static avatar model. In an assembly line, for example, an appropriate working height may be selected during design using a digital human model based on a worker’s stature and

limb lengths. If the same system later monitors trunk inclination and shoulder use from IMU or image data during actual production, updates accumulated exposure, and recommends a subsequent workstation based on task history, it begins to operate according to twin logic. The essential difference is that the model is updated with data and connected to a decision loop (Figure2).

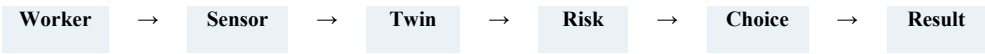


Figure 2. Data and decision loop in a digital human twin

There is a risk of using the digital human twin label too broadly. Not every sensor-based ergonomics application is a digital twin. A dashboard that merely displays data should not automatically be called a twin of the physical worker, and generating a 3D avatar alone does not create one. A scientifically clearer distinction can be made among digital models, digital shadows, and digital twins according to the direction of data flow and the degree to which the decision loop is closed. Kritzinger et al. (2018) proposed a similar distinction for manufacturing. Adapted to ergonomics, this classification helps preserve the technical meaning of the concept (Table 3).

Table 3. Distinguishing the digital human model, digital human shadow, and digital human twin

Structure	Physical-to-digital data	Digital-to-decision feedback	Ergonomic example
Digital human model	Not required / periodic	None	Virtual reach and posture analysis during design
Digital human shadow	Automatic or periodic	Interpreted by a person	Live exposure dashboard and risk history
Digital human twin	Continuous or event-based	Decision support / controlled adaptation	Dynamic adjustment of task, break, or robot parameter

The ergonomic value of a digital human twin extends beyond personalization. It also enables what-if analysis. If a worker’s current exposure level and task history are known, alternative task sequences can be simulated to estimate their effects on cumulative end-of-shift loading. Likewise, the expected physical and cognitive consequences of changing robot speed or workstation height can be compared in advance. Decisions can therefore be based on forward-looking scenario evaluation rather than a single instantaneous risk score.

This capability can nevertheless be misleading when model uncertainty is poorly managed. A digital twin being “up to date” does not mean it is “correct.” Sensor error, missing data, poor calibration, inter-individual variability, and model drift can progressively degrade predictions. Validation, uncertainty reporting, and human oversight should therefore be integral components of a digital human twin architecture. A human-centered twin should not silently take decision authority away from the worker; it should make the rationale for decisions and the associated uncertainty visible.

Another fundamental design issue is how frequently the representation should be updated. Monitoring every variable in real time is neither technically necessary nor ergonomically justified. Anthropometric dimensions may remain relatively stable for months or years, while task, posture, and fatigue indicators can change within minutes. Twin architectures should therefore use layered update rates that reflect the natural time scale of each variable rather than pursuing continuous measurement of everything. This can reduce both data volume and privacy burden while preserving information needed for decisions and preventing slowly changing variables from fluctuating unnecessarily because of sensor noise.

Personalization alone is also insufficient; the twin should be capable of expressing its own uncertainty. Shoulder-exposure estimates may be reliable while fatigue estimates for a particular shift are less certain because of missing data. A decision system should not present the two predictions with equal confidence. When uncertainty is high, additional measurement, expert review, or a more conservative policy may be preferable to automatic intervention. This principle makes ergonomic decisions sensitive not only to the most likely value but also to the consequences of being wrong. For health-related decisions with high consequence severity, making uncertainty explicit is a fundamental requirement of human-centered design.

4. THREE-DIMENSIONAL ANTHROPOMETRY AND PERSONALIZED WORK SYSTEMS

Anthropometry is one of the oldest data foundations of ergonomic design, yet digitalization is changing how anthropometric information can be used. Traditional datasets usually report means, standard deviations, and percentiles for selected body dimensions. Three-dimensional scanning, in contrast, can capture body-surface geometry and large numbers of derived measurements in a short time. Large-scale 3D anthropometry initiatives such as CAESAR were early examples of this approach (Robinette et al., 2002). ISO 7250-1 and ISO 15535 provide foundational guidance for anthropometric measurement and the development of anthropometric databases.

A key shift in next-generation anthropometry is from univariate percentile thinking toward multivariate body representation. A person may be near the 50th

percentile for stature while having arm length, shoulder breadth, or torso proportions at very different percentiles. An “average body” is therefore rarely average in all dimensions simultaneously. Multivariate analysis, principal components, and parametric body models make it possible to represent combinations of body proportions more realistically.

From an industrial engineering perspective, personalization can operate at two different levels (Table 4). The first is design personalization: workstation height, seating, tools, or control layouts are adjusted to individual dimensions. The second is decision personalization: task allocation or job rotation is planned by considering anthropometric fit, physical capacity, and prior exposure history. The second level is more complex because anthropometry alone is insufficient; skill, health, fatigue, and production requirements must also be considered.

Personalization also raises concerns about fairness and privacy. A prediction that a particular worker has “high risk” should not become a basis for systematically excluding that person from selected tasks. Attributing a design deficiency to individual variability conflicts with a basic principle of ergonomics. The first preference, wherever feasible, should be to make work safe and adjustable for a broad user population. Personalization should be used to manage residual risk more precisely, not as a segmentation mechanism that compensates for poor design.

Table 4. Levels of anthropometric data use in ergonomic decision systems

Level	Data type	Decision	Key consideration
Population	Percentiles and distributions	General design range	Avoid a one-dimension 'average person' assumption
Multivariate	Body proportions / components	Representative body set	Sample must represent the target population
Individual	3D scan / personal measurements	Adjustability and personal fit	Privacy and data minimization
Dynamic individual	Anthropometry + exposure history	Task / plan adaptation	Risk of discrimination and over-personalization

5. DATA SCIENCE AND PREDICTIVE MODELS IN ERGONOMICS

The diversification of ergonomic data sources is making data-science methods increasingly relevant to ergonomics. Wearable sensors, motion-capture systems, video, production logs, quality data, work-order histories, and self-report measures can generate large volumes of data at different time scales. Ranavolo et al. (2018) emphasized both the potential of wearable systems for biomechanical risk assessment and the need for field validation. Image-processing-based ergonomic assessment has also demonstrated how visual data can be transformed into quantitative information for established ergonomic assessment methods. For

example, Can and Fırlalı (2017) developed an image-processing-supported extension of RULA (ARULA) to obtain objective angular measurements and support automated upper-extremity assessment, while the integration of image processing with OWAS enabled the identification and classification of working postures (Fırlalı et al., 2015). These developments illustrate an important transition from visual observation toward digitally derived ergonomic information that can subsequently feed predictive and adaptive systems. On the computer-vision side, approaches such as multi-person pose estimation and markerless motion analysis provide further possibilities for measuring human movement (Cao et al., 2017).

Predictive ergonomics aims not merely to classify the current state from these data, but to estimate a future ergonomic outcome. Targets may include the probability of a high-risk posture in the next period, cumulative exposure by the end of a shift, self-reported fatigue, deterioration in task-completion time, or the expected effect of a proposed intervention. More broadly, industrial applications have shown that artificial neural networks can learn relationships from historical operational data to generate useful predictions for decision support, including applications such as manufacturing cost estimation (Özcan & Fırlalı, 2014). The prediction target must be defined so that it is meaningful both ergonomically and operationally. Improving an algorithm's classification accuracy alone does not automatically improve decision quality.

The data structure used by a predictive model also matters. Ergonomic data are often temporal, and successive observations are not independent. Randomly splitting thousands of sensor samples from the same worker into training (Table 5) and test sets may allow the model to see the same individual on both sides and artificially inflate performance. More meaningful designs include leave-person-out validation, leave-shift-out validation, or external validation under new work conditions. If the intended use is prediction for new workers, the test set should contain workers who were never seen during training.

Feature selection is not merely an algorithmic procedure. Joint angles, duration at angle, rate of change, repetition count, task identity, working height, force demand, and prior exposure should be connected to ergonomic theory. If a model uses hundreds of variables but decision makers cannot understand which factors drive its prediction, implementation trust may decline. Explainable-AI methods are therefore relevant to ergonomic decision support (Figure 3). General approaches such as LIME and SHAP can make feature contributions to a model output visible (Ribeiro et al., 2016; Lundberg & Lee, 2017). Yet a technically computable explanation is not necessarily ergonomically meaningful; explanations still require expert review.



Figure 3. Data pipeline from predictive ergonomics to decision support

Model drift is another critical issue in predictive ergonomics. When product design, work methods, worker profiles, or sensor placement change, the distribution of operational data may diverge from the training distribution. A model that once showed high accuracy may then perform poorly in the field. Model performance should therefore be monitored throughout the life cycle, periodically revalidated, and recalibrated when necessary. This approach is consistent with risk-based monitoring principles in AI governance (NIST, 2023).

Table 5. Matching data, target, and validation in predictive ergonomics

Purpose	Example inputs	Prediction target	Appropriate validation
Posture risk	Video/IMU, task	Risk class in the next period	New task / new person
Cumulative exposure	Task sequence, duration, force	End-of-shift dose	New shift
Fatigue	HRV/EMG, task history, self-report	Near-term fatigue level	Leave-person-out + out-of-time
Intervention effect	Design parameter + baseline state	Expected risk reduction	Field experiment / prospective validation

For time-series ergonomic data, the prediction horizon must be defined explicitly. Predicting posture a few seconds ahead and estimating cumulative load at the end of a shift are different modeling problems. Short-horizon models may rely more heavily on movement patterns, whereas long-horizon models require operational variables such as task sequence, breaks, cycle time, and recovery. A “predictive ergonomics model” is therefore not one technical class; it is a system component that must be designed together with its time horizon, decision frequency, and intervention delay. From an industrial engineering perspective, the prediction horizon should be matched to the planning horizon.

The temporal structure of the data creates a second issue: information leakage. If adjacent time points from the same shift are divided between training and test sets, the model may be evaluated on examples much more similar than it will encounter in real deployment. Cross-validation should therefore mimic the actual data-generating process. If generalization to a new shift, product, or worker is required, the test design should preserve that separation. In ergonomics, small samples and dense time series can create a misleading impression of “big data”: thousands of sensor rows may still originate from only a few independent people or shifts.

A further challenge in field deployment is that base rates may change. High-risk postures may be deliberately overrepresented in a laboratory experiment while occurring infrequently in actual work. Even if sensitivity and specificity remain unchanged, the practical meaning of a positive prediction can then differ substantially. Decision thresholds, event prevalence, and false-alarm costs should be recalibrated for field conditions. For this reason, algorithmic performance should not be summarized by a single overall accuracy value.

6. FROM PREDICTIVE ERGONOMICS TO PRESCRIPTIVE ERGONOMICS

Knowing that risk is likely to increase is important, but prediction alone does not generate an action. Predictive ergonomics approaches the question “What will happen?” whereas prescriptive ergonomics asks “What should we do?” (Tablo 6). This distinction is one of the clearest points of integration between ergonomics and industrial engineering because intervention selection is usually made under multiple constraints involving resources, time, skill, production targets, quality, and safety. The broader optimization literature illustrates how complex operational requirements can be translated into explicit objectives and constraints and then incorporated into systematic decision making. For example, Ekiz Bozdemir and Fırlalı (2025) formulated the coverage of multiple disjoint areas by unmanned aerial vehicles as a constrained mathematical optimization problem that incorporates routing decisions and battery-capacity limitations. Data-mining-guided approaches provide another example by extracting structural information from previously generated solutions and using that information to guide subsequent heuristic search (Fırlalı et al., 2026). Although the application domains differ, these approaches illustrate methodological principles relevant to prescriptive ergonomics: feasible alternatives must be represented explicitly, operational constraints must be respected, and optimization or search must be directed toward decisions rather than prediction alone.

A prescriptive system may be as simple as a threshold rule that recommends a break when exposure exceeds a defined level. A more advanced system can compare several interventions. For a worker expected to experience high shoulder exposure, alternatives might include adjusting workstation height, transferring the task to another worker, increasing robotic assistance, changing the task sequence, or adding a micro-break. These options differ in both ergonomic effect and operational cost.

The scientific quality of prescriptive ergonomics depends on the validity of the intervention model, not only on the accuracy of the prediction model. Prediction may be based on association, whereas intervention requires a causal effect. Changing a variable that is associated with risk does not necessarily reduce the risk. Intervention

effects should therefore be validated, where feasible, through controlled experiments, natural experiments, comparative field implementations, or strong causal designs. Otherwise, the system may confuse a risk marker with a risk cause.

The objective function is another central issue. If a prescriptive decision minimizes only an ergonomic score, it may push the production system toward an impractical solution. Conversely, preserving cycle time while treating ergonomic risk merely as a secondary constraint can subordinate worker well-being. The multiobjective optimization, lexicographic prioritization, and health-based hard constraints discussed in Chapter 4 are therefore directly relevant. Prescriptive ergonomics is where prediction and optimization meet.

Table 6. Comparing predictive and prescriptive ergonomics

Dimension	Predictive ergonomics	Prescriptive ergonomics
Core question	What will happen?	What should we do?
Output	Predicted risk / exposure / fatigue	Intervention or plan recommendation
Success criterion	Predictive accuracy and calibration	Actual risk reduction + feasibility
Primary method	Statistics / machine learning	Optimization / policy / decision rule
Greatest risk	Poor generalization	Mistaking correlation for causation

7. ADAPTIVE ERGONOMIC WORK SYSTEMS

Adaptive ergonomics describes a structure in which ergonomic decisions are repeated over time rather than implemented as one-off interventions. The system detects changes in the worker or production conditions, reassesses the current state, changes its decision when necessary, and monitors the result (Figure 4). In this sense it resembles a feedback control system, but because a human is a central component of the controlled system, technical decisions must be bounded by ethical, organizational, and behavioral constraints.

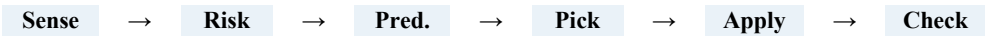


Figure 4. Closed-loop adaptive ergonomic decision system

Adaptation may occur on different time scales. At the millisecond or second scale, adjusting robot speed according to human proximity may support physical safety. Over minutes, work pace or micro-break recommendations may change. Over hours, job rotation can be replanned. Over weeks or months, workstation design, training needs, or capacity policies may be updated. The relevant decision horizon should therefore be stated explicitly rather than subsumed under a single broad label such as “real-time ergonomics” (Table 7).

The most important design question in an adaptive system is which decisions may be automated and which should require human approval. Parasuraman et al. (2000)

showed that automation can be considered across different functions and levels, from information acquisition to action implementation. An ergonomic system likewise need not automate every function to the same degree. Data collection may be automatic, risk prediction may be automatic, while a task reassignment may still require worker and supervisor approval. Human command authority should be preserved for decisions with high consequence severity.

This principle is directly related to the trust calibration discussed in Chapter 3. If the system generates too many alerts, users may develop alarm fatigue and ignore them. If alerts are too rare or too late, protective value declines. Explanations should also be appropriate to the decision context. A shift supervisor receiving a recommendation to change Worker A’s assignment should be able to see which exposure, time horizon, and uncertainty level produced the recommendation. Explanation should support appropriate reliance rather than simply increase acceptance (Lee & See, 2004).

Adaptive ergonomics also intersects with resilience engineering. Resilience approaches emphasize capacities to monitor, respond, learn, and anticipate so that system performance can be sustained under varying conditions (Hollnagel et al., 2006). In human-centered manufacturing, ergonomic adaptation should manage variability around the person rather than using the person as the buffer that absorbs system variability. This distinction is especially important under high demand. An adaptation that merely increases work speed when production pressure rises may be “smart” in a technical sense but is not ergonomically intelligent.

Table 7. Decision time scales in adaptive ergonomics

Time scale	Example signal	Example adaptation	Human oversight
Seconds	Proximity, sudden posture change	Robot speed / motion limit	Predefined safety policy
Minutes	Fatigue trend, rising repetition	Micro-break / pace recommendation	Worker acceptance
Hours	Cumulative exposure	Job rotation / rescheduling	Worker + manager
Week/month	Persistent pattern, performance trend	Work design / training / capacity change	Multi-stakeholder design

Decision stability must also be evaluated in adaptive systems. Small fluctuations in input signals should not cause tasks to move continuously between workers or produce a different break recommendation every few minutes. Just as hysteresis or dead bands reduce unnecessary switching in control systems, ergonomic decision systems can define minimum decision durations, replanning thresholds, and change costs. The result should be a system that is responsive without becoming unstable.

Adaptation should also be understandable and reasonably predictable to the worker. If workers do not know, at least in general terms, what type of signal triggers what type of recommendation, the system may appear arbitrary or punitive. Conversely, displaying all algorithmic detail can create cognitive overload. An appropriate explanation should answer three questions: “Why now?”, “Which risk changed?”, and “What is the expected effect of the proposed action?” These elements provide both a basis for trust and a mechanism for challenge or override by the worker and manager.

Decisions with social consequences, particularly job rotation, should not be driven only by individual risk minimization. Repeatedly labeling one worker as “high risk” may reduce task variety, inhibit skill development, or create stigmatization within the team. Adaptation policies should therefore monitor long-term skill development, fairness, and job-enrichment objectives as well. There is a fine distinction between ergonomic protection and exclusion from the production system, and a human-centered decision system should manage that distinction explicitly.

8. VALIDATION, DATA GOVERNANCE, AND HUMAN AUTONOMY

The weakest link in future ergonomic systems will often be validation design rather than the algorithm itself. A sensor or model that performs well in a laboratory may not maintain the same performance in a workplace because of clothing, lighting, occlusion, vibration, shift differences, new products, or different worker behavior. Validation should therefore occur at a minimum of three levels: technical accuracy, ergonomic validity, and decision impact (Table 8).

Technical accuracy asks whether the sensor or algorithm produces the correct measurement. Ergonomic validity asks whether that measurement actually represents the exposure or human state of interest. Decision impact asks whether the system’s recommendation creates the intended change in risk, performance, or well-being in the field. The third level is particularly important because a good prediction model connected to a poor intervention policy can still generate bad decisions.

For predictive models, discrimination measures such as accuracy or F1 score are not sufficient. When a model produces risk probabilities, calibration—the extent to which events assigned a 70% risk occur approximately 70% of the time—is critical for selecting decision thresholds. The ergonomic costs of false-positive and false-negative errors may also differ. A false negative may be more costly when serious health consequences are possible, whereas frequent low-importance false positives can generate alarm fatigue.

Data governance is not a separate technical issue in ergonomic systems; it is part of system design. Anthropometry, health-related restrictions, fatigue indicators, and

biosignals may constitute personal and, in some contexts, sensitive data. The European Union General Data Protection Regulation (Regulation (EU) 2016/679) establishes principles such as data minimization, purpose limitation, and transparency. Their ergonomic implications are clear: the system should collect only data required for the decision, explain why data are being used, and avoid turning performance monitoring into covert health surveillance.

Algorithmic bias is also directly relevant to ergonomics. If a model is trained mainly on particular body types, age groups, or experience levels, it may make systematic errors for other workers. This is not only an “AI fairness” problem; because it can lead to inappropriate ergonomic interventions, it is a safety and health issue. Model performance should therefore be reported not only as an overall average but also for meaningful subgroups. Results must still be interpreted cautiously because uncertainty may increase in small subgroups with limited data.

Human autonomy is a fundamental boundary condition for closed-loop systems. When an ergonomic system continuously measures a worker’s body and behavior, the line between protection and surveillance becomes narrow. A worker’s ability to reject a recommendation, access relevant personal data, and correct inaccurate records should be balanced with the employer’s responsibility to provide safe work. The strongest design makes the worker an active participant in ergonomic feedback rather than an object of the algorithm.

Table 8. Multilevel validation in intelligent ergonomic systems

Validation layer	Core question	Example metric	Failure consequence
Sensor/ measurement	Is the data accurate?	Error, agreement, repeatability	Incorrect input
Model	Is the prediction valid?	Discrimination, calibration, external validation	Incorrect risk prediction
Decision	Is the recommendation feasible?	Constraint violation, acceptance, decision stability	Operational disruption
Field impact	Does the real outcome improve?	Exposure, health, performance, well-being	Ineffective / harmful intervention
Governance	Is the system legitimate and fair?	Privacy, subgroup performance, transparency	Loss of trust / discrimination

Cybersecurity also becomes an ergonomic safety issue in intelligent work systems. Corruption of a sensor stream, incorrect identity matching, or unauthorized modification of a decision service may lead not merely to data loss but to incorrect task allocation or unsafe robot behavior. Authentication, access control, data integrity, and event logging should therefore be part of the technical foundation of a

digital human twin architecture. The safe fallback mode to be used when connectivity is lost should also be defined in advance.

From an organizational governance perspective, it is useful to distinguish the roles of model owner, data owner, and decision owner. A data-science team may develop the model; an ergonomist may evaluate its human-factors validity; a production manager may assess operational feasibility; and the worker may hold rights over personal data and recommendations. When these roles are unclear, technical error and managerial responsibility can become conflated. Adaptive Ergonomic Intelligence is therefore not only a software architecture but also a sociotechnical governance model in which decision responsibility is explicitly assigned.

9. AUTHOR SYNTHESIS: ADAPTIVE ERGONOMIC INTELLIGENCE

Viewed together, the five chapters of this book show that the contemporary transformation of ergonomics cannot be explained by a single technology. Chapter 1 established the framework of human-centered industrial engineering and systems ergonomics; Chapter 2 showed how ergonomic risk can be measured more continuously through sensors and AI; Chapter 3 addressed cognitive workload, trust, and task allocation in human-AI-robot systems; and Chapter 4 examined how ergonomic information can be translated into optimization and decision-support systems. The final step is to integrate these elements within a closed-loop architecture.

For this purpose, the conceptual framework of Adaptive Ergonomic Intelligence is proposed here. The concept does not imply replacing ergonomics with artificial intelligence. Ergonomic intelligence refers to the capacity to transform data about people, tasks, and technology into a meaningful ergonomic model; anticipate future states; select an appropriate intervention; validate its outcome; and update the system using new information. The term “adaptive” emphasizes that this is not a one-time process but a feedback-based and context-sensitive one (Figure 5).



Figure 5. The Adaptive Ergonomic Intelligence cycle

The first stage of the framework is observation. The system acquires data from sensors, production records, worker input, or expert assessment. The second stage is measurement: raw signals are translated into ergonomic variables. The third is assessment: the current risk or exposure state is determined. The fourth is prediction: the future state is estimated from current trends and context. The fifth is intervention

selection: design, task, break, robot, training, or scheduling alternatives are compared. The sixth is adaptation: the selected action is implemented at an appropriate level of authority. The seventh is learning: the actual outcome of the intervention is fed back into the model (Table 9).

Table 9. Seven stages of the Adaptive Ergonomic Intelligence framework

Stage	Core function	Example tool	Control question
1. Observe	Collect human-work-environment data	Sensor, video, logs, self-report	Are we collecting only necessary data?
2. Measure	Transform raw data into ergonomic variables	Angle, force, duration, HRV, task	Is the measurement valid?
3. Assess	Classify the current state	REBA/RULA/OCRA, dose, workload	Is risk being interpreted correctly?
4. Predict	Estimate the future state	Statistics / ML / simulation	Is uncertainty visible?
5. Select	Compare intervention alternatives	MIP, MOO, decision rules	Is health priority protected?
6. Adapt	Implement the decision under controlled authority	Rotation, break, robot/design adjustment	Is the authority level appropriate?
7. Learn	Feed the outcome back into the model	Field KPI, recalibration	Has the actual effect been validated?

Three protective layers should surround these seven stages. The first is human oversight. As the consequence severity of a decision increases, requirements for human approval and explanation should also increase. The second is data governance. Data minimization, access, privacy, and purpose of use should be defined from the outset. The third is validation. The system should be monitored for technical and ergonomic performance not only at deployment but throughout its life cycle (Table 10).

Table 10. Protective layers of the framework

Layer	Purpose	Minimum requirement
Human oversight	Autonomy and appropriate trust	Explainable recommendation, challenge/override, approval for high risk
Data governance	Privacy and legitimate use	Purpose limitation, data minimization, access control
Validation	Technical and ergonomic validity	External validation, field impact, model-drift monitoring
Fairness and inclusion	Safe performance across subgroups	Subgroup analysis, uncertainty reporting, bias checks

A defining feature of Adaptive Ergonomic Intelligence is that it does not treat the worker as a resource to be optimized. The system measures the person, but the purpose is not to extract more output; it is to make decisions that can sustain human well-being and system performance together under changing conditions. This is consistent with Industry 5.0's emphasis on human-centricity, sustainability, and resilience (European Commission, 2021). It also preserves the systems principle of ergonomics: good design aligns technology and organization with people rather than using technology to push human limits.

10. IMPLEMENTATION ROADMAP AND RESEARCH AGENDA

The transition to adaptive ergonomic systems should not begin with a sudden project to “build a digital twin.” Robust implementation requires gradual development of measurement and decision maturity (Table 11). The first stage should standardize existing ergonomic assessment processes and clarify which decisions depend on which data. The second stage can digitize data collection. The third can develop predictive models from historical data. The fourth can connect model recommendations to human-supervised decision support. Fully automatic adaptation should be considered only for well-validated functions with low consequence severity.

One of the most important research gaps is long-term field validation. Many technology studies examine measurement accuracy or short-term user experience, while much less is known about effects on health, fatigue, performance, acceptance, and work organization over months of use. Future studies should measure not only algorithmic performance but also how the technology reshapes work itself.

A second major topic is the balance between individualization and generalizability. A fully individual model may be highly sensitive but fail to generalize to new workers, while a fully generic model may lose important individual differences. Hierarchical models, transfer-learning approaches, or person-specific calibration can be explored between these extremes. The ethical cost of personalization should also be studied: how well can the system perform while collecting less personal data?

A third research area is causal and prescriptive ergonomics. Moving from risk prediction to intervention selection requires going beyond “Which factor is associated with risk?” to “Which intervention actually changes the outcome, for whom, and under what conditions?” This will require stronger integration of experimental design, causal inference, and operational optimization in ergonomics research.

A fourth area is joint human-AI-robot adaptation. Future systems may not only recommend tasks to workers; robot behavior, workstation parameters, and

production sequences may change simultaneously. A local ergonomic improvement may then create a new risk elsewhere in the system. Decision systems must therefore evaluate system-wide sociotechnical effects. The systems perspectives emphasized by Carayon (2006) and Wilson (2000) become more, not less, important as technology advances.

Finally, “success” in ergonomic systems should be redefined. A lower risk score or higher production rate alone is insufficient. Decision stability, worker acceptance, trust calibration, data privacy, fairness, sustainability of intervention, and long-term health outcomes should be monitored together. Such a multidimensional evaluation positions ergonomics not as a side effect of technology deployment but as a guiding discipline for human-centered system design.

Table 11. Proposed maturity levels for transitioning to adaptive ergonomics

Level	System characteristic	Primary output	Condition for moving to the next level
1. Standardize	Conventional assessments and decision rules defined	Reliable baseline process	Measurement repeatability
2. Digitize	Sensor/electronic data collection	Time-series exposure data	Data quality and governance
3. Predict	Predictive model	Future risk estimate	External validation + calibration
4. Recommend	Human-supervised decision support	Intervention recommendation	Field impact and acceptance validation
5. Adapt	Controlled closed loop	Dynamic work system	Continuous monitoring + safe override

Sector context should also be considered in the implementation roadmap. In repetitive assembly, cycles and task definitions are relatively stable, so cumulative-exposure and rotation models may be particularly useful. In warehousing and logistics, routes, loads, and order mixes are more variable, increasing the value of mobile sensing and dynamic task allocation. Maintenance work is often infrequent and unpredictable, making digital human modeling, augmented reality, and scenario-based preparation more relevant. In health care, physical and cognitive loads can change together, requiring multidomain assessment rather than a single ergonomic score. The maturity model can therefore remain stable while data and intervention layers are adapted to the sector.

A strong experimental strategy for future research is to validate the technology-decision chain in modules. First, the measurement system can be validated against a reference method; second, the predictive model can be tested for generalization to new people and tasks; third, the recommendation policy can be evaluated in a controlled setting; and finally, long-term outcomes can be assessed in actual field

deployment. This sequential validation makes it easier to determine whether a failure originates in sensing, modeling, optimization, or implementation.

Another research priority is shared data and reporting standards. Different studies may all use the term “ergonomic risk prediction” while relying on different task definitions, sensor sampling rates, reference labels, validation splits, and worker characteristics. This makes results difficult to compare. Developing data dictionaries, minimum reporting sets, and shareable anonymized benchmark structures could increase the scientific maturity of AI-enabled ergonomics. Benchmark success, however, should never be assumed to equal field success.

Economic evaluation should also become more visible. Digital twins, sensor infrastructures, and advanced optimization systems are costly, and the same level of technology is not necessary in every workplace. Decision makers should jointly consider risk reduction, implementation cost, maintenance, data management, training, false-alarm burden, and expected benefits over the system life cycle. A human-centered approach treats technological intensity as a means rather than an end. The best system is not the one that collects the most data, but the one that reliably supports the required decision at an acceptable total cost.

For adaptive ergonomics to scale institutionally, interoperability across data and model layers is essential. A manufacturing execution system, human-resources database, maintenance system, sensor platform, and ergonomics application may all use different data structures. Unplanned integration can produce identity errors, timestamp mismatches, and inconsistent task codes. Before technical integration begins, organizations should define a shared data dictionary, task identifiers, worker-anonymization procedures, and time-synchronization rules. For every variable used by the ergonomic model, its source, unit, sampling frequency, and update logic should be documented. Such a data contract improves reproducibility and auditability.

Life-cycle management of digital twins will also become increasingly important. If a workstation is modified, a new product is introduced, or a sensor model is replaced, allowing the twin to continue operating with old parameters can create silent model error. “Model version” and “physical-system version” should therefore be matched, and important changes should trigger revalidation. Change management for an ergonomic twin is broader than software updating: changes in task method, worker profile, PPE use, shift structure, or production pace can all affect the model’s validity domain. The digital twin should thus be treated as an engineering model managed throughout its life cycle, not as a permanent artifact installed once.

Joint learning by the worker and the system also requires attention. Workers may change their behavior in response to ergonomic feedback, and these changes can alter the model’s data distribution. If a system frequently warns about trunk flexion,

for example, workers may adopt a more upright posture but compensate by increasing load elsewhere in the body to complete the task. A model that monitors only the targeted indicator may interpret the change as an improvement while missing risk transfer. Adaptation should therefore be evaluated at the whole-body and task-system level rather than through a single variable. The reciprocal effects of performance and ergonomic objectives should likewise be reviewed regularly.

At the organizational level, adaptive ergonomics can turn individual alerts and recommendations into a knowledge asset. Over time, the organization may learn which tasks repeatedly create problems for which profiles, which interventions yield lasting improvements, and which design changes work across product families. This can form an “ergonomic intervention memory.” Such a memory should not become a permanent labeling history of individual workers. Information should, where possible, be anonymized and stored at task, design, or process level, while retention periods and purposes for individual data are managed separately. Learning can then improve work-system design knowledge without fixing a person into a permanent risk category.

This perspective also changes the role of the ergonomics professional. The ergonomist of the future will not only observe work or score risk; the role will increasingly include systems design and translation among data scientists, production engineers, software developers, occupational safety specialists, and worker representatives. The ergonomist does not need to become an algorithm developer, but should be sufficiently data literate to question what a model measures, which assumptions it makes, when it may become invalid, and what human consequences follow from its decisions. Data-science teams, in turn, need to understand the field meaning of ergonomic measurements. A shared interdisciplinary language is a prerequisite for technological maturity.

Performance indicators for ergonomic digitalization should be defined from the beginning. System usage rate or the number of alerts generated are not sufficient indicators of success. A more meaningful set should monitor outcomes such as change in high-exposure time, intervention acceptance rate, false-alarm rate, time to implement decisions, production effects, and perceived worker benefit. Longer-term applications may also evaluate distal outcomes such as musculoskeletal complaints, absenteeism, or turnover, but these are influenced by many organizational and individual factors. The effect of technology should therefore be examined through appropriate comparative designs rather than assumed to be directly causal.

An important characteristic of mature systems is their ability to choose “less automation” when needed. When model uncertainty rises, a sensor fails, or a new task is introduced, the system should be able to fall back to a safe default, expert review, or conventional ergonomic assessment instead of continuing to make

automatic decisions. This fallback capability is not a failure; it is a feature of resilient design. Human-centered adaptive ergonomics is not a system that automates under every condition, but one that recognizes when automation is insufficiently reliable and returns decision authority to people appropriately.

11. CONCLUSION

The future of ergonomics cannot be defined simply by using more sensors or more complex algorithms. The deeper transformation is a change in where ergonomic knowledge sits within the decision cycle. Digital human modeling enables work to be evaluated before implementation; the digital human twin allows representations of workers and work systems to be updated with new data; predictive ergonomics anticipates future exposure and fatigue; and prescriptive ergonomics selects suitable interventions. Adaptive ergonomics integrates these functions within a feedback system.

Human-centeredness, however, does not mean merely that a system uses “human data.” A human-centered system protects worker health, autonomy, privacy, diversity, and the worker’s role in decision making. As systems become more intelligent, data governance, explainability, field validation, and human oversight become more important rather than less.

The overall transformation proposed in this book is therefore complete: assessment, prediction, optimization, and adaptation are not independent stages, but mutually reinforcing decision functions of human-centered industrial engineering. The Adaptive Ergonomic Intelligence framework expresses this integration through the cycle “Observe → Measure → Assess → Predict → Select → Adapt → Learn.” Its purpose is not to fit the person to an algorithm, but to make the work system more responsive, safer, and more sustainable in the face of changing human characteristics and needs.

Statement on the Use of Generative AI

In preparing this book, the authors used OpenAI’s ChatGPT as an assistive tool for the English translation of the original Turkish manuscript, language editing, consistency checking, and document formatting. The authors reviewed and revised the resulting text and take full responsibility for the accuracy, interpretation, and final content of the book.

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Chapter 6

Ratio Scaling In Anthropometric Product Design: Limitations and Recommendations for Application

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ABSTRACT

Anthropometric data constitute fundamental inputs for designing products and work environments in accordance with user characteristics. However, the development of reliable anthropometric databases requires large samples, standardized measurement protocols, and substantial implementation costs. Because body dimensions may change over time as a result of changes in nutrition, physical activity, and living conditions, the validity of established databases is not permanent. Ratio Scaling, which has been used in the literature as a practical solution to this problem, is based on the assumption that the ratios of anthropometric dimensions to stature remain constant over time. In this study, this assumption was tested using the 1988 ANSUR1 and 2012 ANSUR2 datasets. In addition, predictions obtained from simple linear regression based on stature, regression based on body mass index, and multiple linear regression incorporating both stature and body weight were compared. The findings indicate that Ratio Scaling may retain its applicability over shorter time intervals, but remains reliable for only a limited number of dimensions in long-term database updates. In contrast, multiple regression models incorporating both stature and body weight produced lower prediction errors for many anthropometric dimensions. These results suggest that no single method should be generalized across all anthropometric dimensions and time intervals when updating anthropometric databases.

Keywords: anthropometry, ratio scaling, regression analysis, ANSUR, product design, anthropometric database

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1. INTRODUCTION

Anthropometric measurements constitute fundamental design inputs in product design, workstation design, and the organization of human-machine interaction. Numerous design decisions, including product dimensions, reach envelopes, working heights, seating surfaces, and control elements, are directly related to users' body dimensions. Accordingly, the suitability and applicability of anthropometric data influence not only design effectiveness but also user comfort, productivity, and safety. For such data to be used reliably, measurements should be obtained from sufficiently large and representative samples using standardized methods and appropriate measurement precision; otherwise, errors in the anthropometric database may be directly reflected in design decisions.

Another challenge associated with anthropometric databases is temporal change. Periodic changes in stature, body weight, and other body dimensions may occur within populations as a result of nutrition, physical activity, living conditions, and similar environmental factors. Consequently, the direct use of outdated databases for current design problems may reduce user-product fit. Although updating a database through new anthropometric measurements is the most reliable approach, it requires substantial cost and effort. For this reason, various methods have been developed in the literature to estimate contemporary values from existing measurements; Ratio Scaling is one of the most widely used approaches (Pheasant, 1982; Pheasant and Haslegrave, 2006; İşeri and Arslan, 2009; Chuan et al., 2010).

The ease of application is an important advantage of Ratio Scaling; however, the fact that the method relies solely on stature also constitutes its principal limitation. Assuming that the ratio of a given body dimension to stature remains unchanged while the average body weight of a population changes may lead to prediction errors, particularly for dimensions such as body breadths and depths that may be more strongly influenced by body weight. In this context, regression analysis offers an alternative approach because it allows multiple explanatory variables to be incorporated into the same model. Çavdar's (2014) use of multiple regression based on stature and body weight for anthropometric dimensions relevant to the automotive sector demonstrates the practical applicability of considering these two variables jointly in anthropometric prediction.

The primary objective of this study is to evaluate the Ratio Scaling assumption that "the ratio of body dimensions to stature remains unchanged over time" using large anthropometric databases from different periods, and to examine the predictive performance of alternative regression approaches. For this purpose, the 1988 ANSUR1 and 2012 ANSUR2 databases were used. Simple linear regression models based on stature, simple regression models based on body mass index, and multiple

linear regression models incorporating both stature and body weight were developed. The error rates produced by each approach were calculated relative to the actual measurements in ANSUR2, and comparisons were conducted separately for female and male groups and, where permitted by the data structure, across racial groups. In this way, the conditions under which Ratio Scaling may be sufficient for database updating, and those under which a multivariable model may be required, were evaluated.

2. THE IMPORTANCE OF ANTHROPOMETRY IN DESIGN AND THE CURRENCY OF ANTHROPOMETRIC DATABASES

The importance of anthropometric data in the design process lies not only in describing the physical dimensions of the human body, but also in enabling user variability to be systematically incorporated into the characteristics of products and work environments. However, because anthropometric measurements may vary across populations, user groups, and time periods, the data used in design must both adequately represent the target population and remain up to date.

2.1. Anthropometry, Design, and User Groups

Anthropometry is the scientific field concerned with measuring various dimensions of the human body and with organizing, deriving, and analyzing the resulting data. In ergonomic applications, it enables individual differences to be expressed quantitatively and provides a reference for a wide range of design disciplines. Anthropometric information has broad applicability, ranging from evaluating whether a product physically fits its intended users to determining reach limits within the work environment. Anthropometric measurements are also widely used in the design of physical environments used by large numbers of people, including hospitals, educational facilities, shopping and recreational areas, airports, manufacturing facilities, and residential spaces.

Anthropometry is generally considered under two main categories: static and dynamic anthropometry. Static anthropometric dimensions refer to body measurements obtained while an individual remains in a fixed posture. Stature, sitting height, shoulder breadth, hip breadth, and foot length are examples of measurements that fall within this category. Dynamic anthropometric measurements, in contrast, describe the areas a user can reach and the limits of movement during actions such as reaching, bending, and turning. Because workers are continuously in motion during production activities, workstation and machine-interface design should take into account not only static body dimensions but also reach and movement limits (Pheasant, 2003).

Designs that do not make appropriate use of anthropometric data may fail to accommodate a substantial proportion of the target user population. Such mismatches can lead to poor working postures, unnecessary reaching and physical strain, increased task completion times, or reduced product comfort. Therefore, it is important to define the intended user population and to ensure that the selected anthropometric measurements are representative of that population. Because variables such as sex, age, ethnicity, and geographic region may result in differences in anthropometric dimensions, the suitability of directly applying a database developed for one population to another user group should be carefully evaluated.

Da Silva et al. (2018) compared the anthropometric measurements of Brazilian and U.S. military personnel in the context of cockpit design and demonstrated that U.S. military data did not adequately represent Brazilian users. Sadeghi et al. (2015) identified significant anthropometric differences among different ethnic groups within the Iranian working population, while Widyanti et al. (2015) reported differences in a substantial proportion of mean body dimensions and body proportions among three major ethnic groups in Indonesia. These findings indicate that a “single universal user” approach is insufficient when applying anthropometric data to design and that the physical characteristics of the target population should be explicitly taken into account.

The use of anthropometric measurements is not limited to product design. In engineering applications, these data are employed to reduce static and dynamic muscular strain, ensure compliance with design standards, and improve ease of movement. Direct applications of anthropometry include garment sizing in the textile industry; the design of products such as beds, prostheses, and walking aids in the medical field; the monitoring of physical development and assessment of movement capacity in sports; and the adaptation of hand tools and machinery to users in agricultural applications.

Age-related change is particularly important in designs intended for children. Mokdad and Al-Ansari (2009) showed that anthropometric measurements in Bahraini children aged 6–12 years increased progressively with age. Agha and Alnahhal (2012) reported that some dimensions required for school furniture design could be estimated from more easily measured anthropometric variables and that artificial neural networks could, in some cases, outperform linear regression. Similarly, in the context of agricultural work and equipment design, Dewangan et al. (2010) and Syuaib (2015) emphasized the need to account for anthropometric differences associated with geographic region and ethnic background.

Hand dimensions are of particular importance in the design of control elements and manually operated equipment. Jee and Yun (2016) compared hand

measurements obtained from Korean participants with those reported for populations in other countries, demonstrating the limitations of assuming a single universal user in product and interface design. Abdrahman et al. (2018) similarly compared anthropometric data from different Asian countries and showed that population differences should be taken into account in workstation design. Studies examining the influence of sports participation, including Bostancı et al. (2017) and Çıkmaz et al. (2005), also reported differences in certain anthropometric measurements between physically active and non-active groups.

2.2. Currency of Anthropometric Databases and Prediction-Based Updating

Anthropometric databases developed to represent large user populations contain numerous measurements, and their reliability depends on standardized measurement protocols, appropriate sample structures, and consistency in measurement conditions. ANSUR1, used in this study, includes measurements collected in 1988 from 1,774 men and 2,208 women, whereas ANSUR2 includes measurements collected in 2012 from 4,082 men and 1,986 women (Gordon and Churchill, 1988; Bradtmiller et al., 2014). Because these databases provide large samples obtained from the same country and comparable user groups at different points in time, they are particularly suitable for examining temporal changes in anthropometric characteristics.

Temporal changes in anthropometric measurements have also been demonstrated in various studies. Hanson et al. (2009) compared data from Swedish workers with measurements obtained approximately three decades earlier and highlighted the need to update ergonomic data. Molenbroek et al. (2017) discussed the effects of thirty years of anthropometric change on the dimensional design of transportation and seating spaces. Chuan et al. (2010), comparing data from Singapore and Indonesia between 1990 and 2009, showed that changes occurred both in body dimensions and in the ratios of these dimensions to stature. Recent findings likewise support the need for regular updating of anthropometric databases. Jurda et al. (2025) reported that, although the secular increase in stature had plateaued in the Czech adult population, increases in body breadths and circumferences were still continuing, indicating the need for periodic revision of anthropometric data.

In Türkiye, a number of studies have also addressed the periodic collection and updating of anthropometric data. Çiner (1960) reported anthropometric measurements for Turkish women, while Kayış and Özok (1989) presented data for the Turkish male population. İşeri and Arslan (2009) subsequently updated these earlier datasets using more recent information on stature, age, sex, and geographic region through a Ratio Scaling approach. These studies demonstrate the practical

value of prediction-based methods for updating existing anthropometric data before conducting new large-scale measurement surveys, while also highlighting the importance of carefully evaluating the assumptions underlying such methods.

Because the development and updating of anthropometric databases are costly, estimating unknown body dimensions from easily obtainable variables has become an important area of research. Van Schoor and Konz (1996) compared approaches for estimating female anthropometric values from male anthropometric data, while Çavdar (2014) demonstrated that various anthropometric dimensions could be predicted using multiple regression models incorporating stature and body weight. This approach enables multiple physical characteristics to be included in the model rather than relying on a single scaling variable.

The Ratio Scaling approach is based on the assumption that, within a given age, sex, and ethnic group, the ratios of body dimensions to stature remain constant over time. Originally proposed by Barkla (1961) and later systematized by Pheasant (1982) for the purpose of updating anthropometric data, the method was described in detail by Pheasant and Haslegrave (2006). Its main advantage is that it enables rapid estimation of numerous anthropometric dimensions using only current stature information. However, a major limitation is that it does not directly account for the effects of changes in body weight and body composition on anthropometric dimensions.

3. DATASETS AND METHODS

To evaluate changes in anthropometric databases over time and to determine the extent to which different prediction approaches can represent these changes, datasets from different periods with comparable characteristics are required. In this context, ANSUR1 and ANSUR2, which were obtained from the same country and comparable user populations, provide an appropriate basis for comparing Ratio Scaling with regression-based prediction methods.

3.1. Datasets and Anthropometric Measurements Examined

In this study, ANSUR1 was used as the reference dataset and ANSUR2 as the target dataset. There is an interval of approximately 24 years between ANSUR1 and ANSUR2. Because both databases contain large samples drawn from military populations within the same country, they provide an appropriate basis for comparing temporal anthropometric changes and the performance of prediction methods. Analyses were conducted separately for female and male participants. Where permitted by the structure of the data, racial groups were also examined separately.

Although the ANSUR databases contain more than one hundred measurements, this study focused on dimensions that are commonly used in product and work-environment design. In addition to stature and body weight, 35 anthropometric measurements covering lengths, breadths, depths, and reaches were selected. The measurements used in the study are consistent with the anthropometric definitions adopted by Gordon and Churchill (1988), Bradtmiller et al. (2014), and Pheasant (2003). Table 1 lists the selected anthropometric measurements using the terminology employed in the ANSUR database.

Table 1. Selected anthropometric measurements

Abdominal Extension Depth, Sitting	Functional Grip Reach
Acromial Height	Hand Breadth
Acromial Height, Sitting	Hand Length
Biacromial Breadth	Head Breadth
Bideltoid Breadth	Head Length
Buttock Height	Hip Breadth
Buttock-Knee Length	Knee Height, Sitting
Buttock-Popliteal Length	Popliteal Height
Chest Depth	Shoulder-Elbow Length
Dactylion Height	Sitting Height
Dactylion Reach From Wall	Span
Elbow Rest Height	Stature
Elbow Rest Height, Standing	Thigh Clearance
Elbow Span	Vertical Grip Reach
Eye Height	Vertical Grip Reach Down
Eye Height, Sitting	Vertical Grip Reach, Sitting
Foot Breadth, Horizontal	Weight
Foot Length	Wrist Height
Forearm-Hand Length	

The measurements listed in Table 1 represent a wide range of design requirements, including seated and standing height dimensions; hand, foot, head, and torso measurements; reach distances; and dimensions related to the shoulders, hips, and knees. This diversity enables the database-updating method to be evaluated not only for length-related dimensions that are strongly associated with stature, but also for breadth and depth measurements that may be more strongly influenced by body weight and overall body morphology.

3.2. Ratio Scaling Method

The Ratio Scaling Method is applied under the assumption that the reference and target populations are comparable in terms of age range, sex, and ethnic characteristics. When population A is treated as the reference population and population B as the target population, the value of variable y in the target population

can be estimated using variable x , which is known for both populations, together with variable y , which is known only for the reference population. In practice, x is most commonly stature and is used as the scaling dimension (Pheasant, 1982; Pheasant and Haslegrave, 2006).

The ratio of the mean value of an anthropometric dimension in the reference population to the mean stature of the reference population defines the E_1 coefficient, while the ratio of the standard deviation of the same anthropometric dimension to the standard deviation of stature defines the E_2 coefficient. These coefficients can then be combined with the mean stature and stature standard deviation of the target population to estimate the corresponding mean and standard deviation of the anthropometric dimension in the target population. This approach is based on the assumption that the relevant anthropometric ratios remain stable between the two populations.

$E_1 = \text{Mean of the anthropometric measurement in the reference population} / \text{Mean stature of the reference population}$

$E_2 = \text{Standard deviation of the anthropometric measurement in the reference population} / \text{Standard deviation of stature in the reference population}$

In the individual-level prediction procedure used in this study, ratios of the 35 anthropometric measurements in ANSUR1 to stature were calculated, and the mean values of these ratios were obtained. The resulting coefficients were then multiplied by the stature of the corresponding participant in ANSUR2 to estimate each anthropometric measurement. The percentage error was calculated by dividing the absolute difference between the predicted value and the actual ANSUR2 measurement by the actual value.

Predicted measurement: $\hat{Y}_i = k_i \times \text{Stature}$

Error rate (%) = $|\text{Actual value} - \text{Predicted value}| / \text{Actual value} \times 100$

Ratio Scaling is computationally straightforward and enables rapid estimation of multiple anthropometric dimensions when up-to-date stature data are available. However, the accuracy of the method depends directly on the stability of the underlying ratios. The relatively long time interval between ANSUR1 and ANSUR2 is therefore particularly important for testing this assumption. Accordingly, the analysis was not limited to comparing prediction errors; it also examined whether the measurement-to-stature ratios observed in the two periods could be considered statistically equivalent.

3.3. Regression Models for Anthropometric Prediction

Regression analysis enables relationships between variables to be expressed mathematically and used for prediction. When a single independent variable is included in the model, the approach is referred to as simple regression, whereas models incorporating two or more independent variables are classified as multiple regression. In linear regression, the suitability of the model depends on the characteristics of the data and the nature of the relationship between the dependent and independent variables. Therefore, distributional characteristics, linearity, and the relationships among the variables should be evaluated before interpreting the resulting regression model.

In simple linear regression, an anthropometric measurement was defined as the dependent variable, while stature or body mass index was used as the independent variable. The general form of the model is $Y = a + bX + \varepsilon$, where Y represents the anthropometric measurement to be predicted, X the independent variable, a the intercept, b the regression coefficient, and ε the error term. In multiple regression, more than one independent variable is included in the same model. In this study, the model incorporating both stature and body weight was specified as $Y = a + b_1\text{stature} + b_2\text{body weight} + \varepsilon$.

$$\text{Simple linear regression: } Y = a + bX + \varepsilon$$

$$\text{Multiple linear regression: } Y = a + b_1 (\text{stature}) + b_2 (\text{body weight}) + \varepsilon$$

In the first approach, separate simple linear regression equations were developed for female and male groups using the relationship between each anthropometric measurement and stature. The coefficients derived from ANSUR1 were applied to the stature values in ANSUR2, and error rates were calculated by comparing the predicted values with the actual ANSUR2 measurements. Similar to Ratio Scaling, this approach relies solely on stature; however, instead of using a constant ratio, it represents the linear relationship within the data through regression coefficients.

In the second approach, body mass index (BMI) was used as the independent variable. BMI values were calculated for the 1,774 male and 2,208 female participants in ANSUR1, after which separate simple regression equations were developed for each of the 35 anthropometric measurements as a function of BMI. Because BMI is calculated as body weight divided by the square of stature, it combines information on stature and body weight into a single variable. Although this simplifies model application, it prevents the separate effects of stature and body weight from being modeled directly.

$$BMI = \text{Body weight (kg)} / \text{Stature}^2 (m^2)$$

In the third approach, stature and body weight were included as separate independent variables in a multiple linear regression model. The models developed using ANSUR1 were applied to the ANSUR2 data, and predictions for the 35 anthropometric measurements were generated using each participant's stature and body weight. Unlike Ratio Scaling, this model directly incorporates body weight and therefore allows changes in body dimensions that may be associated with weight to be reflected in the predictions.

To illustrate the structure of the multiple regression equations, selected female and male equations for several anthropometric measurements are presented in Table 2. Rather than reproducing all models, the table provides representative examples of the model structure across different types of measurements; however, the corresponding equations for all 35 measurements were used in the analyses.

Table 2. Multiple Regression Equations Based on Stature and Body Weight for Selected Anthropometric Measurements

Anthropometric Measurement	Female Multiple Regression Equation	Male Multiple Regression Equation
Abdominal Extension Depth, Sitting	$Y=0.24*(W)-0.139*(S)+291.71$	$Y=0.2934*(W)-0.1455*(S)+277.5842$
Acromial Height	$Y=0.035*(W)+0.86*(S)-101.31$	$Y=0.031*(W)+0.8593*(S)-86.12$
Bideltoid Breadth	$Y=0.21*(W)-0.04*(S)+395.858$	$Y=0.230*(W)-0.0258*(S)+331.8$
Chest Depth	$Y=0.18*(W)-0.089*(S)+252.3$	$Y=0.23*(W)-0.109*(S)+271.85$
Hand Breadth	$Y=0.015*(W)+0.0149*(S)+52.0$	$Y=0.015*(W)+0.016*(S)+42.67$
Head Breadth	$Y=0.018*(W)-0.007*(S)+149.9$	$Y=0.0179*(W)-0.002*(S)+137.9$
Thigh Clearance	$Y=0.107*(W)-0.04*(S)+164.05$	$Y=0.127*(W)-0.04*(S)+147.50$
Vertical Grip Reach	$Y=0.013*(W)+1.28*(S)-157.94$	$Y=-0.003*(W)+1.27*(S)-130.4$
Wrist Height	$Y=0.031*(W)+0.502*(S)-60.76$	$Y=0.027*(W)+0.49*(S)-33.98$
Note: S denotes stature and W denotes body weight.		

3.4. Evaluation of Prediction Accuracy and Statistical Differences

The performance of the prediction methods was evaluated using the percentage error between the actual ANSUR2 values and the corresponding predicted values. For each participant, the mean and standard deviation of the calculated error rates were determined separately. This made it possible to assess how each method performed not only for an average user but also with respect to individual variability within the database. In addition, because aggregated anthropometric data are often represented through mean values in design applications, prediction errors were also calculated for an “average-sized individual” using mean stature and, where required, mean body weight.

Following the individual-level predictions, the female and male data were further

stratified according to the racial groups represented in the database. For each subgroup, stature-based Ratio Scaling coefficients and multiple regression equations based on stature and body weight were recalculated. The purpose of this analysis was to determine whether prediction errors decreased when more homogeneous subgroups were considered and whether the superior predictive performance of multiple regression was maintained across these subgroups.

The statistical evaluation of the fundamental assumption underlying Ratio Scaling was conducted in two stages. First, the mean ratios of the anthropometric measurements to stature in ANSUR1 and ANSUR2 were compared, and the acceptability of the differences between the two datasets was examined at different confidence levels. This analysis was intended to directly assess the effect of the approximately 24-year time interval on the stability of anthropometric ratios.

In the second stage, data from the same time period were randomly divided into two groups, and the group means within the same database were tested to determine whether they differed statistically. Normality tests were first conducted; an independent-samples t-test was used for measurements that followed a normal distribution, whereas the Mann–Whitney U test was applied to measurements that did not meet the normality assumption. This comparison was used to evaluate the stability of the Ratio Scaling assumption in the absence of a temporal difference.

4. FINDINGS

The applicability of prediction methods depends not only on their theoretical assumptions but also on how accurately they estimate actual anthropometric values. Therefore, the performance of Ratio Scaling and regression-based approaches was compared using the error rates between the actual ANSUR2 measurements and the corresponding predicted values. The results were also evaluated according to measurement type, sex, and subgroup to examine how prediction performance varied across different anthropometric characteristics and population groups.

4.1. Comparative Performance of Prediction Methods

When the Ratio Scaling coefficients derived from ANSUR1 were applied to the stature values in ANSUR2, the prediction errors were found to vary substantially across anthropometric measurements. Error rates remained relatively low for several height- and reach-related dimensions that were strongly associated with stature, whereas higher errors were observed for torso-depth and certain breadth measurements. Among men, the mean error was approximately 11.83% for sitting abdominal depth, 8.63% for chest depth, 10.30% for sitting elbow height, and 8.26% for thigh clearance. Among women, mean errors of 10.69% for sitting abdominal

depth, 8.70% for chest depth, and 7.27% for thigh clearance were observed.

In contrast, the mean prediction errors obtained using Ratio Scaling remained relatively low for several dimensions, including shoulder height, eye height, elbow height, knee height, sitting height, and vertical grip reach. This variation indicates that the performance of Ratio Scaling cannot be represented by a single overall coefficient and should instead be evaluated separately for different types of anthropometric measurements. In other words, while the method may provide acceptable results for some dimensions, it can produce errors large enough to affect design decisions for others.

When the simple regression equations based on stature were developed using ANSUR1 and applied to the ANSUR2 data, no consistent or substantial improvement over Ratio Scaling was observed. For example, the R^2 value of approximately 0.019 for the female regression model of sitting abdominal depth indicates that stature alone explains only a very small proportion of the variability in this measurement. This finding demonstrates that not all anthropometric dimensions are equally strongly associated with stature and that a single-predictor model may be insufficient, particularly for measurements such as torso depth.

The simple regression approach based on BMI was considered a potential alternative for addressing one of the limitations of Ratio Scaling, namely its failure to account for body weight, because BMI combines information on stature and body weight into a single derived variable. However, the resulting prediction errors did not show sufficient improvement across all anthropometric measurements. Because BMI combines the effects of stature and body weight within a single index, it does not allow the potentially different directions and magnitudes of these two variables to be represented separately for specific anthropometric dimensions. Therefore, in the subsequent analysis, stature and body weight were included directly as separate independent variables in the multiple regression model.

The multiple regression model incorporating both stature and body weight reduced prediction errors for the majority of anthropometric measurements. Among men, the error rates obtained with multiple regression were lower than those from Ratio Scaling for nearly all measurements. For the limited number of dimensions in which Ratio Scaling produced lower errors, the differences were generally small; the largest difference was approximately 0.26% for hand breadth. Among women, multiple regression yielded lower prediction errors for all but four measurements, and in three of these four cases the differences between the two methods were relatively minor.

Table 3 presents the mean prediction error rates obtained using Ratio Scaling and multiple regression for 35 anthropometric measurements in both female and male

groups. The table highlights the improvement achieved by multiple regression, particularly for dimensions that are more closely associated with body weight and overall body morphology.

Table 3. Comparison of Prediction Errors Obtained with Ratio Scaling and Multiple Regression (%)

Anthropometric Measurement	Male Ratio Scaling	Male Multiple Regression	Female Ratio Scaling	Female Multiple Regression
Abdominal Extension Depth, Sitting	11.84	5.79	10.69	7.11
Acromial Height	0.94	0.89	0.85	0.80
Acromial Height, Sitting	3.15	2.93	3.34	3.20
Biacromial Breadth	4.95	4.09	3.39	3.18
Bideltoid Breadth	5.60	2.38	9.08	2.62
Buttock Height	2.59	2.51	2.47	2.43
Buttock-Knee Length	2.32	2.15	2.88	2.50
Buttock-Popliteal Length	2.81	2.78	3.20	3.02
Chest Depth	8.64	4.01	8.70	5.48
Dactylion Height	2.93	2.84	3.01	3.00
Dactylion Reach From Wall	3.10	3.00	3.46	3.35
Elbow Rest Height	10.30	9.43	10.02	9.59
Elbow Rest Height, Standing	1.69	1.52	1.47	1.41
Elbow Span	3.01	3.01	3.08	3.07
Eye Height	0.60	0.61	0.47	0.47
Eye Height, Sitting	2.56	2.43	2.58	2.49
Foot Breadth, Horizontal	3.89	3.27	4.70	3.71
Foot Length	2.71	2.61	2.84	2.69
Forearm-Hand Length	2.51	2.60	2.91	2.94
Functional Grip Reach	3.29	3.17	3.60	3.50
Hand Breadth	4.37	4.63	3.99	4.09
Hand Length	3.05	3.05	3.35	3.28
Head Breadth	4.15	2.69	4.11	2.92
Head Length	3.41	2.55	3.64	2.91
Hip Breadth	6.19	2.93	6.41	3.60
Knee Height, Sitting	2.03	2.09	2.21	2.21
Popliteal Height	2.73	2.35	2.94	2.78
Shoulder-Elbow Length	2.65	2.75	2.39	2.39
Sitting Height	2.09	1.95	2.21	2.07
Span	2.17	2.21	2.38	2.40
Thigh Clearance	8.26	4.22	7.27	3.63
Vertical Grip Reach	2.04	2.00	1.77	1.76
Vertical Grip Reach Down	2.31	2.36	2.41	2.43
Vertical Grip Reach, Sitting	2.59	2.59	2.77	2.85
Wrist Height	2.05	1.95	2.02	1.98

The comparison shows that multiple regression provides a clear advantage for measurements such as sitting abdominal depth, bideltoid breadth, chest depth, head

breadth, head length, sitting hip breadth, and thigh clearance. Because many of these dimensions are influenced not only by stature but also by body weight and overall body morphology, including stature and body weight within the same model helps reduce prediction error. In contrast, the error rates produced by the two methods are more similar for dimensions such as eye height, shoulder height, and certain reach measurements.

4.2. Analysis of Mean Anthropometric Profiles and Population Subgroups

In anthropometric design, mean values representing the target population are as important as individual measurements. Therefore, the coefficients and regression equations derived from ANSUR1 were re-evaluated using the mean stature and mean body weight values of ANSUR2. The prediction results obtained for the mean anthropometric profile were generally consistent with the patterns observed in the individual-level error analyses. Because stature-based simple regression and BMI-based models produced relatively high errors for some measurements, the primary comparison at this stage focused on Ratio Scaling and multiple regression.

The results for the mean anthropometric profile indicate that the performance of a prediction method may differ not only at the individual level but also for design values intended to represent a population. In mass production and in products designed for large user populations, designers often rely on selected percentile values or population means. Therefore, even small deviations in mean values should be taken into account, as they may affect the extent to which product dimensions accommodate a substantial proportion of the target population.

When the racial groups represented in the database were evaluated separately, both the Ratio Scaling coefficients and the multiple regression equations were found to vary across groups. Separate models were developed for three racial groups within both the male and female samples, and prediction errors were calculated using the ANSUR2 data. This approach was intended to assess whether the use of anthropometrically more homogeneous subgroups within a large sample could improve prediction accuracy.

The overall pattern remained unchanged when the results were evaluated by racial group. For both women and men, multiple regression incorporating stature and body weight produced lower prediction errors than Ratio Scaling for nearly all of the stratified measurements. This finding indicates that the superior performance of multiple regression was not attributable solely to heterogeneity in the overall sample; even within narrower subgroups, the two-predictor model provided an advantage for most anthropometric measurements.

Table 4. Prediction Error Rates of Multiple Regression and Ratio Scaling for Selected Measurements by Racial Group (%)

Anthropometric Measurement	M:White Reg./Rat.	M:Black Reg./Rat.	M:Asian Reg./Rat.	F:White Reg./Rat.	F:Black Reg./Rat.	F:AsianR eg./Rat.
Abdominal Extension Depth, Sitting	5.74 / 11.81	5.93 / 12.53	5.90 / 11.26	7.47 / 10.52	6.73 / 11.18	7.35 / 10.11
Acromial Height	0.86 / 0.91	0.96 / 1.00	0.91 / 0.95	0.79 / 0.85	0.85 / 0.86	0.89 / 0.94
Acromial Height, Sitting	2.58 / 2.77	3.05 / 3.26	2.87 / 2.87	2.57 / 2.70	2.75 / 3.04	2.86 / 3.06
Biacromial Breadth	4.07 / 4.82	4.41 / 5.41	3.86 / 5.02	3.14 / 3.34	3.32 / 3.50	3.73 / 3.30
Bideltoid Breadth	2.30 / 5.47	2.49 / 5.88	2.45 / 5.55	2.68 / 5.33	2.67 / 5.94	2.26 / 5.08
Buttock Height	2.32 / 2.39	2.46 / 2.52	2.35 / 2.38	1.93 / 4.71	2.08 / 2.12	1.90 / 1.99
Chest Depth	4.13 / 8.59	3.49 / 9.06	4.43 / 7.71	5.32 / 8.31	5.59 / 9.04	4.91 / 8.71
Elbow Rest Height	8.14 / 8.86	10.28 / 11.52	8.26 / 9.10	7.65 / 8.06	1.38 / 1.43	1.52 / 1.59
Eye Height	0.60 / 0.60	0.65 / 0.61	0.78 / 0.75	0.51 / 0.49	0.47 / 0.46	0.65 / 0.53
Hand Breadth	4.22 / 4.20	5.45 / 4.76	4.52 / 4.26	3.34 / 3.67	4.38 / 4.25	4.88 / 4.11
Head Breadth	2.62 / 3.91	2.65 / 4.15	2.62 / 4.01	2.69 / 3.63	2.85 / 4.24	3.04 / 3.95
Thigh Clearance	4.23 / 8.24	4.33 / 8.86	4.06 / 8.15	3.69 / 7.09	3.58 / 7.77	3.89 / 7.15

In Table 4, the notation “Reg./Rat.” refers, respectively, to the multiple regression and Ratio Scaling error rates for the same subgroup. Among the selected measurements, the regression approach produces substantially lower error rates, particularly for dimensions such as abdominal depth, bideltoid breadth, and chest depth. Although the differences are more limited for some height-related measurements, the overall pattern favors multiple regression.

4.3. Statistical Evaluation of the Ratio Scaling Assumption

While the comparison of prediction errors reflects the practical performance of the methods, the theoretical basis of Ratio Scaling was evaluated separately by examining whether the ratios of anthropometric measurements to stature could be considered statistically equivalent between the two databases. Given the approximately 24-year interval between ANSUR1 and ANSUR2, this analysis provides a direct test of the long-term stability of these ratios.

In the male dataset, the ANSUR1 and ANSUR2 ratios could be considered equivalent for only six measurements at the 90% confidence level. Even at the 68%

level, which approximately corresponds to one standard deviation, the number of measurements for which equivalence could be accepted remained limited to ten. For women, the corresponding numbers were four measurements at the 90% level and nine at the 68% level. Thus, for a substantial proportion of the 35 anthropometric measurements, the assumption that the measurement-to-stature ratio remains unchanged over time is not supported when the two databases are separated by a long temporal interval. The number of measurements supporting the Ratio Scaling assumption at the 90% and 68% confidence levels is summarized in Table 5.

Table 5. Temporal Stability of the Ratio Scaling Assumption

Group	Number of Measurements at 90% Level	Number of Measurements at 68% Level
Male	6	10
Female	4	9

The magnitude of change over time in the ratios that could be considered equivalent was also relatively small. For male measurements, the maximum proportional change was approximately 0.3% at the 90% confidence level and 0.55% at the 68% level; for female measurements, the corresponding values were approximately 0.5% and 1%, respectively. However, a small proportional change does not necessarily imply statistical equivalence between the ratios observed in the two periods. Therefore, when applying Ratio Scaling, it is not sufficient to consider only the magnitude of percentage change; measurement-specific statistical evaluation is also required.

The analyses showed that, in the male dataset, the mean measurements for Acromial Height in ANSUR1 and ANSUR2 could be considered equivalent at the 80% confidence level, while for Buttock Height the confidence level of equivalence reached 99%. In contrast, Biacromial Breadth and Bideloid Breadth exhibited significant differences between the two periods even at the 50% confidence level. These examples demonstrate that, even within the same databases and over the same time interval, the stability of anthropometric ratios can vary substantially depending on the measurement type.

To isolate the effect of the temporal difference, the ANSUR1 and ANSUR2 datasets were randomly divided into two subgroups for both female and male participants, and the mean measurements of the two subgroups drawn from the same period were compared. Normality tests were conducted first; independent-samples t-tests were used for normally distributed measurements, whereas the Mann–Whitney U test was applied to the remaining measurements. In the male ANSUR1 dataset, 10 of the 35 measurements were found to conform to a normal distribution.

When the ANSUR1 male data from the same time period were randomly divided into two groups, analyses including all observations, including outliers, showed that the group means could not be considered equivalent at the 95% confidence level only for head breadth. When the significance level was set at 4%, equivalence could also be accepted for this measurement. No statistically significant differences between the two subgroup means were observed for any measurement in the ANSUR2 male or ANSUR1 female datasets. In the ANSUR2 female dataset, a significant difference at the 95% confidence level was observed only for thigh clearance. When the significance level was reduced to 4%, equivalence could also be accepted for this measurement.

These results indicate that the Ratio Scaling assumption can largely be maintained in comparable samples collected within the same or very similar time periods, but loses validity for most measurements when databases separated by approximately 24 years are compared. Thus, the applicability of the method appears to depend not only on population similarity but also on the temporal distance between the reference and target datasets.

5. DISCUSSION

The findings indicate that temporal changes in anthropometric measurements do not follow the same pattern across all body dimensions, suggesting that a single updating method may not be appropriate for every measurement. In particular, the temporal interval between datasets, changes in body weight, the morphological characteristics of the measurement, and the characteristics of the target user population emerge as key factors influencing the accuracy of prediction methods.

5.1. Limitations of Ratio Scaling and Method Selection

Ratio Scaling is a practical approach for updating anthropometric databases because it enables rapid estimation of multiple body dimensions using current stature data. Pheasant (1982), Pheasant and Haslegrave (2006), İşeri and Arslan (2009), and Chuan et al. (2010) demonstrated various applications of the method. However, the findings of the present study show that its underlying assumption cannot be considered automatically valid across different time periods. Over the approximately 24-year interval between ANSUR1 and ANSUR2, equivalence of the relevant ratios was maintained for only a limited number of the 35 measurements, whereas substantially greater consistency was observed between randomly formed subgroups drawn from the same period.

This finding suggests that Ratio Scaling is not an inherently invalid method; rather, its reliability is particularly sensitive to the temporal interval between

datasets, the characteristics of the anthropometric measurement, and the structure of the population. When the reference data are relatively close to the target period and the ratio of the relevant measurement to stature remains stable, the method may offer an advantage because of its limited data requirements. In contrast, for longer time intervals - particularly for measurements that are more strongly influenced by body weight and environmental factors - regression-based alternatives may provide a more appropriate approach.

A major limitation of Ratio Scaling is its reliance solely on stature, particularly under conditions in which the average body weight of a population changes over time. Multiple regression incorporating both stature and body weight produced substantial reductions in prediction error for measurements such as torso depth and shoulder and hip breadth, which may be more strongly influenced by body weight. The development of anthropometric regression models based on stature and body weight by Çavdar (2014) further supports the applicability of this approach. In contrast, simple regression based on BMI did not yield the same improvement, because combining stature and body weight into a single index may obscure the separate direction and magnitude of their effects on a given anthropometric dimension. Changes in body weight may influence not only overall body size but also the morphology of specific body regions. In a three-dimensional analysis of 490 children aged 3–17 years, Jung et al. (2026) reported that higher BMI values were associated with greater foot breadth, larger circumferences and thicknesses, and lower arch height. This finding provides a recent example supporting the view that some anthropometric dimensions may not be adequately predicted on the basis of stature alone.

The findings indicate that no single method performs equally well across all anthropometric measurements. Although multiple regression generally produces lower prediction errors, the differences compared with Ratio Scaling are relatively small for some height- and reach-related dimensions. Method selection should therefore be made at the level of individual measurements rather than applied uniformly across an entire anthropometric database. For design-critical dimensions, acceptable error thresholds should also be defined explicitly, and the functional importance of the relevant measurement should be incorporated into method selection in applications such as school furniture, vehicle accommodation, control-element design, and workstation design.

5.2. Subgroups, Representativeness, and User Coverage

Variation in anthropometric dimensions across sex and ethnic groups makes sample composition an important consideration in anthropometric database

updating. Sadeghi et al. (2015) and Widyanti et al. (2015) demonstrated significant anthropometric differences among different ethnic groups. In the present study, the lower prediction errors obtained for some measurements using models stratified by racial group likewise indicate the potential benefit of developing models within more homogeneous subgroups. At the same time, when product design aims to accommodate a large proportion of the population, even small prediction deviations may become important. Kaewdok et al. (2020) emphasized the importance of accommodating a high percentile range of the population in designs intended for older users. Subgroup modeling, sample adequacy, and representativeness should therefore be evaluated together.

Anthropometric variation is important not only with respect to sex or ethnicity but also across occupational user groups. Bolaji et al. (2025) compared data obtained from 187 female firefighters with those of the general U.S. female population and found that female firefighters were, on average, 6.7 cm taller and also differed in waist and hip dimensions, highlighting the importance of anthropometric data specific to the intended user population. Inadequate representation of user diversity also poses an important challenge to the generalizability of products and systems based on anthropometric data. In a systematic review of 191 exoskeleton studies, Kazemi et al. (2026) reported that approximately 78% of participants were young men, that anthropometric diversity remained limited, and that this constrained the generalizability of the findings to different user populations.

5.3. Methodological Contribution and Limitations of the Study

The methodological contribution of this study lies in evaluating the prediction methods not merely through goodness-of-fit measures within the same database, but by testing them against an actual database collected in a different period. The coefficients and equations derived from ANSUR1 were applied to ANSUR2, and the predicted values were compared with the corresponding observed measurements. In addition, individual prediction errors, estimates for the mean anthropometric profile, race-based analyses, and statistical testing of the underlying Ratio Scaling assumption were considered together.

The findings should be interpreted within the characteristics of the databases used. Although ANSUR1 and ANSUR2 include large samples, both consist of military personnel, whose age distribution, occupational characteristics, and physical attributes may differ from those of the general population. Sample sizes also vary across racial groups. Therefore, the coefficients and equations derived in this study should be validated in the relevant target population before being directly generalized to other populations.

6. CONCLUSIONS AND RECOMMENDATIONS FOR APPLICATION

In this study, the Ratio Scaling method used for updating anthropometric databases was evaluated using the 1988 ANSUR1 and 2012 ANSUR2 datasets and compared with simple regression based on stature, simple regression based on BMI, and multiple regression incorporating both stature and body weight. The results showed that the performance of Ratio Scaling varied across anthropometric measurements and that, over long time intervals, its underlying assumption was maintained for only a limited number of dimensions.

Ratio Scaling should not be disregarded entirely because of its low data requirements and ease of application. However, as the temporal gap between the reference database and the target period increases, the assumption of stable ratios should be tested on a measurement-specific basis. The high level of agreement observed between randomly formed groups from the same period indicates that temporal distance is one of the key factors determining the reliability of the method.

Simple regression models based on stature and BMI did not provide sufficient improvement across all anthropometric measurements. In contrast, multiple regression models that treated stature and body weight as separate independent variables reduced prediction errors, particularly for torso and breadth dimensions that are more strongly associated with body weight. Therefore, the method selected for database updating should be determined not only by computational simplicity but also by the biomechanical and morphological characteristics of the specific anthropometric measurement.

In practical applications, the age of the anthropometric database and the temporal interval between the reference data and the target period should first be evaluated. If the reference data are relatively recent and the ratio of the relevant measurement to stature remains stable, Ratio Scaling may provide a practical option. When the temporal gap increases, or when the measurement is influenced by body weight and body composition, regression models incorporating both stature and body weight should be preferred. Where the sample size is sufficient with respect to user characteristics such as sex and ethnic group, subgroup-specific models should also be considered.

Anthropometric database updating should not be regarded as a fixed substitute for direct measurement, but rather as a predictive decision-support process to be used when new field measurements cannot be conducted. The prediction error generated by the selected approach should be evaluated together with the sensitivity of the design decision and the characteristics of the target user population. In this way, anthropometric data can be updated more reliably through approaches that account for temporal change, jointly incorporate easily obtainable variables such as stature and body weight, and are validated on a measurement-specific basis.

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Statement on the Use of Generative AI

In preparing this book, the authors used OpenAI's ChatGPT as an assistive tool for the English translation of the original Turkish manuscript, language editing, consistency checking, and document formatting. The authors reviewed and revised the resulting text and take full responsibility for the accuracy, interpretation, and final content of the book.

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