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MODELING AND VALIDATING OF A TIME ANALYSIS SYSTEM FOR INTEGRATION INTO THE VIRTUAL 3D SOFTWARE PRODUCT

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
Génie industriel

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Cette thèse intitulée :

MODELING AND VALIDATING OF A TIME ANALYSIS SYSTEM FOR INTEGRATION INTO THE VIRTUAL 3D SOFTWARE PRODUCT

présentée par **Farhad MAZAREINEZHAD**
en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

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DEDICATION

To my Parents, For supporting me all these years. I am thankful for having you in my life....

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RÉSUMÉ

Dans le paysage industriel actuel, l'optimisation de la conception des lieux de travail tout en garantissant la sécurité et l'efficacité des travailleurs est d'une importance primordiale. Les systèmes de modélisation humaine numérique (Digital Human Modeling, DHM) sont devenus des outils indispensables pour atteindre ces objectifs. En simulant les interactions humaines avec les espaces de travail, les outils et les tâches avant la création de prototypes physiques, ces systèmes soutiennent le processus de conception, permettant l'identification et l'atténuation précoces des risques potentiels pour les travailleurs. L'estimation du temps joue un rôle crucial dans ce contexte en fournissant des prévisions précises des durées des tâches et en soutenant l'optimisation des processus, ce qui est essentiel pour améliorer la productivité et l'efficacité dans les environnements industriels.

Les systèmes DHM sont largement utilisés dans les analyses ergonomiques pour évaluer les exigences physiques des tâches et concevoir des lieux de travail plus sûrs et plus efficaces. Traditionnellement, de nombreux systèmes DHM se sont principalement concentrés sur l'évaluation des risques ergonomiques statiques basés sur les données de planification des processus. Cependant, l'intégration de méthodes d'estimation du temps, telles que la technique de séquence d'opérations de Maynard (Maynard Operation Sequence Technique, MOST), dans ces systèmes permet l'analyse des opérations conçues sur des périodes prolongées. En effectuant des analyses temporelles au sein des systèmes DHM, une évaluation plus complète des risques ergonomiques dynamiques devient possible. Ce passage de l'analyse statique à l'analyse dynamique offre une évaluation plus nuancée des tâches en tenant compte de la variabilité et de la séquence des mouvements, souvent négligées dans les évaluations statiques. Une telle intégration aide les concepteurs à créer des processus de travail plus précis et efficaces, contribuant ainsi à améliorer la sécurité et la productivité sur le lieu de travail.

L'objectif principal de cette thèse est de développer une méthode d'estimation du temps au sein des systèmes DHM, en se concentrant sur l'intégration du système de temps MOST. Les sous-objectifs incluent l'évaluation de l'applicabilité et de la fiabilité du système MOST et de la nouvelle méthode d'estimation du temps DHM dans des contextes industriels réels, ainsi que la validation et l'affinement de la précision de MOST à travers des expériences en laboratoire contrôlées. La recherche est structurée en trois études distinctes, chacune abordant un aspect critique de cet objectif global.

Dans la première étude, une approche automatisée pour l'analyse du temps dans les systèmes

DHM a été développée, en se concentrant sur l'intégration du système de temps MOST dans l'environnement 3D de ces systèmes. Cette automatisation réduit le besoin d'intervention manuelle et soutient la création de conceptions et de processus de travail humain plus efficaces dès la phase de conception initiale. En utilisant le logiciel Ergonomic Workplace Design (EWD) de DELMIA, l'étude démontre comment les estimations de temps pour les tâches conçues en 3D peuvent être générées automatiquement tout en effectuant des évaluations ergonomiques simultanément. Cette analyse intégrée fournit aux ingénieurs de conception un outil pour évaluer l'efficacité de la conception, permettant potentiellement d'économiser du temps et des ressources avant la création d'un prototype physique. En améliorant l'accessibilité des systèmes DHM, cette approche rend l'estimation du temps réalisable pour les utilisateurs ayant une connaissance limitée des méthodes d'estimation du temps, contribuant à un processus de conception plus rationalisé et à une amélioration potentielle de la productivité et de la sécurité sur le lieu de travail.

La deuxième étude a comparé le système MOST et la méthode d'estimation du temps DHM développée avec les temps mesurés réels dans un contexte industriel spécifique. Menée sur une ligne d'assemblage automobile au Canada, l'étude a consisté à observer et enregistrer les opérations à 26 postes de travail. Les temps opérationnels ont été estimés à l'aide des systèmes DHM et MOST, puis comparés aux temps mesurés pour évaluer leur précision. Le test d'accord de Bland-Altman a été appliqué pour évaluer la concordance et les écarts de ces estimations. Les résultats ont montré une forte concordance entre la méthode de temps DHM et le système MOST, avec une limite d'accord étroite (95% LOA : -3,24 à 1,79 secondes). La méthode DHM a démontré un écart de précision moyen de -5,45%, contre -7,04% pour MOST. Ces résultats indiquent que la méthode de temps DHM offre une approche fiable pour l'estimation du temps opérationnel dans le cadre de la modélisation humaine numérique. Bien que ces résultats mettent en évidence le potentiel d'intégration de la méthode de temps DHM pour la planification des tâches, l'ordonnancement et l'allocation des ressources dans les environnements industriels, la portée de l'étude était limitée à un seul contexte industriel. Des recherches futures sont nécessaires pour évaluer l'applicabilité de la méthode dans divers secteurs et environnements de travail afin de mieux comprendre son potentiel plus large.

La troisième étude a évalué la précision du système MOST à travers une expérience en laboratoire contrôlée en comparant ses estimations avec des mesures directes et la loi de Fitts. En analysant 300 mouvements simples effectués par 20 participants, l'étude a examiné des variables clés, notamment la distance d'action, le poids de l'objet, le niveau de mouvement, la difficulté de préhension et la précision de placement. Les résultats ont montré que MOST sous-estimait les temps réels de 38% en moyenne, avec un temps de mouvement moyen de

3,83 ± 0,46 secondes. Une analyse de Bland-Altman a mis en évidence des écarts significatifs entre les estimations de MOST et les temps mesurés, incitant à une investigation des causes sous-jacentes de ces écarts. Pour améliorer la précision des estimations de MOST, des analyses de régression ont été menées à l'aide des données collectées. Ces efforts ont abouti à des améliorations du système de codage de la distance d'action de MOST, offrant une granularité accrue pour les mouvements à courte distance. De plus, de nouveaux schémas de codage ont été développés pour le poids de l'objet et le niveau de mouvement, abordant des facteurs précédemment négligés dans le système original. Ces améliorations visent à accroître la fiabilité de MOST et son intégration dans le cadre d'estimation du temps DHM, tout en reconnaissant la nécessité d'une validation supplémentaire dans divers contextes.

En résumé, l'investigation approfondie menée à travers ces trois études souligne la valeur de l'intégration de méthodes d'estimation du temps précises dans les systèmes DHM. En adaptant le système MOST pour une utilisation dans les environnements DHM, cette recherche permet des évaluations ergonomiques dynamiques qui améliorent l'efficacité opérationnelle et la sécurité de la conception. La validation du système MOST et les améliorations introduites dans ce travail démontrent le potentiel d'amélioration de l'application des systèmes d'estimation du temps dans des contextes industriels spécifiques, fournissant une base pour des avancées supplémentaires en matière de productivité et de sécurité des travailleurs grâce à des cadres d'analyse plus précis et automatisés.

Le système d'estimation du temps développé dans cette recherche a le potentiel d'être largement mis en œuvre sur diverses plateformes DHM et dans divers secteurs industriels, bien que son applicabilité au-delà des contextes étudiés nécessite des investigations supplémentaires. Les méthodes de validation établies ici peuvent servir de modèle pour évaluer d'autres systèmes d'estimation du temps, contribuant à leur raffinement et à leur alignement sur les exigences du monde réel. De telles avancées peuvent aider à atténuer le risque de troubles musculo-squelettiques (TMS) en permettant des estimations de temps plus précises qui offrent un temps de récupération suffisant et réduisent la fatigue. Une estimation précise du temps soutient une meilleure planification et allocation des ressources, aidant à éviter la surcharge des travailleurs et à garantir que les tâches sont conçues dans des délais réalistes. Cet équilibre prévient non seulement l'épuisement et augmente la satisfaction au travail, mais traite également les inefficacités des flux de travail, permettant des interventions ciblées pour rationaliser les opérations. En fin de compte, ces efforts contribuent au développement d'environnements de travail plus sûrs, plus efficaces et plus productifs.

ABSTRACT

In today's industrial landscape, optimizing workplace design while ensuring worker safety and efficiency is of paramount importance. Digital Human Modeling (DHM) systems have emerged as invaluable tools for achieving these objectives. By simulating human interactions with workspaces, tools, and tasks prior to the creation of physical prototypes, these systems support the design process, enabling the early identification and mitigation of potential risks to workers. Time estimation plays a critical role in this context by providing precise predictions of task durations and supporting process optimization, which are essential for enhancing productivity and efficiency in industrial settings.

DHM systems are widely utilized in ergonomic analyses to assess the physical demands of tasks and to design safer, more efficient workplaces. Traditionally, many DHM systems have primarily focused on evaluating static ergonomic risks based on process planning data. However, integrating time estimation methods, such as the Maynard Operation Sequence Technique (MOST), into these systems enables the analysis of designed operations over extended periods of time. By conducting time analyses within DHM systems, a more comprehensive evaluation of dynamic ergonomic risks becomes possible. This shift from static to dynamic analysis provides a more nuanced assessment of tasks by considering the variability and sequence of movements, which are often overlooked in static evaluations. Such integration supports designers in creating more accurate and efficient work processes, contributing to improvements in workplace safety and productivity.

The main objective of this thesis is to develop a time estimation method within DHM systems, focusing on the integration of the MOST time system. The sub-objectives include assessing the applicability and reliability of both the MOST system and the newly developed DHM time estimation method in real-world industrial contexts, as well as validating and refining the accuracy of MOST through controlled laboratory experiments. The research is structured into three distinct studies, each addressing a critical aspect of this overarching objective.

In the first study, an automated approach for time analysis in DHM systems was developed, focusing on the integration of the MOST time system within the 3D environment of these systems. This automation reduces the need for manual intervention and supports the creation of more efficient designs and human work processes in the early design phase. Utilizing DELMIA's Ergonomic Workplace Design (EWD) software, the study demonstrates how time estimations for 3D-designed tasks can be generated automatically while performing er-

gonomic assessments simultaneously. This integrated analysis provides design engineers with a tool to evaluate design effectiveness, potentially saving time and resources before creating a physical prototype. By improving the accessibility of DHM systems, this approach makes time estimation feasible for users with limited prior knowledge of time estimation methods, contributing to a more streamlined design process and potentially enhancing workplace productivity and safety.

The second study compared the MOST system and the developed DHM time estimation method with actual measured times in a specific industrial setting. Conducted at an automotive assembly line in Canada, the study involved observing and recording operations at 26 workstations. Operational times were estimated using both the DHM and MOST systems and then compared to measured times to evaluate their accuracy. The Bland-Altman agreement test was applied to assess the agreement and deviations of these estimations. The findings showed strong concordance between the DHM time method and the MOST system, with a narrowly defined limit of agreement (95% LOA: -3.24 to 1.79 seconds). The DHM method demonstrated a mean accuracy deviation of -5.45%, compared to MOST's -7.04%. These results indicate that the DHM time method offers a reliable approach to operational time estimation within the scope of digital human modeling. While these results highlight the potential of integrating the DHM time method for task planning, scheduling, and resource allocation in industrial settings, the study's scope was limited to a single industrial context. Future research is needed to evaluate the method's applicability across diverse industries and work environments to better understand its broader potential.

The third study assessed the accuracy of the MOST system through a controlled laboratory experiment by comparing its estimates with direct measurements and Fitts' law. Analyzing 300 simple movements performed by 20 participants, the study examined key variables, including Action Distance, Object Weight, Motion Level, Grasp Difficulty, and Placement Precision. The results showed that MOST underestimated actual times by an average of 38%, with a mean movement time of 3.83 ± 0.46 seconds. A Bland-Altman analysis highlighted significant discrepancies between MOST estimates and measured times, prompting an investigation into the underlying causes of these deviations. To improve the precision of MOST estimates, regression analyses were conducted using the collected dataset. These efforts resulted in refinements to the MOST Action Distance coding system, providing greater granularity for short-distance movements. Additionally, new coding schemes were developed for Object Weight and Motion Level, addressing previously overlooked factors in the original system. These enhancements aim to increase the reliability of MOST and its integration within the DHM time estimation framework, while recognizing the need for further validation in diverse contexts.

In summary, the comprehensive investigation across these three studies underscores the value of integrating accurate time estimation methods within DHM systems. By adapting the MOST system for use in DHM environments, this research enables dynamic ergonomic assessments that enhance operational efficiency and design safety. The validation of the MOST system and the refinements introduced in this work demonstrate the potential for improving the application of time estimation systems in specific industrial settings, providing a foundation for further enhancements in productivity and worker safety through more precise and automated analysis frameworks.

The time estimation system developed in this research has the potential for broad implementation across various DHM platforms and industries, though its applicability beyond the studied contexts requires further investigation. The validation methods established here can serve as a model for evaluating other time estimation systems, contributing to their refinement and alignment with real-world requirements. Such advancements can help mitigate the risk of musculoskeletal disorders (MSDs) by enabling more accurate time estimates that allow sufficient recovery time and reduce fatigue. Accurate time estimation supports better planning and resource allocation, helping to avoid overburdening workers and ensuring tasks are designed within realistic time constraints. This balance not only prevents burnout and increases job satisfaction but also addresses workflow inefficiencies, enabling targeted interventions to streamline operations. Ultimately, these efforts contribute to the development of safer, more efficient, and productive workplace environments.

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LIST OF SYMBOLS AND ACRONYMS

EWD Ergonomic Workplace design
MSD Musculoskeletal Disorder
MOST Maynard operation sequence technique
PMTS Predetermined motion time systems
OCRA Occupational Repetitive Actions
RULA Rapid Upper Limb Assessment
REBA Rapid Entire Body Assessment
DHM Digital Human Model
EAWS The European Assembly Worksheet
HARM Hand-Arm Risk Assessment Method
BTCS Body-based Trunk Coordinate System
MTM Method Time Measurement
MODAPTS Modular Arrangement of Predetermined Time Standards
OHS Occupational Health and Safety
OSHA Occupational Safety and Health Administration
CCOHS Canadian Centre for Occupational Health and Safety
SPE Smart Posturing Engine
TMU Time Measuring Unit

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CHAPTER 1 INTRODUCTION

1.1 Motivation

In recent years, ergonomic assessment has gained significant importance due to its direct impact on workplace safety and efficiency. Work-related musculoskeletal disorders (MSDs) are a global public health challenge, causing disabilities, lost productivity, and substantial economic costs [3]. These disorders, primarily caused by poor posture, repetitive motions, and forceful exertions, account for a significant portion of workplace injuries worldwide. The economic impact of MSDs is considerable, with costs ranging between 1.2% and 6.2% of national gross domestic products—figures comparable to those associated with cancer [4]. In the European Union alone, MSDs represent up to 50% of all work-related illnesses, resulting in an estimated annual economic burden of €240 billion [3]. Similarly, in the United States, MSDs account for nearly one-third of workplace injuries, costing employers approximately $50 billion annually in direct and indirect expenses [5]. These statistics underscore the widespread nature of MSDs and the significant financial strain they place on economies.

Neglecting ergonomic considerations can severely undermine a company's profitability and competitive edge. The financial costs of work-related injuries extend beyond immediate compensation claims, encompassing loss of skilled labor, decreased productivity, increased absenteeism, and higher turnover rates. Investing in preventive measures, such as comprehensive ergonomic assessments, is therefore essential for ensuring long-term business viability and fostering sustainable growth.

A critical aspect of workplace optimization is balancing productivity with safety, which hinges on accurately estimating the time required for various operations. PMTSs, such as MOST, are widely used to estimate task durations based on standardized motion data. These systems break down tasks into specific motion elements and assign time values to each, providing structured estimates for industrial operations. However, PMTS methods often overlook critical ergonomic factors, such as repetitive motions, awkward postures, and cumulative physical strain. This oversight can lead to discrepancies between estimated and actual task durations, increased worker fatigue, and a higher risk of MSDs. The lack of rigorous validation for these systems in real-world conditions poses significant risks to workplace safety and efficiency, highlighting the need for more reliable and accurate models [6].

The inability of existing systems to account for essential motion factors—such as action distance, object weight, and motion level—further exacerbates these challenges. These factors significantly influence task performance and worker fatigue, and their neglect in current systems undermines both productivity and worker well-being. Addressing these limitations is essential to developing more reliable systems that align with real-world working conditions and promote safer, more efficient workplaces [6].

Due to the inherently distinct nature of time estimation and ergonomic analyses, organizations typically require two specialized teams to evaluate the same design separately—one focusing on ergonomic factors and the other on time estimation. This separation creates a cumbersome and inefficient process, increases operational costs, and results in fragmented analyses that lack cohesion. Consequently, there is a pressing need for an integrated system that unifies ergonomic and time assessments, reducing redundancy and improving accuracy [6, 7]. Such an integrated system must provide time estimations that closely approximate real-world conditions while also accounting for ergonomic factors such as posture variability and worker fatigue. These dynamic factors, which evolve over time, significantly influence worker performance and are critical for accurate time estimation and ergonomic analysis.

Dynamic ergonomic assessment, which evaluates ergonomic risks over extended periods, is essential for understanding how factors like fatigue and posture changes evolve over time and impact worker performance. Incorporating time-dependent analyses allows for a more accurate representation of ergonomic risks, enabling proactive interventions to improve long-term worker well-being and efficiency [8]. Unlike static assessments, which evaluate risks at a single point in time, dynamic assessments account for how risks evolve during task performance, as highlighted by Wang et al. (2023) [8].

Digital Human Modeling (DHM) systems have emerged as powerful tools for creating virtual human models and simulating their interactions with the environment. These systems enable the design and analysis of safer, more efficient workplaces by incorporating anthropometric data, biomechanical principles, and ergonomic guidelines. Widely used across industries such as manufacturing, automotive, and healthcare, DHM systems reduce the need for physical prototypes, optimize workflows, and ensure compliance with safety standards. Their ability to simulate diverse human populations and scenarios makes them indispensable for addressing the complexities of modern workplace design [9]. This approach, often referred to as virtual ergonomics, leverages digital tools to analyze and optimize human interactions with work environments in a virtual setting, providing a cost-effective and scalable alternative to traditional physical evaluations.

While DHM systems have advanced workplace design, most ergonomic assessments within these systems remain static, focusing on isolated postures rather than continuous workflows [8,9]. This limitation prevents an accurate representation of task sequences, repetitive motions, and cumulative physical strain over time—factors critical for assessing long-term musculoskeletal risks. Without a dynamic approach, ergonomic evaluations may overlook progressive fatigue, posture shifts, and the accumulation of biomechanical stress during prolonged work shifts [8]. To address this, there is a growing need to refine DHM ergonomic assessment methods to incorporate continuous task evaluations rather than isolated momentary assessments. Time estimation plays a pivotal role in this context, providing a structured framework for analyzing motion sequences and laying the groundwork for dynamic ergonomic evaluations.

Integrating time estimation into DHM systems is critical, as it enables a deeper understanding of task durations, workflow efficiency, and the dynamic nature of human-environment interactions. This integration not only streamlines the design process but also supports dynamic ergonomic assessments by analyzing repetitive tasks and identifying cumulative risks that static analyses might miss [2,7,9]. However, automating the translation of task descriptions—often expressed in natural language—into structured time estimation codes remains a significant challenge. Currently, this process relies on manual intervention, which hinders efficiency and scalability. A systematic approach to categorizing and converting these descriptions into predefined PMTS codes, such as those used in the MOST system, is essential for achieving automated time estimation within DHM systems. Additionally, discrepancies between estimated and actual task durations often arise due to factors such as task complexity, human variability, and environmental constraints. Addressing these challenges is crucial to ensure that time estimation models produce reliable, real-world predictions, ultimately contributing to safer and more efficient workplaces.

Our research focuses on adapting and refining MOST predetermined motion time system within DHM systems. This integration bridges the gap between time prediction and dynamic ergonomic evaluation, enabling comprehensive workplace assessments and contributing to safer, more efficient industrial practices. We aim to validate and refine the system's accuracy through rigorous testing and iterative improvements. While the primary objective is its development within the DHM framework, subsequent goals focus on ensuring its predictions align with real-world working conditions and practical standards.

The significance of this research is underscored by the long-standing and widespread use of PMTS in the manufacturing industry. By critically evaluating these systems and proposing refinements, our work contributes to both academic knowledge and practical industry applications. The results of our analysis will help companies adopt time estimation systems that are more accurate and better aligned with real-world conditions. This alignment between theoretical models and practical applications will lead to more efficient production processes, reduced costs, and improved worker satisfaction.

In conclusion, the increasing importance of dynamic ergonomic assessment in contemporary workplaces highlights the need for integrated time estimation systems within DHM frameworks. Our research aims to provide a comprehensive approach that enhances safety and efficiency by establishing a foundation that connects time and ergonomic assessments in DHM systems. By achieving this integration, we hope to contribute to more sustainable and productive industrial practices, benefiting both employers and employees alike.

1.2 Research Questions

Given the issues presented and through a feasibility analysis of different methods, three major research questions have been identified that have not been addressed in depth in this area :

RQ1 : How can we identify and establish the process of time estimation using a PMTS for a sequence of actions/operations expressed in natural language and translated into 3D models ?

— What types of information are required to estimate operation times accurately within a DHM system using the MOST (Maynard Operation Sequence Technique) PMTS ?
— How can task descriptions in natural language be parsed and categorized into structured MOST time codes ?
— How can we automate the translation of this information into structured time codes that can be integrated seamlessly into the 3D modeling process ?
— What mechanisms can ensure the accuracy and reliability of automated time estimations in DHM systems ?

RQ2 : What are the potential discrepancies between the estimated times using the developed time system in RQ1, MOST, and the actual measured times in real workplace conditions ?

— What factors cause discrepancies between estimated and measured times, and how can they be identified ?
— How can these discrepancies be minimized to ensure realistic time estimations in DHM systems ?

RQ3 : How can we validate the MOST system through controlled laboratory experiments ?

— What experimental methods can ensure the accuracy and reliability of MOST-based time estimations for simple movements ?

— Which essential motion factors, such as the traveled distance of motions (action distance), mechanical loads (e.g., object weight), motion level, and placement and grasping precision, have been overlooked in the current MOST system and affect the MOST system's accuracy ?
— How can these overlooked factors be integrated into experimental designs to refine MOST data cards ?
— What refinements to the MOST system can improve its precision based on experimental results ?

These research questions aim to address key challenges in bridging the gap between theoretical models and practical applications, ensuring that time estimation systems in DHM environments are both accurate and ergonomically sound, thereby enhancing their relevance and effectiveness across multiple industrial sectors.

1.3 Research Objectives

In modern industrial environments, accurate time estimation is critical for optimizing workplace design and enhancing productivity. DHM systems have emerged as powerful tools for simulating and analyzing human interactions within virtual workspaces. While these systems excel in ergonomic analysis, their lack of integrated time estimation methods limits their ability to fully optimize work processes. Incorporating time estimation techniques into DHM systems enhances their functionality by enabling dynamic ergonomic assessments, which evaluate how ergonomic risks evolve over time during task performance. Unlike static assessments, which focus on isolated moments, dynamic assessments capture the progression of risks, such as fatigue buildup and repetitive strain, that accumulate over extended periods. These cumulative ergonomic risks are critical to understanding long-term worker health and performance but are often overlooked in traditional evaluations. By analyzing task durations and variations over time, this integration offers the potential to identify and mitigate cumulative risks, fostering a more comprehensive understanding of workplace efficiency and supporting long-term ergonomic sustainability.

Integrating time estimation methods into DHM systems, however, presents notable challenges. Current PMTS, such as MOST, are primarily designed for real-world observations. Adapting these methods to 3D virtual environments introduces complexities, particularly in accurately simulating task durations and human movements within a digital framework.

To address these challenges, the primary objective of this research is to develop and validate a time estimation system for DHM systems using the MOST time system. This integration focuses on enabling reliable and automated time estimation to address the limitations of current methods. By adapting MOST to 3D environments, the research aims to demonstrate the potential of this approach in enhancing the accuracy and reliability of time analysis within DHM systems. Furthermore, this study seeks to validate MOST's accuracy through field studies in real-world conditions and controlled laboratory experiments, identifying and addressing key motion factors often overlooked in current MOST data cards. These findings will contribute to refining MOST's predictive accuracy and improving its applicability in both real-world and virtual task modeling. The sub-objectives of this research are as follows :

- **Sub-objective 1 : Develop an Automated Time Estimation System for DHM Based on MOST**
  - Assess existing approaches for applying PMTS in 3D environments, identifying key challenges and limitations in current time estimation methods.
  - Investigate recent advancements in DHM and time estimation techniques to highlight opportunities for refinement.
  - Identify essential data inputs and parameters required for accurate time estimation in DHM systems, focusing on motion characteristics, workspace constraints, and object properties.
  - Develop strategies to address missing data and information gaps affecting time analysis in 3D environments.
  - Investigate methods for parsing and categorizing task descriptions from natural language into structured MOST time codes for seamless integration into DHM systems.
  - Develop an algorithm to estimate time for sequences of actions and operations designed in DHM systems, prioritizing automation and minimizing manual intervention.
  - Illustrate the impact of the developed DHM time system on design processes, safety considerations, and productivity improvements through case examples demonstrating how time estimation streamlines the design process.
- **Sub-objective 2 : Evaluate and Address Discrepancies Between Estimated and Actual Task Durations in Real Workplace Conditions**
  - Assess the applicability of the MOST and the MOST-based algorithms developed for DHM time system by analyzing externally obtained field data, such as video recordings and production data, in selected industrial contexts.
  - Analyze discrepancies between estimated times from MOST, the developed DHM-based system, and actual measured times.
  - Investigate factors contributing to these discrepancies, including task complexity,

worker variability, and environmental constraints.
  - Develop strategies to minimize discrepancies, refining the DHM-integrated system for more accurate and realistic time estimations.
- **Sub-objective 3 : Validate the Accuracy and Reliability of MOST Through Controlled laboratory Experiments**
  - Develop a structured validation framework to assess the accuracy and reliability of MOST-based time estimation in controlled laboratory experiments.
  - Identify and evaluate gaps in time estimation methods, particularly overlooked factors such as mechanical load exposure (object weight), motion level (movement height), action distances, grasp difficulty, and placement precision.
  - Design experimental methods to systematically refine MOST time estimates for improved applicability in virtual and real-world environments.
  - Investigate discrepancies between estimated times from MOST and actual measured times, identifying key contributing factors.
  - Refine MOST's structure to provide more realistic and reliable time estimations.

By achieving these objectives, this research aims to advance automated time estimation within DHM systems, enhancing accuracy through validation studies and providing the potential to support dynamic ergonomic assessments, improving design efficiency and promoting worker safety. The proposed approach seeks to bridge theoretical advancements and real-world applications, offering a framework for more accurate and reliable workplace simulations within the scope of the study.

1.4 Contributions

In line with the research objectives, this dissertation offers several key contributions to the field of virtual ergonomics and time systems :

- **Development of an Automated Time Estimation Algorithm for DHM Systems :** This research introduces an automated time estimation algorithm that minimizes manual intervention, enhances efficiency, and improves usability within DHM systems. By making time estimation more accessible, the algorithm supports diverse industrial applications and users with limited expertise.
- **Provides a Foundation for Enabling Dynamic Ergonomic Analyses in DHM Systems :** Integrating time estimation into DHM systems paves the way for dynamic ergonomic assessments, overcoming previous limitations that stemmed from the absence of temporal factors. By embedding time into ergonomic evaluations, this research creates a foundation for analyzing human performance over extended periods,

capturing critical factors such as fatigue and repetitive strain. This advancement not only enhances the accuracy of ergonomic assessments but also facilitates proactive workplace design and early risk identification, ultimately improving worker safety and efficiency.

- **Industrial Evaluation and Practical Insights :** The developed DHM time system and the MOST framework were assessed using real-world industrial data, analyzing 26 workstations. This evaluation demonstrates the applicability of the methods in industrial environments, supporting improved task analysis, resource allocation, and workplace design.
- **Validation and Refinement of the MOST System for application in dynamic work environments :** Through controlled laboratory experiments, this research validates key movement parameters in the MOST system, including action distance, mechanical loads, motion levels, grasp difficulty, and placement precision. The findings contribute to refining MOST data cards and improving their applicability in dynamic work environments and DHM-based time estimation.

These contributions collectively advance the field of virtual ergonomics and time systems by addressing key challenges in workplace design and optimization. The development of an automated time estimation algorithm reduces reliance on manual intervention, making time estimation more accessible and scalable for industrial applications. By incorporating time estimation into DHM systems, this research lays the foundation for future dynamic ergonomic analyses, enabling the study of cumulative risks such as fatigue and repetitive strain. The industrial evaluation of the DHM time system and MOST framework demonstrates their practical applicability, offering insights for improved task analysis, resource allocation, and workplace design. Furthermore, the validation and refinement of the MOST system enhance its accuracy and suitability for dynamic work environments, supporting more reliable time estimations in DHM systems.

The research improves workplace safety, reduces musculoskeletal disorder (MSD) risks, and enhances productivity. By providing tools for accurate time estimation and enabling sophisticated ergonomic analysis, it helps industries minimize injuries, absenteeism, and turnover rates, leading to cost savings and sustainable task planning practices. This work bridges theoretical research with real-world industrial applications, offering practical solutions for safer and more efficient workplaces.

1.5 Outline

This thesis is composed of eight chapters. Following this introductory chapter, Chapter 2 provides a comprehensive background and literature review on time analysis methods, DHM systems, and current validation approaches in the field. The review not only offers insights into existing systems but also identifies critical gaps that motivate this research.

Chapter 3 outlines the overarching methodology adopted for this research, detailing the identification of core problems, the selection of applicable case studies, key research milestones, and the presentation of final results through research articles. This chapter establishes a roadmap for the research, ensuring that each phase of the study aligns with the central objectives.

Chapters 4, 5, and 6 represent the core of the thesis, with each chapter corresponding to a distinct research article that addresses specific research objectives. These chapters form the backbone of the research and present the development, validation, and comparison of the proposed time estimation methods.

Chapter 4 focuses on the development of a comprehensive framework for implementing time analysis within DHM systems using the MOST Predetermined Motion Time System. This chapter introduces an automated approach to time analysis derived from DHM data, demonstrating its application through the DELMIA Ergonomic Workplace Design (EWD) software. Notably, the contributions presented in Article 1 have been patented, and the patent documentation is included in the appendix, underscoring the innovation's practical impact.

Chapter 5 offers an empirical comparison between the newly developed time estimation method for DHM systems and the MOST system. This comparison is conducted using real-world data collected from an automotive assembly line, validating the developed method's accuracy by comparing its estimations with actual measured times from field studies.

Chapter 6 presents the validation and refinement of the MOST time estimation system through controlled laboratory experiments. This chapter delves into the examination of previously unexplored aspects such as action distances, mechanical loads, motion levels, grasp difficulty, and placement precision. The findings from Article 3 were presented at the AHFE Conference in France and published in the conference proceedings, which are attached in the appendix. Additionally, the research presented in this chapter is under review for potential patenting, indicating its substantial contribution to the field.

Chapter 7 provides a summary of key findings, addressing the limitations of the research and offering recommendations for future studies. The chapter synthesizes the major contributions and contextualizes the research within broader industry applications.

Finally, Chapter 8 concludes the thesis by highlighting the overall contributions, implications, and potential impact of the research on the fields of digital human modeling, time analysis, and workplace design.

1.6 Publications

The chapters mentioned above are based on the published and submitted articles introduced in this section. The articles are as follows :

Journal Articles

1. Mazareinezhad, F., Sekkay, F. Imbeau, D. Development of a framework to implement time analysis in digital human modeling systems using predetermined motion time systems. *Discover Applied Sciences*, 7, 356 (2025). https ://doi.org/10.1007/s42452-025-06813-9. Submitted : 16 September 2024 ; Accepted : 27 March 2025 ; Published : April 16, 2025.
2. Mazareinezhad, F., Sekkay, F., Imbeau, D. Evaluating the Accuracy of MOST and a MOST-Based Time Method in Digital Human Modeling : Field Study Insights from Advanced Manufacturing Environments. *The International Journal of Advanced Manufacturing Technology*. Submitted : March 24, 2025.
3. Mazareinezhad, F., Sekkay, F. Imbeau, D. Improving time estimation accuracy in manufacturing systems : experimental assessment of MOST predetermined motion time system using laboratory data and Fitts' law. *The International Journal of Advanced Manufacturing Technology*, (2025). https ://doi.org/10.1007/s00170-025-15791-6. Submitted : 18 December 2024 ; Accepted : 20 May 2025 ; Published : May 31, 2025.

Patents

1. Mazareinezhad, F., Brouillette, D., Charland, J., Imbeau, D., & Sekkay, F. (2024). U.S. Patent Application No. 18/390,174. *Systems and methods for assessing dynamic ergonomic risk.*
2. Mazareinezhad, F., Sekkay, F., & Imbeau, D., Brouillette, D., Charland, J. U.S. Patent Application No. 4316.1029-000. *Systems and Methods for Validating and Enhancing Accuracy in Predetermined Motion Time Systems*, Submitted : September 5, 2024.

Conference Papers

1. Mazareinezhad, F., Sekkay, F., & Imbeau, D. (2024). Evaluating the Accuracy of the MOST Predetermined Motion Time System Through Lab Experiments. Human Aspects of Advanced Manufacturing, Production Management and Process Control, 116. http ://doi.org/10.54941/ahfe1005157. Submitted : December 11, 2023 ; Accepted : January 8, 2024 ; Presented : July 26, 2024.

CHAPTER 2 LITERATURE REVIEW

For decades, industrial and manufacturing engineers have relied on Predetermined Motion Time Systems (PMTS) to design production systems and establish production standards [6]. PMTS are widely used across various sectors, including manufacturing, services, and administration, to estimate task durations and optimize workflows [10]. A key application of PMTS in manufacturing is estimating the time required for a worker to produce a specific product unit within a simulated assembly line, which is critical for determining product costs [11]. Several PMTS methods exist, such as MTM, MOST, Work Factor, and MODAPTS, each offering unique approaches to time estimation [12].

Recent advancements in digital design tools have enabled the integration of ergonomic analysis into 3D design software, such as DELMIA's Ergonomic Workplace Design (EWD) and Siemens' Jack [13]. These tools enhance the design process by incorporating ergonomic principles within a 3D environment, enabling ergonomic risk assessments. However, traditional time and ergonomic analyses are often conducted by separate teams, requiring distinct expertise and technical languages. This separation leads to assessments being performed at different stages of the design process, making the overall approach cumbersome and inefficient [14].

By incorporating PMTS into unified 3D design software, the time evaluation process can be significantly streamlined, as most workplace data is already captured within the 3D environment [9,13]. This integration can be automated, reducing analysis time and ensuring a more efficient design process. Additionally, it improves worker safety and well-being by enabling advanced ergonomic assessment methods like OCRA, which utilize task duration data to evaluate risks over time. Such refined analyses proactively minimize the potential for injuries and related costs, ultimately supporting companies in achieving higher operational efficiency while fostering safer and healthier work environments.

Despite advancements in Digital Human Modeling (DHM) systems, most ergonomic assessments in these systems rely on static snapshots of posture rather than tracking how movements change over time [8,14]. While these methods help identify immediate risks, they fail to capture the bigger picture—how fatigue builds up, how postures shift throughout a task, and how repetitive motions can lead to long-term strain [9]. As a result, real-world workflow efficiencies are often difficult to evaluate, as the natural flow of movement and task transitions is not fully considered.

To bridge this gap, researchers have begun exploring dynamic ergonomic assessment methods. Wang et al. (2023) [8] developed a 3D-based framework to track how fatigue accumulates over time in long-duration tasks, emphasizing the role of time in ergonomic analysis. Similarly, Schaub et al. (2013) [9] proposed using task duration data to assess the strain caused by repetitive actions in assembly processes. However, these approaches are still in their early stages, and their integration into automated DHM-based time estimation frameworks—particularly those using PMTS—remains largely unexplored.

While PMTS are widely used, they face challenges in accounting for human variability and dynamic task conditions [6]. Additionally, PMTS are based on rigid assumptions about task execution, offering limited flexibility to accommodate variations in human movements and postures [15,16]. Studies have shown that PMTS often underestimate the impact of variables such as lifting height, object weight, and movement frequency, leading to overly optimistic productivity assessments and increased risks of overexertion [17–19]. Thus, designing workstations solely based on PMTS for time efficiency may pose significant health risks to workers.

Several studies have also emphasized the importance of integrating physiological and biomechanical factors into time estimation methods. For instance, Aquilano and Wyndham highlighted the need to align time estimation with physiological demands, particularly for high-energy tasks [20, 21]. Similarly, Garg and Saxena demonstrated the value of incorporating workload limits into time estimation frameworks, especially for tasks involving repetitive lifting or heavier loads [22].

These limitations highlight the need for integrating PMTS into more dynamic and adaptive frameworks, such as 3D digital environments, and validating these systems to improve accuracy and applicability in real-world scenarios. The integration and automation of PMTS into a DHM system allow for real-time time analysis, reducing analysis time and improving design efficiency. Furthermore, validation efforts in both real-world and controlled conditions can ensure the reliability of these integrated systems, bridging the gap between theoretical time estimates and practical application. This approach supports the development of adaptive, human-centric work environments that cater to diverse worker needs and minimize injury risks.

This chapter begins with a review of common time analysis tools in Section 2.1. Section 2.2 explores advancements in virtual ergonomics, while Section 2.3 introduces existing tools for integrated time-ergonomic analysis. Finally, Section 2.4 examines various attempts to validate PMTS and DHM systems.

2.1 Frequently used time analysis tools

2.1.1 Maynard Operation Sequence Technique (MOST)

MOST is a widely used PMTS in industrial environments for measuring work and establishing standard task times [1]. It analyzes operations by breaking them down into method steps and sequence models, assigning parameter time values to each motion element. The total standard time for an operation is calculated by summing the times for all motion elements and allowances [1].

One of MOST's key advantages is its efficiency in reducing the extensive documentation typically required by traditional PMTS systems, such as MTM-1 (Methods-Time Measurement), without compromising accuracy [1]. For example, while MTM-1 might require 16 pages of documentation to analyze a three-minute operation, MOST achieves the same analysis with only half a page [1]. This streamlined approach enables faster, more consistent, and convenient analyses, facilitating smoother integration into time estimation frameworks [1, 12].

MOST's simplicity and structured methodology make it highly desirable for industrial applications. It requires fewer observations to measure motions accurately, and its motion sequences and index values are easily accessible and interpretable, enhancing the reproducibility of time analyses compared to other techniques [1]. These qualities make MOST particularly well-suited for integration into Digital Human Modeling systems, where efficient and precise time estimation is essential for simulating human interactions in virtual environments.

In this study, MOST was chosen as the foundation for developing a time estimation method for DHM due to its structured methodology, efficiency, and widespread industrial adoption. Despite its frequent use, limited validation studies exist for MOST. Therefore, this research also aimed to systematically evaluate its accuracy and applicability in both controlled and real-world conditions. By integrating MOST into a DHM framework, this study enhances time estimation capabilities while addressing discrepancies between estimated and actual task durations, ensuring a more reliable and adaptable system for virtual human modeling applications.

2.1.2 Methods-Time Measurement (MTM)

Developed in the 20th century in the United States, Methods-Time Measurement (MTM) was the first Predetermined Motion Time System. It established a foundational methodology for analyzing manual processes by breaking down tasks into standardized motion elements.

The term "Methods-Time Measurement" refers to the time required to perform activities based on the specific methods used. MTM's structured approach makes it one of the most complex yet highly accurate work measurement systems within PMTS [23].

MTM has been widely applied to analyze manual processes and remains a standard tool for developing building block systems. These systems describe, quantify, and model a wide range of production processes, enabling engineers to systematically define and estimate the time required for various operations. This versatility enhances its applicability across diverse production scenarios [23].

MTM exists at different levels of detail, with MTM-1 being the most comprehensive. While MTM-1 offers high accuracy, it is also time-intensive due to the extensive details required for motion and time analysis. Analysts must precisely measure and label all motion distances, which increases the potential for errors due to the system's complexity [1]. To address these challenges, simplified versions such as MTM-2, MTM-3, and MTM-UAS were introduced. These versions streamline the analysis process by standardizing specific movements and using predefined variables, reducing analysis time and minimizing the likelihood of errors [1].

2.1.3 MODAPTS (Modular Arrangement of Predetermined Time Standards)

MODAPTS is a PMTS that uses descriptive language and simple codes to characterize work activities and determine the time required for specific actions. The letters in MODAPTS codes correspond directly to the actions they represent, making them easier to memorize compared to other systems [24].

The MODAPTS coding system is based on the time required for each body part to perform an action at a comfortable pace. Calculated times are expressed as multiples of 0.129 seconds, a standardized unit that simplifies the translation of coded actions into real-time values. This uniform approach enables analysts to accurately quantify tasks without extensive training or documentation [24].

A key distinction between MODAPTS and other PMTS is its focus on body part movements rather than the distances traveled by the worker. By emphasizing specific movements over spatial coverage, MODAPTS provides a more direct and action-oriented approach to task analysis. This makes it particularly effective in environments where movement complexity is more critical than the distances covered [24].

2.1.4 Work Factor

Work Factor is a PMTS that analyzes motions based on standard movement elements. It accounts for key factors such as the body part involved, object weight, and distance covered, assigning time values based on the difficulty of each motion. Movements requiring minimal human energy are classified as primary motions [25].

To simplify analysis, Work Factor consolidates details related to the movement of specific body parts, avoiding the complexity of multiple tables. Like other PMTS, it breaks tasks into elemental work units, identifies influencing factors, and calculates standard time by summing the time values assigned to these elements [26].

A unique feature of Work Factor is its inclusion of mental processes, such as cognitive activities. These processes involve seeing and recognizing (e.g., focusing, inspecting, reacting), memorizing and recalling (e.g., reading, counting, writing), and decision-making tasks [26]. However, the system's approach of assigning uniform values to all movements of a specific body part may obscure differences in motion difficulty, making it challenging to differentiate the complexity of various tasks [25].

2.2 Virtual Ergonomics

The limitations of traditional ergonomic evaluation methods have led experts to develop a virtual ergonomics platform, allowing for proactive ergonomic evaluations within a virtual work environment using 3D mannequins [27].

2.2.1 Digital Human Modeling System (DHM)

DHM systems are software-based representation of the human body [2], designed to simulate real-world work scenarios within a virtual 3D environment. Its primary goal is to replicate human motion capabilities, either partially or fully. While DHMs can generate static postures, they currently struggle to fully capture the variability of human postures. Additionally, developing algorithms that accurately generate postures based on human motion patterns remains a significant challenge [28].

DHM systems are applied across various fields, including ergonomics, cognition, medical science, and biometrics [9]. They integrate ergonomic evaluation tools such as EAWS, RULA and REBA to assess musculoskeletal disorder (MSD) risks in virtual environments. These tools provide numerical risk values, enabling designers and occupational health and safety (OHS) managers to propose solutions early in the design process and mitigate risks efficiently

[29, 30]. By facilitating virtual simulations, DHMs support preventive solutions throughout the ergonomic design and production process [28]. Figure 2.1 illustrates the various terms used for DHMs in English literature [2].

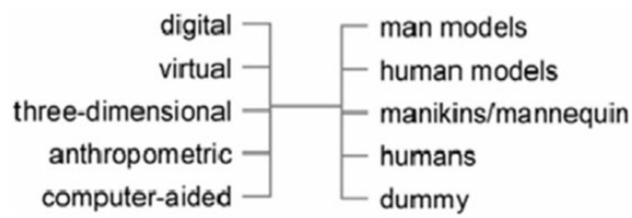

Figure 2.1 Different terms used for DHMs [2].

Background of DHMs in Production Ergonomics

The concept of DHM was first introduced in 1969 by Ryan, P.W., in a study comparing reach distances in airplane cockpits using anthropometric data and a mathematical man-model [31]. Since then, DHMs have evolved significantly, becoming integral components of many CAD-CAM systems in production and manufacturing environments. Bubb and Fritzsche (2009) conducted a comprehensive review of DHM development in North America and Europe, highlighting their expanding capabilities—from physical manipulation of mannequins (e.g., handling objects) to advanced ergonomic analyses assessing risks related to musculoskeletal disorders (MSDs), postures, and visual fields [32].

Over the past two decades, DHMs have advanced considerably, enabling engineers and designers to simulate human tasks virtually within production systems. However, their potential for innovation has plateaued, largely due to limited integration of ergonomic evaluations in human model design [33]. While many researchers have proposed methods to integrate ergonomic assessments into DHMs, effectively implementing these evaluations in virtual environments remains a challenge [34–36].

A major barrier to the effective use of DHMs is the limited ergonomic knowledge among engineers and designers, leading to misinterpretations or improper application of ergonomic assessments. This gap increases the risk of occupational injuries due to poorly designed workspaces, underscoring the need for better training and more intuitive DHM systems [37].

Today, widely used DHM systems such as Human Builder (DELMIA), Jack, and the Realistic Anthropological Mathematical System provide comprehensive CAD models based on anthropometric data to support ergonomic evaluations during product development [2]. Other systems, such as Anyman (part of the Tecnomatix System) and Manikin (within the CREO CAD system), offer more limited capabilities. Emerging DHM solutions like EDW from Dassault Systèmes focus on integrating time management methods with ergonomic features, while the newer EMA system (developed by IMK Automotive) combines ergonomics and productivity based on MTM standards [9]. Despite the advancements in DHM systems, only Jack by Siemens offers integrated automated ergonomic and time analysis. However, the lack of documentation for its integration limits its effectiveness, hindering broader adoption and comprehensive design evaluations in complex industrial environments.

General Functions of DHMs for Production Ergonomics

DHM systems offer a wide range of standard features and functions designed to support production ergonomics. These functionalities encompass various types of analysis, including distance analysis, which examines movement space and reach distances, and force analysis, which evaluates the forces exerted on different joints. Other essential features include load handling and energy consumption assessments to provide a comprehensive evaluation of ergonomic factors within work environments [2].

In DHM systems, static postures are represented using both forward and reverse kinematics, enabling ergonomic evaluations of various work scenarios. Figure 2.2 illustrates the different methods used within DHMs to analyze postures and motions [2].

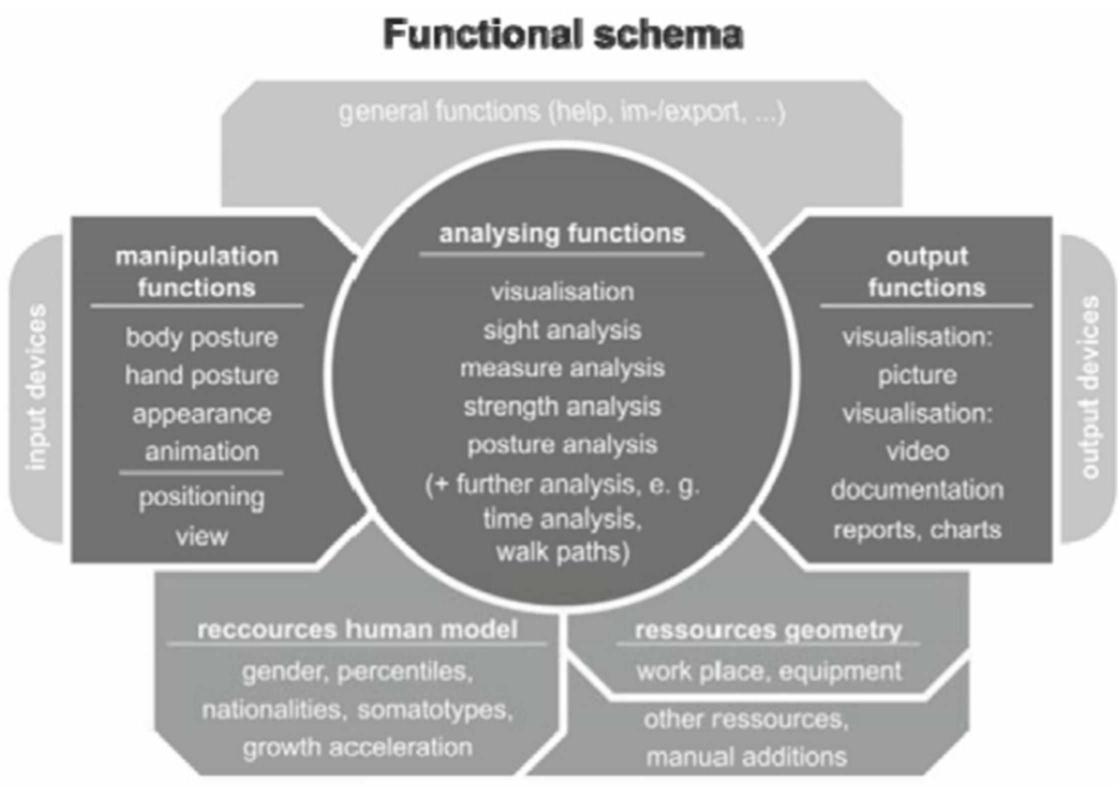

Figure 2.2 Different functions of DHMs [2].

Posture Generation in DHMs

Human models within DHM systems are built using a skeletal framework, connecting extremities to joints. Postures are generated based on the three-dimensional freedom of movement provided by these joints. However, designing realistic postures is complex due to constraints related to joint mobility and human movement limitations, making manual posture creation time-consuming [2].

A significant limitation of DHM systems is their potential to generate unrealistic or anatomically impossible postures due to simplified joint models. These discrepancies can lead to inaccuracies in ergonomic assessments and unrealistic design expectations. Additionally, the inability to create repeatable standard postures complicates ergonomic evaluations. Manual posture creation often results in inconsistencies across sessions or designers, undermining the validity and reliability of assessments [2, 38].

To address these challenges, integrating automated posture and motion prediction methods into DHM systems is essential. These methods can rapidly generate realistic and repeatable postures, reducing manual intervention and improving simulation accuracy. For example, DELMIA's EWD has introduced the Smart Posturing Engine (SPE), a platform designed to consistently generate realistic postures for digital human models. The SPE enables designers to validate work environments and establish ergonomic guidelines early in the design process, enhancing both efficiency and accuracy [39].

2.3 Existing Tools for Simultaneous Time and Ergonomic Analyses

Time estimation methods and ergonomic assessment tools, such as MTM-Ergonomics, ErgoSAM, and MTM-HWD, have been developed to enhance workplace evaluations. These methods aim to provide both time measurement and ergonomic risk analysis, offering structured approaches for assessing work sequences. However, they are primarily designed for real-world applications rather than digital DHM environments, limiting their applicability in fully virtual simulations [2, 40, 41].

Among these methods, MTM-Ergonomics extends traditional MTM coding by incorporating ergonomic risk assessments based on posture, distance, and force [2]. Similarly, ErgoSAM combines the Sequence-Based Activity Method (SAM) with ergonomic evaluation models, focusing on preproduction analysis and workstation layout optimization [41, 42]. MTM-HWD, developed in collaboration with major automotive manufacturers, provides time and ergonomic assessments using MTM-based motion descriptions. However, these methods do not integrate time and ergonomic analyses into a single system ; instead, they allow for separate but simultaneous evaluations. This separation often results in compatibility challenges with widely used DHM software and CAD/PLM systems, requiring manual input and lacking seamless automation for virtual task simulations [40, 43].

Despite their contributions, these methods do not fully address the adaptation of PMTSs, such as MOST, MTM, and MODAPTS, to DHM environments. Existing PMTS tools require significant adjustments to function efficiently in 3D modeling environments, where task descriptions may be expressed in natural language and need to be translated into structured time codes. This research seeks to bridge this gap by developing an automated and adaptable PMTS-based time estimation system for DHM systems, enabling more efficient and accurate evaluations in virtual environments.

2.4 Validity and Reliability in Time Measurement Systems

Ensuring the validity and reliability of Predetermined Motion Time Systems is critical, not only for their integration into Digital Human Modeling environments but also to reassess their accuracy after decades of industrial use. A valid system accurately predicts task durations, while a reliable system produces consistent time estimates across different conditions. Despite their widespread adoption, PMTS methods—including MOST, MTM, and MODAPTS—have undergone limited validation studies, raising uncertainties about their accuracy in modern work environments. Given advancements in manufacturing technologies and evolving work processes, it is essential to validate these systems to ensure their applicability in both real-world and 3D virtual task simulations.

2.4.1 Validation in Time Measurement Systems

Validation of time estimation systems typically involves assessing content validity, construct validity, criterion-related validity, and internal validity [44]. Content validity ensures the system adequately represents all relevant aspects of the concept, typically evaluated through expert judgment. Construct validity determines whether the system accurately reflects the intended concept and distinguishes it from unrelated constructs, often assessed using statistical correlation tests. Criterion validity evaluates whether the system's results align with independently verified time measurement methods, commonly measured through correlation coefficients [44]. Internal validity ensures study rigor by minimizing confounding variables that could distort findings. Common threats include test effect bias (insufficiently diverse samples), instrumentation effect bias (non-representative sample distributions), and history or maturation effects (time-based changes like operator learning curves) [45]. Addressing these biases strengthens the reliability of time estimation methods and enhances their applicability in both experimental and real-world contexts.

PMTS validation studies typically compare estimated times against actual measured times in controlled experiments and workplace settings. Studies such as those by Bahcivancilar (2012) and Bures et al. (2015) [46, 47] have evaluated PMTS accuracy, identifying discrepancies in grasp, move, and reach motions.

Despite these efforts, existing PMTS often overlook critical factors such as mechanical loads, motion planes, grasp difficulty, and placement precision [6]. Additionally, they fail to incorporate task variability, environmental constraints, and worker-specific factors (e.g., age, body weight, and anthropometric differences). These gaps raise concerns about their adaptability in DHM-based simulations, where tasks are translated into structured time codes.

2.4.2 Reliability in Time Measurement

Reliability in time estimation ensures consistent results across observers, time points, and measurement instruments. A system must be reliable to be valid, as inconsistent results undermine accuracy [48]. Reliability is typically assessed using the true value model, which accounts for random errors (e.g., fatigue) and non-random errors (systematic bias) [45].

For PMTS, reliability is evaluated through interrater reliability (consistency between analysts) and test-retest reliability (stability over repeated measurements) [49]. Studies show that PMTS estimations vary due to analyst experience and judgment, highlighting the need for structured validation to refine these methods.

Common statistical tools for assessing reliability include correlation coefficients, intra-class correlation (ICC), and paired T-tests, which quantify agreement between repeated measures [49]. Internal consistency, measured using Cronbach's Alpha, ensures coherent results across a tool's components [49]. Test-retest reliability, determined by Pearson's R coefficient, evaluates stability over time, with values closer to 1 indicating stronger reliability [49].

By employing these assessments, time measurement methods can be refined for greater accuracy and consistency, enhancing their applicability in real-world and digital human modeling environments.

2.4.3 Comparison of Reliability, Validity, and Precision in Time Studies

Reliability, validity, and precision are fundamental to evaluating time measurement systems. Reliability refers to measurement consistency, ensuring stable results across analysts and repeated trials [50]. This includes intra-observer reliability (consistency within the same analyst) and inter-observer reliability (agreement among different analysts) [51].

Validity determines whether a system accurately reflects actual task durations. A system may be reliable but invalid if it consistently measures the wrong construct [52]. Validity is typically evaluated by comparing PMTS estimates with real-time observations, stopwatch recordings, or established methods like MTM or MOST [53].

Precision refers to the reproducibility of time estimates and the detail of the measurement scale. Estimates can be recorded in seconds, minutes, or Time Measurement Units (TMUs), with TMUs offering the highest precision [54]. However, a system can be precise yet invalid, underscoring the need to balance precision with accuracy and reliability [55].

While reliability and precision are often conflated, they serve distinct purposes. A reliable system ensures consistency but may not accurately estimate task durations without proper validation. Thus, validity, reliability, and precision must be assessed separately to ensure a PMTS's effectiveness [50].

2.4.4 History of PMTS Validation

Despite their widespread use, validation studies on PMTS remain limited, with inconsistencies observed between estimated and actual times across different contexts. A genuine validation process involves comparing estimated times to observed times, ensuring alignment with real-world task durations. However, some studies misuse the term "validation," focusing on precision rather than accuracy. Genaidy (1989) [6] argues that "validity" should replace "precision" in PMTS evaluation, as these systems rely heavily on analyst judgment, influenced by experience and training.

Since the introduction of MTM-1, numerous PMTS have been developed, with MTM-1 often used as a benchmark for validation studies [40]. However, MTM-1 itself lacks comprehensive validation, and the evolution of manufacturing technologies necessitates revalidation to ensure modern applicability [6].

For example, Bahcivancilar (2012) [46] compared MTM-1 estimates with real-time video observations, revealing significant discrepancies in motion categories like grasp, move, and reach. Bures et al. (2015) validated the accuracy of both MTM-1 and MOST through direct task observation, concluding that deviations between estimated and actual times remained within acceptable limits of 10% [47]. Kurkin (2011) [56] compared MTM-UAS and MTM-1 in a digital factory environment, finding deviations ranging from 8% to 17%.

Some studies have compared different PMTS directly. Davidson (1952) [57] compared Work

Factor and MTM, concluding that MTM time values were generally higher.

Genaidy (1989) [6] noted that PMTS validity often relies on assumptions like uniqueness, independence, and additivity, which have been both supported and questioned. Schmidtke and Stier (1961) [19] highlighted PMTS's failure to account for repetition frequency's impact on motion time. Genaidy also identified gaps in addressing weight handling, motion planes, and variables like lift height, object dimensions, worker demographics, and environmental conditions.

In summary, while PMTS are widely used in industry, their validation remains limited, and academic focus on their accuracy is relatively low. Most validation efforts compare new PMTS with MTM-1, but MTM-1 itself requires reevaluation for modern contexts. The evolving manufacturing landscape underscores the need to ensure these systems remain relevant and accurate.

2.4.5 Advantages and Limitations of PMTS Regarding Validity

In assembly companies, where capacity and output depend on time estimations, validated PMTS can significantly improve manufacturing processes. Using a validated PMTS during pre-production—before workplaces are operational—can enhance future methods, optimize equipment selection, and refine workplace design and production planning.

Validation ensures PMTS accuracy and can lead to method improvements. For example, it can train manufacturing staff to be more motion-minded, boosting efficiency [58]. Once validated, new PMTS methods can be assessed at lower costs, leveraging the credibility of the validated system without requiring precise timing. This also eliminates the need for complex performance ratings, reducing validation time and costs.

However, PMTS validation has limitations that can lead to inconsistencies :

-Inaccuracy in Motion Elements : PMTS may suffer from inaccuracies due to unclear definitions of motion elements, ambiguous work analysis criteria, and inadequate consideration of influencing factors. These issues can diminish the value of the validation study.
-Analyst Experience : Inexperienced analysts may overlook motion elements or work complications, affecting validation accuracy. Effective validation depends on the analyst's familiarity with the production process and expertise in applying the system.
-PMTS Complexity : Both system complexity and analyst inexperience can impact validity. Experienced analysts are crucial, as incorrect motion analyses can lead to significant time estimation errors [6].

Burns and Simerson (1959) [59] emphasize that PMTS requires expertise, and misinterpretations by analysts can lead to inaccurate time estimates, undermining validation.

Additionally, PMTS often neglects the human body's capacity, creating discrepancies between estimated and actual task performance. PMTS-based designs may prioritize time efficiency over worker health, increasing musculoskeletal disorder (MSD) risks. Analysts should consider worker performance during validation to mitigate this [6].

Performance analysis in validation studies is challenging due to natural variability in worker pace. Workers may consciously or unconsciously alter their speed when observed. For instance, they may slow down if they believe new standards will affect compensation or speed up under pressure, leading to inconsistent performance data [47].

2.4.6 PMTS Aspects That Need to Be Validated

There are several key aspects that must be considered when validating different PMTSs. Based on priority, these measures are outlined below :

1- Validation of Mechanical Load Exposure (Weight and Force Exertion in Different Planes of Motion)
Many PMTS underestimate the impact of weight during material handling and the effects of moving objects through different planes of motion. Mechanical exposure varies based on movement directions and distances, yet these factors often have minimal impact on the time estimates provided by PMTS. It is therefore essential to develop metrics and conduct validation studies to compare estimated times with actual times when workers are exposed to mechanical forces due to weight or movement in different planes [6].

2- Validation of Task, Worker, and Environmental Variables
Most PMTS do not account for the effects of various task, worker, and environmental variables. Task variables include factors such as the height of a lift, the dimensions of an object, grasp difficulty, and placement precision. Worker variables encompass attributes like age, gender, body weight, and anthropometric characteristics. Environmental variables may include temperature, humidity, lighting, and vibration. A comprehensive validation study should assess discrepancies between estimated and actual times as these variables change in real workplace scenarios [6].

3- Validation of Newly Translated Motions
PMTS are indirect methods of measuring operations and often fail to reflect how operators actually perform tasks in real settings. In production systems with fewer strict rules regarding task execution, PMTS tend to relate more to standardized performance than actual performance. This limitation becomes more apparent for tasks that cannot be described

by a sequence of standardized actions, such as maintenance work. Consequently, many actions commonly performed in production environments that are not currently represented in PMTS need to be translated into the system and validated [6].

In summary, while Predetermined Motion Time Systems are widely used in the industry, they face significant limitations, particularly in integrating with DHM systems and reflecting real-world task conditions [6, 9, 60]. PMTSs mainly lack flexibility in accounting for mechanical load exposure, and task-specific complexities, leading to discrepancies between estimated and actual times. Additionally, they are designed for structured environments and often fail to capture variability in human motions, especially in less standardized tasks. These gaps highlight the need for a more adaptive and accurate time estimation system that can seamlessly integrate into DHM environments while addressing the limitations of traditional PMTS.

This research seeks to bridge these gaps by developing and validating a time estimation framework within a DHM system using the MOST methodology. By adapting MOST to 3D environments and integrating task descriptions expressed in natural language into structured time codes, this study enhances the accuracy and automation of time estimation in DHMs. Automation enables the precise modeling of motion factors, such as action distances, which are often overlooked in traditional MOST analyses but significantly impact task performance and worker fatigue. This leads to more realistic time estimates that better align with actual worker performance, reducing discrepancies and improving operational efficiency.

Through controlled laboratory experiments and field studies in real-world manufacturing environments, this research validates the accuracy of MOST under dynamic conditions, ensuring its applicability in both virtual and actual work settings. The validation process addresses critical limitations in existing MOST data cards, such as the omission of motion factors like mechanical loads and motion levels [17, 18], by performing tasks that account for these factors. This ensures that the adapted MOST system accurately reflects real-world conditions, bridging the gap between theoretical time estimates and practical application.

The findings contribute to the refinement of MOST data cards, enhancing their reliability for modern industrial applications. Additionally, the integration of MOST within DHM systems establishes a solid foundation for conducting dynamic ergonomic assessments. This research paves the way for future studies that incorporate task duration as a key factor in fatigue assessments of newly designed operations. By bridging this gap and enabling dynamic ergonomic analysis, it supports the development of safer, more efficient workplaces while promoting sustainable task planning practices [8, 9].

The next chapter presents the methodology for developing and validating this automated time estimation system using the MOST framework.

CHAPTER 3 RESEARCH METHODOLOGY

As outlined in Chapters 1 and 2, this work aims to develop and validate time estimation methods within DHM systems, focusing specifically on the integration of MOST due to its structured methodology, efficiency in task analysis, and widespread industrial adoption. The proposed methodology is organized into three primary steps, each addressing specific research questions and contributing to the project's overall objective : Developing a reliable time estimation framework within a DHM system. This chapter provides an overview of our methodology, highlighting the identification of gaps in time estimations within 3D environments, applicable cases, key milestones, validation studies, and final outcomes, as presented in the accompanying articles. Figure 3.1 illustrates the comprehensive procedure and interconnections between these phases.

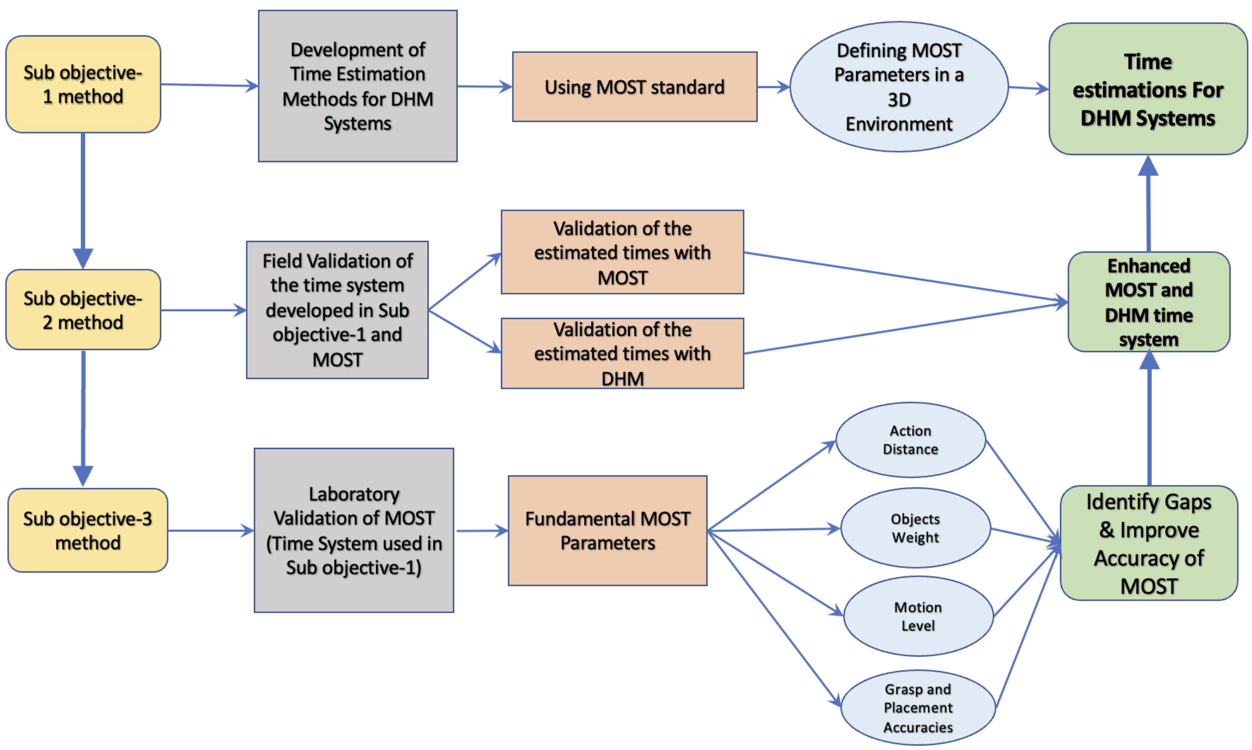

FIGURE 3.1 Overview of the procedure and the links between the sub-objectives.

The methodology is designed to progress through three interrelated phases, each building upon the previous stage to form a comprehensive solution.

Phase 1 - Developing the Time Estimation Framework in DHM Systems : The first phase focuses on establishing the groundwork by creating a framework for automated time analysis within DHM systems using the MOST time system. This involves defining key MOST parameters such as action distance, body motions, and grasp and placement accuracies within a 3D environment. These parameters lay the foundation for generating MOST codes specific to the designed work sequences. Subsequently, a decision tree algorithm was developed to automate the time estimation process, efficiently streamlining the workflow.

Phase 2 - Field Validation Study : The second phase involved conducting a field validation study to compare the developed DHM time estimation method in phase 1 and the MOST system with actual measured times in an industrial environment. This step was crucial for validating the applicability of the developed method in real-world scenarios, ensuring that the solution was robust and reliable for industrial applications.

Phase 3 - Laboratory Validation Study : The final phase involved a controlled laboratory validation of the MOST system, focusing on assessing its accuracy and refining its parameters. This study identified and addressed critical gaps by analyzing key motion characteristics and workplace factors—such as object weight and motion levels—that influence motion times. The objective was to resolve discrepancies and enhance MOST's alignment with real-world conditions. Findings from this phase led to a more precise and robust time estimation system while also refining the algorithms developed in Phase 1, further strengthening the overall framework.

The three key studies resulting from this research are summarized in the following subsections, presented in Chapters 4, 5, and 6 in chronological order, following a cohesive sequence that addresses the main research objectives.

3.1 Development of a Framework for Automated Time Analysis in DHM Systems

Chapter 4 details the development of a comprehensive framework for automated time analysis within DHM systems, focusing on the integration of the MOST system. This process involved systematically defining key MOST parameters within a 3D environment, standardizing the terminology used across both systems in alignment with industry practices, and meticulously documenting relevant actions. These elements were then incorporated into a decision-making algorithm designed to generate accurate MOST codes.

3.1.1 Identifying Data Available for Time Estimation in DHM Systems

The first step was to understand the input data required for human modeling and the output data generated after the modeling process within DHM systems. To achieve accurate time estimation, an interface was developed to gather and utilize information from both the input and output of the 3D-designed human models.

The input data for modeling human interactions within the 3D task environment included natural language descriptions of the actions to be performed. This ensured that the DHM system could accurately interpret and simulate the intended task sequences. For instance, specifying actions like "lift object" or "move tool to position" provided clarity for task execution. Additionally, task-specific details were essential, including information about tool or object properties, the hand used for the action, and any workspace constraints. These details enabled the system to replicate realistic interactions and conditions. After creating the human model, CAD data played a crucial role in defining the MOST parameters. These data elements were vital for defining key MOST parameter such as action distances, body motions, Gain control, and placement precision.

3.1.2 Unification and Translation of Actions between MOST and the DHM System

After identifying the available data in the DHM system, the next step was to unify the language between MOST and DHM system. A standardized lexicon was developed to maintain consistency and align the MOST language with common industrial terminology used in the DHM system. This mapping facilitated clear communication between MOST-specific actions and industry terms. Each action was meticulously documented in a comprehensive directory within the DHM system, with every entry linked to an identity card specifying its motion category, action description, and required parameters. This integration ensured the accurate representation of action verbs and consistency in time estimation across both the MOST and DHM systems.

3.1.3 Definition of MOST Parameters within 3D Environments

After unifying and translating actions between the MOST system and the DHM environment, the next step in the time estimation process was the systematic identification and definition of critical MOST parameters within the task sequences represented in the 3D environment. Each parameter possessed distinct motion characteristics that influenced its corresponding time value. To facilitate this, we developed an interface capable of extracting relevant data from user inputs and CAD data after creating a human model. This interface efficiently transferred time-relevant information from the DHM system to identify the appropriate MOST parameter for each designed motion.

While there are many specific parameters based on different motion categories, we mention here the fundamental ones relevant to general movements. Detailed descriptions of these and other parameters are provided in Chapter 4.

The fundamental MOST parameters include :

1. **Action Distance** : Calculated using CAD models by determining the start and end points of each given motion. This CAD-based tracking was crucial for simulating realistic distances covered by virtual human models.
2. **Body Motions** : Assessed through a motion tracking system that categorizes joint angles into various body motions. This detailed categorization allowed for accurate analysis of body mechanics during task performance.
3. **Gain Control and Placement Accuracies** : Evaluated based on user-defined inputs such as tool/object weight and dimensions to capture variability in grasping and placement actions within the simulated tasks.

3.1.4 Development of the Decision-Tree Algorithm for Automated Time Estimation

A decision-tree algorithm was developed to automate the time estimation process within the DHM system, enabling efficient and accurate analysis. The algorithm performed the following core functions :

1. **Mapping User-Defined Actions to MOST Codes** : User-defined actions, such as "grasp" or "place," were automatically linked to corresponding MOST motion sequence models within the DHM software. This mapping was essential for maintaining consistency and precision in time estimation.
2. **Dynamic Adjustment Based on User Inputs and CAD Data** : Key parameters, including Action Distance, Body Motions, Gain Control, and Placement, were dynamically calculated using real-time data from CAD models and user-defined inputs based on defined thresholds for each parameter level. For example, the algorithm calculated accuracy-related parameters, such as Gain Control, using object weight and dimensions. If any critical information was missing, the system prompted the user to provide the necessary data during task design, ensuring a high level of accuracy and completeness.
3. **Generating MOST Codes** : The system aggregated relevant information from user inputs and CAD data to generate accurate MOST codes for each action within the designed task sequences.

The successful establishment of this framework provided a solid foundation for automated time analysis within DHM systems. By linking user-defined actions to MOST codes and automating key parameter calculations, the framework aimed to enhance both the consistency and efficiency of time estimation processes. This foundational framework was critical for subsequent validation studies conducted in controlled laboratory conditions and real-world industrial environments.

3.2 Validation of MOST and the Developed DHM Time Estimation Method in a Real-World Field Study

Chapter 5 presents a validation study that evaluates the robustness of the developed DHM-based time estimation method and the MOST system in an industrial setting. The study aimed to assess the practical applicability of both systems by comparing their estimated operation times with actual times observed in a dynamic, real-world environment.

3.2.1 Data Collection and Sample Selection

The validation study was conducted on an automotive assembly line in Canada and encompassed 26 distinct operations, each corresponding to a different workstation. These operations involved typical car assembly tasks such as part fitting, fastener installation, electrical wiring, and quality control. A total of 633 tasks were analyzed across these workstations, performed by different operators working on various shifts. These tasks reflect real-world variability in task execution and were systematically broken down into 5,411 discrete actions using the MOST framework. Each action was coded based on standard parameters—Action Distance (A), Body Motions (B), Gain Control (G), and Placement (P)—which collectively represented approximately 90% of the total time codes assigned during the analysis.

Video recordings were captured using iPhone X devices to obtain detailed footage of each task performed on the line. The videos were recorded at 30 frames per second to facilitate precise motion analysis. The recordings were processed using IINA software, which provided millisecond-level precision for detailed time measurements.

3.2.2 Time Analysis using the MOST and DHM Time Systems

The recorded task data was used to estimate task durations using the DHM-based time estimation method. In this study, the DHM-based method was executed manually, simulating the automated process through the application of algorithms. To achieve this, data was gathered from various sources, including the bill of materials used in the assembly line, the workspace layout, and task descriptions, to define the relevant MOST parameters.

In contrast, the MOST system relied on visual analysis to assign time values to specific actions based on established parameters. The objective of the analysis was to identify potential discrepancies between the traditional observation-based MOST estimates and the estimates generated by the DHM method.

3.2.3 Comparison Metrics and Statistical Analysis

Bland-Altman tests were performed to measure the agreement between time estimates generated by the DHM and MOST systems and the actual times obtained from the video recordings. These tests provided insight into the limits of agreement and the mean differences between estimated and measured times, offering a comprehensive view of each method's alignment with actual task durations.

In addition, an ANOVA test and pairwise t-tests were conducted to identify any statistically significant differences between the two methods. A regression analysis was also performed to explore the influence of key variables—namely, Action Distance and Task Duration—on the observed discrepancies between the estimated and actual times. This analysis aimed to provide a deeper understanding of how these variables affect the accuracy of both methods.

3.2.4 Findings and Implications for Time Estimation Methods

The study revealed that both the DHM-based and MOST methods demonstrated acceptable levels of agreement with the actual measured times, although some minor discrepancies were observed. By validating the developed DHM-based time estimation method in a real-world industrial setting, the study confirmed its applicability and reliability for practical use. The findings also highlighted areas for potential improvement in both the DHM and MOST methods, particularly in terms of handling variations in task duration and action distance. These insights pave the way for refining the time estimation methods to enhance their robustness and accuracy in diverse industrial applications.

3.3 Validation of the MOST System Through Laboratory Experiments

In line with the research objectives, Chapter 6 presents a validation study conducted under controlled laboratory conditions to assess the accuracy of the MOST. The primary aim of this phase was to systematically identify and address discrepancies between MOST-based time estimates and actual measured times by evaluating critical factors that influence motion times. The study was structured into three stages to analyze various variables affecting task performance and to propose refinements aimed at enhancing the accuracy of MOST-based estimations.

3.3.1 Experimental Design and Setup

The study involved an experimental setup with twenty participants performing a series of "Get-and-Place" tasks in seated conditions. These tasks were carefully selected to represent common industrial motions and were divided into three distinct experiments. Each experiment focused on evaluating different variables, including Action Distance, Object Weight, Motion Level, Grasp Difficulty, and Placement Precision. The specific experimental design was modeled after prior research to ensure reliability and consistency in capturing essential motion characteristics.

The experiments utilized both fixed-height and adjustable-height tables to assess the impact of different Action Distances and Motion Levels. During these tasks, participants interacted with colored markers, rubber bands, and weights of varying masses (0.5 kg, 1 kg, and 2.26 kg). Across all experiments, a total of 6,000 samples were collected to provide comprehensive insights into how each factor impacted motion times, and to highlight potential discrepancies in the MOST system.

3.3.2 Data Collection and Recording Methods

To ensure accurate data collection, participants' movements were recorded using both wrist-mounted accelerometers and high-definition video recordings. The accelerometer data captured detailed information on movement acceleration and deceleration phases, enabling precise time measurements. Additionally, video recordings helped identify outliers, minimize errors, and validate the accuracy of the accelerometer data.

3.3.3 Experimental Variables and Analysis Approach

Action Distance and Motion Levels The first experiment focused on evaluating Action Distances at a fixed table height. Participants performed reach tasks with varying Action Distances to measure the effect of distance on motion times. The analysis segmented Action Distances into predefined ranges, based on prior research, to explore how these variations influenced task performance. In subsequent experiments, adjustable-height tables were introduced to incorporate Motion Level variations, examining the relationship between table height and motion times. Action Distances were adjusted to lengths within each participant's maximum comfortable reach zone, ensuring ergonomic compliance while exploring the impact of these distances on task performance.

Object Weight The second set of experiments investigated the influence of Object Weight on task completion times. Participants handled objects of varying weights (0.5 kg, 1 kg, and 2.26 kg) to identify discrepancies in the MOST system's time estimations for tasks involving different weights. This setup aimed to reveal the effects of weight variations on motion times.

Placement Precision and Grasp Difficulty The final set of experiments examined the effects of Placement Precision and Grasp Difficulty on task performance. Participants were required to place objects with varying levels of precision, ranging from approximate placements to high-precision insertions. For instance, one task involved inserting a marker into a hole with a tolerance of less than 3 millimeters, simulating high-precision placement conditions. Additionally, tasks of varying Grasp Difficulty were incorporated to assess how challenges in grasping influenced time estimates.

3.3.4 Statistical Analysis and Results

A comprehensive set of statistical analyses was performed on the collected data to evaluate the accuracy of the MOST system. Descriptive statistics were used to summarize time estimates across all experimental variables. Bland-Altman tests were conducted to assess the agreement between measured and estimated times, revealing discrepancies in several key variables. Additionally, regression analyses were applied to examine the effects of independent variables, such as Action Distance and Object Weight, on task completion times.

The analyses revealed a 38% underestimation in MOST-based time estimates and significant discrepancies between MOST predictions and actual measured times for critical variables. These findings indicated that the existing MOST coding scheme needed refinement to account accurately for variations in motion characteristics and task parameters.

The results from these statistical assessments informed targeted refinements to the MOST system. The proposed improvements aimed to address gaps in the coding scheme, enhance the accuracy of time estimates for various motions, and incorporate additional parameters for Object Weight and Motion Levels to better align with real-world conditions. These findings prompted a field study to evaluate how the MOST system and the developed DHM-based method perform under real-world industrial conditions.

3.3.5 Novel Contributions of the Proposed Methodology

The methodologies employed in this research represent a significant advancement in integrating the MOST system into 3D environments within DHM systems for automated time analysis. A key contribution of this study is the development of new techniques for identifying critical MOST parameters in a 3D setting. For instance, the approach includes using static postures to approximate dynamic postures for defining body motions, and establishing boundaries for different levels of grasp based on the weight and dimensions of objects, allowing the system to automate the process seamlessly.

Secondly, our field validation study utilized a robust dataset and a combination of statistical techniques to rigorously assess the robustness of the developed DHM-based time estimation method. Through regression analysis, we examined various variables influencing discrepancies between estimated and actual times. This empirical approach provided valuable insights for refining the estimation methods and demonstrated their reliability in real-world settings.

Finally, this research introduces an innovative approach to addressing gaps in the MOST system through the careful design and selection of motion experiments. Key gaps, such as the effects of object weight and movement height, were specifically targeted in laboratory experiments to assess their influence on motion times. Unlike previous studies, these experiments comprehensively investigated these factors. A notable contribution of this research is the application of regression analysis to refine MOST parameters based on experimental results. This analysis led to the creation of new data cards to supplement existing MOST parameters and the development of additional coding schemes to accommodate action distances in short-distance tasks, object weight, and motion height levels. These enhancements improve MOST's adaptability to complex industrial scenarios, filling a critical gap in its traditional application.

These methodological innovations establish a comprehensive framework for precise time analysis within DHM systems. By adapting MOST to a virtual context, refining key parameters, employing targeted experimental designs, leveraging a robust dataset, and applying statistical methods, this research sets a new benchmark for achieving accurate time estimates in complex 3D environments.

CHAPTER 4 ARTICLE 1 : DEVELOPMENT OF A FRAMEWORK TO IMPLEMENT TIME ANALYSIS IN DIGITAL HUMAN MODELING SYSTEMS USING PREDETERMINED MOTION TIME SYSTEMS

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4.1 Abstract

Digital human modeling (DHM) systems are increasingly utilized to design and optimize human work processes. A key challenge in employing DHM systems is precisely estimating task times for activities depicted through 3D human models. This study introduces an automated approach for time analysis derived from DHM data, focusing on integrating the Maynard Operation Sequence Technique (MOST) time system.

Traditional time analysis using MOST often requires extensive manual effort from trained analysts to evaluate task execution, which can be both time-consuming and costly, particularly when applied to 3D designs. However, the automated methodology presented in this study significantly streamlines this process by minimizing manual intervention, thereby facilitating the creation of efficient and ergonomic human work processes during the design phase.

The proposed method offers a systematic approach to integrating the data required for a Predetermined Motion Time System (PMTS) analysis, such as MOST, within a 3D environment. The study specifies the data that simulation tools can automatically generate for time analysis and highlights where manual input is needed during DHM simulation. By combining automated data with manual input, the method ensures a complete PMTS analysis.

The method was validated through a field study, showing acceptable performance compared to both MOST estimates and actual observed task times. To illustrate its application, the method is implemented using Dassault Systèmes Delmia Ergonomic Workplace Design (EWD) software in a case example. EWD enables automatic time estimations for 3D-designed tasks while allowing for comprehensive ergonomic assessments. This multifaceted analysis equips design engineers with a powerful tool to evaluate design effectiveness, significantly saving time and resources before creating a physical prototype.

keywords : Digital Human Modeling (DHM) System, Ergonomic Workstation Design, Time Analysis, Maynard Operation Sequence Technique (MOST), Predetermined Motion Time System (PMTS), Dynamic Risk Assessment.

4.2 Introduction

Work-related musculoskeletal disorders (MSDs) have a significant impact on body movement and musculoskeletal systems, including muscles, tendons, ligaments, nerves, and other soft tissues [61]. These disorders mainly result from poor posture and repetitive or forceful movements. MSDs are significant public health problems that lead to disability and lost productivity worldwide [3].

The economic burden of MSDs is substantial, and work-related injuries cost nations between 1. 2% and 6. 2% of their gross domestic product, figures comparable to the economic impact of cancer [4]. A report from the European Agency for Work and Safety estimates that MSDs constitute up to 50% of all work-related illnesses within the European Union, resulting in annual costs of approximately €240 billion [3]. In the United States, MSDs represent nearly one-third of all workplace injuries, with direct and indirect costs to employers reaching an estimated $50 billion per year [5].

Ergonomics is a scientific discipline that focuses on designing products, processes, and systems to enhance both human well-being and system performance. It ensures that workspaces, tools, and equipment are adapted to workers' physical and cognitive capabilities, thereby preventing MSDs and boosting productivity. Employing ergonomic methods, such as biomechanical analysis, observational studies, and self-report surveys, facilitates the identification and mitigation of risk factors linked to musculoskeletal disorders [62].

Boosting productivity while maintaining safety is essential for any company's success. Improving productivity not only fuels growth, but also enhances competitive advantage. Accurate time estimation for various operations is critical in monitoring and enhancing productivity. By precisely identifying time requirements, companies can streamline processes, optimize efficiency, and elevate overall productivity levels [14].

Predetermined Motion Time Systems have been vital for decades in estimating the time needed for human work sequences, which involve a series of sub-activities required to perform tasks. Utilizing a PMTS involves deconstructing a task into its basic motions and assigning predefined time values to each. The primary goal of PMTSs is to estimate the time required for a worker to execute a series of activities necessary to produce a specific product unit within a simulated future assembly line scenario. This time estimation is essential for calculating the expected cost of the product [1]. PMTSs encompass several categories, including MTM, MOST and MODAPTS, each with distinct attributes, parameters, and applications. These systems serve as valuable tools across various industrial and manufacturing environments [55].

The design of human work processes is pivotal in industrial companies, where productivity and ergonomics are key performance indicators. Professionals employ various methods to analyze and design work processes to enhance these indicators. However, most methods focus either on productivity or ergonomics, rather than addressing both concurrently. Furthermore, existing approaches often demand substantial manual effort for data collection and interpretation, complicating both time and ergonomics analyses [7].

The diverse nature of time and ergonomics analyses necessitates that two groups with different expertise, technical language, and perspectives analyze the same design at different times, making the process cumbersome and inefficient [14]. Therefore, it is increasingly apparent that effective workplace design requires an integrated approach that encompasses both time estimations and ergonomics analysis. This integration eliminates the need for separate procedures to describe and evaluate work times, as well as ergonomics aspects such as postures and force exertions [41].

Digital Human Modeling systems are software solutions that create virtual human models and simulate their interactions with the environment. DHM systems have gained popularity as tools for simulating and analyzing workplace design. They facilitate ergonomics analysis by integrating various methods to evaluate workstations, assess workers' physical demands, and optimize work processes before physical implementation. This leads to improved productivity in the design process, reducing the costs and time associated with physical prototyping and testing [2]. Moreover, DHM systems can evaluate existing environments, such as manufacturing lines, and identify ergonomic improvements to enhance worker health [41, 63–65].

One of the primary challenges in applying DHM systems is the lack of integration between time estimation and ergonomic analyses for tasks designed in 3D environments [7]. Traditional ergonomic assessment tools, such as RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body Assessment), and EAWS (Ergonomic Assessment Worksheet), are widely utilized within DHM systems to evaluate risks associated with static postures or movements at specific moments by assessing joint angles, body positions, and exerted forces to identify ergonomic risks during the design phase [2, 66]. These methods are now commonly incorporated into different DHM systems and can be performed in parallel with other analyses, such as time analysis.

While these methods effectively identify isolated ergonomic risks and ensure compliance with standards, they lack direct connection or integration with time analysis, limiting their ability to provide comprehensive insights into the dynamic interactions between time and ergonomic factors. Additionally, these methods do not account for the cumulative risks associated with repetitive motions or prolonged task cycles. This limitation is particularly significant in industries where tasks involve repetitive actions over extended periods, as it can lead to overlooked risks that contribute to chronic health issues [67].

Dynamic ergonomic methods, such as the Occupational Repetitive Actions index (OCRA), address this limitation by incorporating temporal factors like task duration, frequency, and recovery periods [68]. Other methodologies, such as Fatigue Failure Proactive Ergonomics, also integrate task duration into fatigue analysis by combining task time and force dynamics to estimate fatigue thresholds [69]. These methods offer a comprehensive evaluation of worker exposure to cumulative risk factors, enabling a deeper understanding of the long-term impacts of repetitive tasks. Integrating time estimation into DHM systems has the potential to bridge the gap between static and dynamic ergonomic analyses, providing the temporal data necessary for more effective risk evaluations.

Identifying potential ergonomic risks and implementing design interventions to mitigate fatigue and musculoskeletal disorder (MSD) risks can significantly enhance worker safety and health. However, the absence of integrated time estimation in DHM systems limits their ability to assess the risks associated with sequential or repetitive tasks over time. This gap in temporal context hinders accurate risk evaluations, constraining the design and optimization of human-centric systems. Additionally, the reliance on separate analyses for time and ergonomics increases both the complexity and cost of assessments [2].

Efforts have been made to integrate time and ergonomics analysis in methods like ErgoSAM [41], Ergo-UAS [70], and MTM-HWD [40]. However, these methods are primarily paper-based and lack integration into automated software solutions, making them time-consuming and challenging to use with complex in-house integrated software systems.

Several DHM systems, such as Jack, RAMSIS, Pro/ENGINEER, and HumanBuilder, are capable of performing ergonomics analysis on a 3D simulated work sequence. These systems enable the creation of realistic virtual human models, simulate human-environment interactions, and provide a comprehensive approach to ergonomics evaluation [71, 72]. Notably, Jack by Siemens is a DHM system that enables integrated ergonomics and time analysis using MTM-1 standards and simulation techniques [73].

Despite these advancements, there remains a shortage of virtual ergonomics tools capable of integrating PMTS with ergonomics analysis within a DHM environment. This gap presents significant challenges in effectively implementing and utilizing DHM tools [7]. Further research is essential to clearly define the boundaries and research problems and to address the gaps in DHM and PMTS integration.

The primary objective of this research paper is to describe the development of a framework for conducting time analysis using the MOST predetermined motion time system within the 3D environment of DHM systems. MOST was selected for its simplicity, practicality, and widespread use across various industrial settings, making it an ideal choice for integration with DHM systems. The novelty of this framework lies in the specific assumptions and techniques adopted to streamline the procedure, enabling reliable time estimation for motions designed in a three-dimensional context while addressing critical gaps in existing manual methods.

This framework facilitates automated time analyses for 3D-designed operations of workstations, even for users without prior knowledge in the field. By implementing this proposed method, DHMs can automatically conduct time analysis, resulting in a more streamlined and accelerated design process, ultimately enhancing workplace productivity and safety.

By enabling the integration of time and ergonomic analyses, the framework facilitates a more comprehensive design process and supports sophisticated ergonomic evaluations by incorporating time as a critical factor.

It is important to note that achieving precise time estimation in a 3D environment is challenging due to inherent gaps in virtual data. Despite these limitations, the goal is to develop a method that closely approximates reality by integrating assumed data with additional input information to define temporal parameters as precisely as possible. This integration ensures a user-friendly and automated process while maintaining reliability, effectively balancing the method's inherent complexities with the need for reliable time analysis.

4.2.1 Time Estimation with MOST

MOST is a widely adopted time system in various industrial domains. It offers a structured approach for describing and analyzing the diverse actions performed by workers during task execution. These actions encompass a wide range of activities typical of handling objects, such as grasping, moving them over distances, placing them at precise locations, etc., which are commonly found in manual assembly tasks.

MOST utilizes a coding system, known as 'MOST data cards,' with standardized codes to accurately describe actions performed during manual work tasks. This system also provides guidelines for quantifying activities such as walking, machine operation, and tool use, which can be components of work content. To estimate the total time required for a given work content, one aggregates the predetermined time values associated with each MOST code used to describe the work content, as outlined by Zandin [1]. The analysis process involves specifying the work content through observation of the tasks performed by experienced workers, assigning MOST codes that best describe the work content, and summing the time values associated with each code.

Table 4.1 presents the three movement categories in MOST, along with their corresponding sequence models and parameters [1]. The sequence model specifies the order in which different parts of a motion are executed (e.g., the motion of the hand from one point to another to reach an object, grasp it, and then place it at a precise location). The parameters are characteristics of the motion that affect the time required to perform it. For instance, a longer distance traveled by the hand (Action Distance) results in a longer motion time, thereby increasing the associated time value. To assign time values to all parts of a motion sequence model, one must characterize all of the parameters ; for example, measuring the Action Distance in centimeters. This detailed parameter description is typically done manually while observing a worker performing a task, making it a very time-consuming process.

Table 4.1 Sequence models for motions in MOST (Adapted from Zandin [1])

Motion Sequences in MOST		
Activity	**Sequence Model**	**Parameter**
General Move	ABGABPAA	A : Action distance, B : Body motion, G : Gain control, P : Placement
Controlled Move	ABGMXIA	M : Move controlled, X : Process time, I : Alignment
Tool Use	ABGABP*ABPA	F/L : Fasten/loosen, C : Cut, S : Surface treat, M : Measure, R : Record, T : Think

Table 4.2 presents the MOST General Move coding scheme, which illustrates how motion characteristics, as defined by various parameters, impact the time needed to complete a motion. MOST codes are generated once index values are assigned to these parameters

based on the specific characteristics of a motion that influence the time required to execute it.

For instance, the Action Distance parameter includes up to six levels. As the level increases, so does the index value, leading to a longer time needed to cover the Action Distance. Similarly, the Placement parameter comprises four levels. At its highest level, if the final placement of an object requires precision due to a tight fit, more time is needed to perform the action than at a lower level, such as a simple pickup or toss. The inclusion of two identical index columns in Table 4.2 enhances usability and clarity, facilitating a more straightforward recording and analysis of tasks.

To perform a time analysis using Table 4.2, the value for each parameter is identified, typically using the left or right index column of the coding scheme. In this setup, a higher index value indicates a longer duration needed to perform an action. The basic time measurement unit in MOST is the TMU (Time Measurement Unit). To determine the time required for an activity, the index values of the parameters in the sequence model, representing the task's sub-activities, are summed. This total is then multiplied by 10 to convert it into TMUs, with each TMU equating to 0.036 seconds [1].

4.3 Methods

In real-world work settings, time analysts observe a worker's movements during task performance, documenting the fundamental aspects of these movements and mapping them to corresponding MOST codes. These codes are then assigned time values to enable time estimation based on empirical data.

However, in a 3D environment within a DHM system, workstations are often still in the design phase, which means physical observation of real tasks is not possible. As a result, traditional observation-based methods become inapplicable. Instead, the application of MOST in DHM requires analyzing DHM-specific data to define MOST parameters and their determinants accurately.

A comprehensive dataset and specific parameters are necessary to precisely simulate human work processes (tasks) within a DHM system. The simulation process includes detailed modeling of the human mannequin's postures and movements, as well as spatial characteristics, dimensions of objects or tools involved, and other task-specific details, many of which are represented within CAD models.

TABLE 4.2 General move coding scheme (Adapted from Zandin [1])

BasicMOST System : General Move (ABGABPA)					
Index × 10	**Action Distance (A)**	**Body Motion (B)**	**Gain Control (G)**	**Placement (P)**	**Index × 10**
0	≤ 2 Inches (5 cm)	–	–	Pick up, Toss	0
1	Within reach distance	–	Light Object/Light Object Simo	Lay aside, Loose Fit	1
3	1-2 steps	Sit, Stand, Bend and Arise 50% occurrence	Light Object non-simo, Heavy/Bulky, Blind/Obstructed-Disengage, Interlocked, Collect	Loose fit blind/Obstructed Adjustment, Light pressure, Double placement	3
6	3-4 steps	Bend and Arise	–	Care/Precision, Heavy Pressure, Blind/Obstructed, Intermediate Moves	6
10	5-7 steps	Sit & Stand with adjustment	–	–	10
16	8-10 steps	Bend and Sit, Climb on/off, Stand and Bend, Through Door	–	–	16

4.3.1 DHM Input Data

To simulate tasks in a DHM system, it is essential to provide specific inputs that accurately represent real-world task characteristics. These inputs enable the replication of human actions and postures within a virtual work context, facilitating both time and ergonomic evaluations. The resulting human model, or mannequin, is often depicted in a fixed posture and tasked with scenarios involving force exertion, such as lifting components from a jig or applying force to tools.

An interface within a DHM system allows users to input the necessary data for designing digital human models and their tasks. The complexity of this process varies depending on the sophistication of the DHM system. Advanced systems, such as Delmia Ergonomic Workplace Design (EWD) or Siemens Jack, leverage automation to streamline simulations, dynamically adjusting joint angles, object placements, and motion trajectories. This reduces user input requirements and improves design efficiency.

In contrast, simpler DHM systems rely heavily on manual inputs for task trajectories, workspace attributes, and detailed model biomechanics, such as joint angles. While this approach demands greater user effort, both advanced and simpler systems ultimately produce the same essential output : 3D models that simulate task sequences and human interactions, enabling time and ergonomic analyses.

Regardless of the level of automation, the following inputs represent the essential requirements for time estimation in DHM systems. These foundational elements are typically available in most DHM platforms, enabling effective time analyses :

1. Actions Performed
   A comprehensive understanding of the task's workflow or the specific motions performed by the virtual human is crucial for time analysis. This involves identifying the sequence of operations, including all actions involved, such as "Get," "Place," "Move," "Screw," "Operate," or "Assemble." These predefined actions, or operational verbs, form the foundation for systematic mapping to MOST equivalents, ensuring consistency in parameterization. By aligning these actions with the MOST framework, the system facilitates accurate time estimation based on established standards.
2. Human Interactions, Movement Patterns, and Biomechanical Data
   This includes the interactions between a worker and their environment, focusing on movements, postures, and forces during task performance. Human interactions involve how a person engages with objects, tools, or other elements in their workspace. Movement patterns refer to the sequence and coordination of motions required for specific tasks, while biomechanical data covers parameters like joint angles and physical effort, crucial for evaluating task demands and ensuring ergonomic safety.

   For example, specifying the active hands or body parts involved in performing a task is critical for accurately modeling motion effort parameters, such as Gain Control. Determining whether a task requires the coordinated use of both hands, such as lifting an object or assembling components, or single-handed operations, like manipulating a tool, provides valuable input for time estimation and ergonomic assessments.
3. Object and Tool Characteristics
   Details about the dimensions, weights, and functional attributes of objects and tools

are essential for defining parameters such as Gain Control. For instance, object weight influences classifications like "light" or "heavy," while tool characteristics specify motion requirements, such as "tightening" or "cutting." These attributes directly impact time estimations and ensure that simulations accurately represent the physical interactions between humans and objects, providing a realistic basis for both time and ergonomic analyses.

4. 3D Locations for the Designed Tasks
   The spatial arrangement of the operational environment, including workspace layouts and the start and end positions of actions, forms a critical component of task simulations. These 3D locations define parameters such as Action Distance and Placement, enabling the system to calculate spatial relationships and durations accurately. This precise mapping is essential for aligning tasks with real-world scenarios and ensuring accurate time estimations.

Once a human model is designed within the DHM system, the interface facilitates linking the model's data to MOST parameters for time estimation. This process utilizes detailed task descriptions and CAD data, such as task sequences, spatial layouts, and object characteristics, to capture the critical aspects of the task. These inputs form a comprehensive foundation for identifying and assigning MOST parameters, ensuring accurate and consistent time estimations.

The proposed method systematically extracts fundamental MOST parameters—such as Action Distance, Body Motion, Gain Control, and Placement—directly from 3D models, while user inputs complete the remaining parameters to ensure accuracy. While the specific data extraction process may vary across DHM systems due to platform differences, the method provides a structured framework adaptable to diverse systems and contexts. By leveraging the common output of DHM systems—3D-designed models—the framework ensures consistency in time estimation across platforms while accommodating unique features, data structures, and varying levels of automation or manual inputs. This adaptability broadens its applicability to a wide range of industrial scenarios.

4.3.2 Harmonizing Language Across MOST and DHM Systems (Action Definition)

One of the initial steps in integrating MOST into a DHM system is harmonizing the language between systems to ensure consistency in action definitions. Task descriptions from DHM systems must be translated into MOST's standardized lexicon to ensure consistency and accurately define the actions that best describe the simulated work sequences. These actions are categorized into specific MOST motion categories and aligned with their corresponding sequence models, as detailed in Table 4.1. Establishing the sequence model helps determine the relevant MOST parameters.

This translation process presents challenges due to differences between the industry-standard natural language used to describe tasks and MOST's specialized terminology, potentially leading to interpretation inconsistencies. Additionally, some PMTS actions might not have direct equivalents in DHM, necessitating careful translation.

An interface has been developed to convert DHM action descriptions into their respective MOST actions. This tool serves as a linguistic bridge, converting natural language descriptions into structured MOST sequences. Since not every natural language action directly translates into MOST actions, the interface includes a list of commonly used natural language actions in industrial settings, along with their associated MOST parameters. Users select the closest matching action from the menu lists, ensuring verb uniformity and bridging the gap between everyday and technical terminologies.

The interface's development involved standardizing synonyms, defining actions within the DHM framework, and creating a directory that links MOST terms with DHM terminology. In this directory, the categorized actions are assigned appropriate MOST parameters, streamlining the translation and time estimation process.

For instance, the action verb "Place" in everyday language can translate to "Put" or "Position." Variants like "Placement with light pressure" or "Placement with heavy pressure" in MOST, correspond to "Insert" or "Press" in DHM terminology. Within the MOST framework, each variation of the verb "Place" is given a specific interpretation and corresponding time value. Standardizing these terms across DHM and MOST through the interface addresses the challenge of language differences, enhancing the reliability of time estimates.

Expanding the DHM Action Verbs Directory

The DHM systems' directory of action verbs often lacks several actions utilized in the MOST system. For instance, the "Assembly" action in MOST is more nuanced, with time evaluations varying depending on whether the assembly involves applying pressure. DHM systems typically generalize these actions under "Assembly," without considering the force aspect. To address this, refined classifications such as "Assembly with pressure" and "Assembly without pressure" have been added to the DHM vocabulary, thereby enhancing the specificity of these actions.

Similarly, the "placement" action is enriched with more detailed descriptors like placement with "precision," "adjustment," and "care" to better align with MOST actions.

The expanded directory also incorporates actions that pose challenges for 3D modeling or were previously absent in DHM but are necessary for MOST analysis. These might include abstract or complex actions, such as "Thinking" or "Grasping interlocked objects," which require a higher level of interpretation.

Additionally, DHM sometimes uses verbs that do not have direct equivalents in MOST, such as "Grinding." This action is a composite, combining "Get and Place a grinder" (a MOST General Move) with "execute movements against resistance" (a MOST Controlled Move). In DHM, these composite actions are interpreted and linked to the corresponding MOST time values, ensuring alignment with MOST's analytical framework.

4.3.3 Determination of MOST Parameters Using Digital Human Simulations

Integrating the MOST system into DHM systems requires specific assumptions to align real-world observations with 3D simulations. These assumptions simplify virtual work environments by establishing predefined thresholds for key MOST parameters, such as Action Distance (A), Body Motion (B), and Gain Control (G), to systematically categorize task elements in 3D environments. While these thresholds enhance consistency and support automation, they introduce approximations that may influence time estimations. This section outlines the derivation of MOST parameters within the DHM environment and examines the potential impact of these approximations.

Actions are first identified and mapped to their corresponding MOST motion categories, such as General Move or Tool Use. The relevant MOST parameters are then derived from DHM-generated data, combining CAD inputs with user-provided information to enable time estimation. The section begins with General Move parameters—Action Distance, Body Motion, Gain Control, and Placement—which are foundational to defining MOST codes across all movement categories. It then addresses the Controlled Moves and Tool Use parameters, detailing their representation in the DHM environment.

Table 4.3 summarizes the General Move parameters, highlighting their movement characteristics, influence on task execution times, and representation within DHM systems. This concise framework aids in understanding the integration of MOST parameters into virtual simulations.

While many motion characteristics can be readily identified within a DHM system, others are more challenging to discern, and some cannot be recognized at all. These limitations stem from inherent technological constraints in DHM systems, rather than the proposed method

Table 4.3 MOST Parameters : Motion Characteristics, 3D Availability, and Explanation

MOST Parameters	Motion Characteristics	3D Availability / Input Required	Explanation
Action Distance (A)	A1-A16	Available ; Auto-determined from 3D coordinates	Calculated using start and endpoint coordinates in the 3D environment. See Section 4.3.4 for details.
Body Motion (B)	Sit, Stand, Bend and Arise	Available ; Auto-determined from 3D models	Postures categorized based on joint angles. See Section 4.3.5 for details.
	Climb On/Off, Through Door, Adjustments	Not Available ; User input required	Manual input needed for abstract or complex motions.
Gain Control (G)	Light, Heavy, or Bulky Object	Available ; Auto-determined from 3D models	Determined by object geometry and weight. See Section 4.3.6 for details.
	Simultaneous/Non-Simultaneous Handling	Available ; User input required	Manual input determines simultaneous handling.
	Blind/Obscured Accessibility	Available ; Auto-determined via DHM/layouts	Specified via 3D layout.
	Disengage, Interlocked, Collect	Not Available ; User input required	Complex interactions need manual time assignment.
Placement (P)	Loose Fit, Double Placement, Obstructed	Available ; Auto-determined via DHM/layouts	Specified by action verb and 3D layout.
	Adjustments, Precision, Heavy Pressure	Not Available ; User input required	Force and precision require abstract variables added as action verbs.

itself. For instance, cognitive activities like "thinking" or "reading" cannot be directly simulated. Instead, users must manually input details, such as the number of digits read or words inspected, to incorporate these actions into time estimations. Similarly, complex physical postures, such as precise hand positions for pinch grasps or crawling movements in confined assembly tasks, exceed the modeling capabilities of current DHM systems. Additionally, detailed tool interactions—such as counting hammer strokes or screwdriver turns—require nuanced representations that are currently dependent on manual input for accuracy. These challenges highlight the gap between the abstract nature of certain actions and the representational abilities of existing DHM systems. The following sections explain, in more detail, the method of defining MOST parameters within the constraints of DHM systems, highlighting potential challenges.

4.3.4 Action Distance (A)

The Action distance, a critical parameter in time analysis, represents the distance a worker travels during a task. Traditionally determined through manual observations, this parameter is now calculated more precisely within DHM simulations. By leveraging 3D layouts, DHM systems provide accurate coordinates for body movements within a workstation, enabling the calculation of distances as the vector sum of start and end points in motion sequences.

To align with the predefined action distance levels in the MOST system (e.g., "Reach distance" or "1-2 steps"), these distances are mapped to standardized thresholds representing typical human movement. For instance, a step length of approximately 60 centimeters—based on the 5th percentile of females as specified in ISO 7250-1 [74]—is used for categorization. Distances are then grouped into levels, with numerical values assigned accordingly. For example, a distance between 60 and 120 cm is categorized as A3, corresponding to the “1-2 steps” level outlined in Table 4.2. This systematic approach ensures consistency and compatibility with the 3D environment across all parameter levels.

Despite these advantages, the use of fixed thresholds can introduce classification inaccuracies. A movement slightly exceeding 60 cm, for instance, might be categorized as A3 rather than A1, even if it falls within a worker’s natural reach. Such approximations may inflate time estimates, highlighting the trade-off between maintaining systematic consistency and capturing real-world variability.

4.3.5 Body Motions (B) (Postures Definition)

The next step in time estimation within DHM systems is defining the body motion parameter. Traditionally, analysts rely on visual assessments to categorize body motions during real-time observations, providing sufficient precision for conventional MOST analysis. In MOST, these motion levels are categorical rather than numerical. However, DHM systems generate detailed 3D posture data, including joint angles and body positions, which presents challenges in aligning these with MOST-defined body motions.

To address this, the methodology aligns MOST body motion levels with 3D posture data by using algorithms that compare critical postures against neutral postures. These comparisons analyze joint angles and body positions to determine deviations, categorizing postures into

MOST-defined levels such as "sit," "stand," "bend," as detailed in Table 4.2.

The method is inspired by Ma et al. [75], who developed a posture definition system that analyzes motion data frame by frame. Their approach involves two key steps :

1. Static Posture Analysis : Each frame of motion data is described using natural language and technical parameters. For example, a "sitting" posture is defined by the trunk's position and leg angles relative to a neutral posture.
2. Dynamic Motion Recognition : A sequence of static postures is analyzed to identify transitions, marking the start and end of motions. This categorization makes the data suitable for MOST-based time estimation.

In DHM systems, however, tasks are typically represented by only two static postures : the mannequin's neutral posture and a critical posture during task execution. To adapt Ma et al.'s method, the critical posture is compared to the neutral posture by analyzing joint angles and body positions. Algorithms are used to calculate the extent of deviation (including the establishment of boundaries and criteria for each body motion category), matching postures to MOST motion categories and assigning corresponding temporal values.

For example, defining a "sitting" posture involves analyzing the trunk's position and leg angles. As shown in Table 4.4, the trunk should remain upright, with an acceptable forward tilt of up to 20 degrees, and both legs should form a 90-degree angle, allowing a variance of ± 20 degrees. An algorithm detects these parameters to identify the sitting posture.

TABLE 4.4 Technical Parameters for Defining Sitting Postures

Parameter	**Mean Value (degrees)**	**Allowable Variance (degrees)**
Trunk Position	Upright	± 20
Left Leg Angle	90	± 20
Right Leg Angle	90	± 20

This process is extended to define other body motion levels, such as "stand," or "bend," using biomechanical limits and ergonomic guidelines (e.g., EN 1005-4 :2005). However, certain complex motions, such as "sit or stand with adjustments," "through door," or "climb on/off," cannot be automatically categorized due to their abstract nature and lack of direct representation in the 3D model. These scenarios require manual input to ensure accurate time estimation.

Despite the systematic approach, small deviations in joint angles can introduce variability.

For instance, a 5-degree deviation might shift a category from B0 to B3, which could potentially affect estimated task times. To minimize inaccuracies, thresholds and algorithms must be refined. Ma et al. [75] recommend using empirical observation and motion capture technology to collect precise joint angle measurements from diverse samples. Analyzing this data validates mean angles and natural ranges of motion, establishing robust thresholds. By integrating these refinements, DHM systems can effectively categorize body motions, enhancing posture analysis and aligning time estimation with MOST parameters.

4.3.6 Defining Accuracy Parameters : Gain Control (G) and Placement (P)

The next step in time estimation within DHM systems involves defining the Gain Control and Placement parameters. Gain Control represents the effort required to handle objects, while Placement reflects the precision necessary for positioning objects. These parameters are partially derived from 3D models, using object dimensions, weights, and workspace layouts.

For Gain Control, the DHM system analyzes object characteristics to classify them into predefined categories, such as "light," "heavy," or "bulky" (see Table 4.2 for levels of the Gain Control parameter). To align with MOST's coding scheme, explicit thresholds were established to address ambiguities in traditional classifications. For example, objects weighing under 2 kilograms are categorized as "light," while those over 2 kilograms are considered "heavy." Bulkiness is determined by dimensions : an object is classified as "bulky" if any main dimension exceeds 90 cm or if two dimensions exceed 40 cm. These thresholds, based on the TMU Calculator software guidelines validated by the MTM Association [76,77], ensure consistency and improve the accuracy of time estimation within 3D environments.

Complex Gain Control parameters such as "Disengage," "Interlocked," and "Collect" require sophisticated algorithms and precise data to simulate interactions between body parts and external objects effectively. These challenging elements are assigned predefined time values and incorporated into the DHM action directory to enhance system versatility and usability.

Placement tasks leverage the 3D layout of designated placement points, which are endpoints of actions within simulations. Common placement methods such as "Lay aside," "Loose fit," and “Blind/Obstructed positioning” can be derived automatically. However, more nuanced actions like "Placement with precision" or "Placement with heavy pressure" require user input due to their abstract nature. These actions have been encoded as distinct action verbs in the DHM directory, complete with assigned time values, enabling their integration into simulations and automatic determination during task analysis.

This framework facilitates the systematic analysis of handling and placement tasks while recognizing the potential for variability introduced by predefined thresholds. For instance, weight and dimension thresholds may lead to conservative classifications. An object slightly exceeding a threshold (e.g., weighing just over 2 kilograms or marginally crossing the bulky dimension criteria) might be classified as "Difficult grasp" (G3) instead of "Easy grasp" (G1). Such overclassification could inflate time estimates compared to traditional observational methods.

4.3.7 Defining Controlled and Tool Use Move Parameters

Current DHM systems do not inherently capture all characteristics required to define parameters for Controlled and Tool-Use moves in simulations. For instance, cognitive activities like reading or thinking, classified under the Tool-Use category, cannot be represented in a DHM model. Additionally, many complex tool-use activities remain challenging to model accurately within existing DHM systems.

To address these limitations, an extension panel automatically appears during DHM modeling whenever actions require additional inputs for precise time estimation. This interactive panel prompts users to provide complementary details, enabling accurate representation of motion characteristics. The panel facilitates the inclusion of : (1) Processing times for controlled moves involving machine interaction ; (2) Quantities such as the number of steps, stages, crank revolutions, and alignment points for controlled moves ; (3) Details like finger spins, screwdriver turns, wrench strokes, hammer taps, and ratchet cranks for fastening or loosening actions ; (4) The number of scissor cuts or knife slices for cutting actions ; (5) The extent of the area for surface treatment actions, including methods like air nozzle cleaning, brushing, or wiping ; (6) The selection of measurement tools and distances for measurement actions ; (7) The number of digits or words written or marked for recording actions ; and (8) The number of digits or words to be read or inspected for thinking actions.

These manual inputs are essential to account for motion characteristics that DHM systems cannot automatically simulate. Tables C.1, C.2, and C.3 in the Appendix provide reference coding schemes detailing the Controlled and Tool-Use motion categories.

4.3.8 Developing a Decision-Making System for Time Estimation in DHM Systems

The DHM system uses decision tree algorithms to translate user inputs and CAD data into the most appropriate MOST code for the simulated work sequence. The process begins by mapping user-defined actions to their corresponding MOST motion sequence models (Table

4.1). Each action in the DHM directory is linked to an identity card, which defines the motion category and describes all available parameters. For example, the action "Assemble with pressure" inherently determines the Placement parameter index value, as it specifies placement accuracy in addition to describing the assembly process. For actions categorized as "Controlled Move" or "Tool Use," a supplementary interface prompts the user to provide additional details required to define associated parameter index values.

The decision tree algorithm establishes the Gain Control parameter by analyzing object or tool weight and dimensions based on user inputs. Once the work sequence is simulated, the decision system integrates time-relevant data from CAD-generated information, including details about the human model, tools, objects, and workspaces. This analysis enables the determination of Action Distance parameters, the assessment of joint angles for Body Motion parameters, and the evaluation of workspace layouts for Placement accuracy.

After determining the index values for all MOST parameters in the sequence model, the DHM system generates a specific MOST code for the simulated work sequence. This code is then used to calculate the time required for the simulated work sequence.

Figure 4.1 illustrates the contribution of input data to the time analysis for the General Moves category. Approximately one-third of the required time estimation data is derived from 3D CAD information, while the remaining data comes from user inputs, including both standard DHM inputs and additional details provided via extension panels.

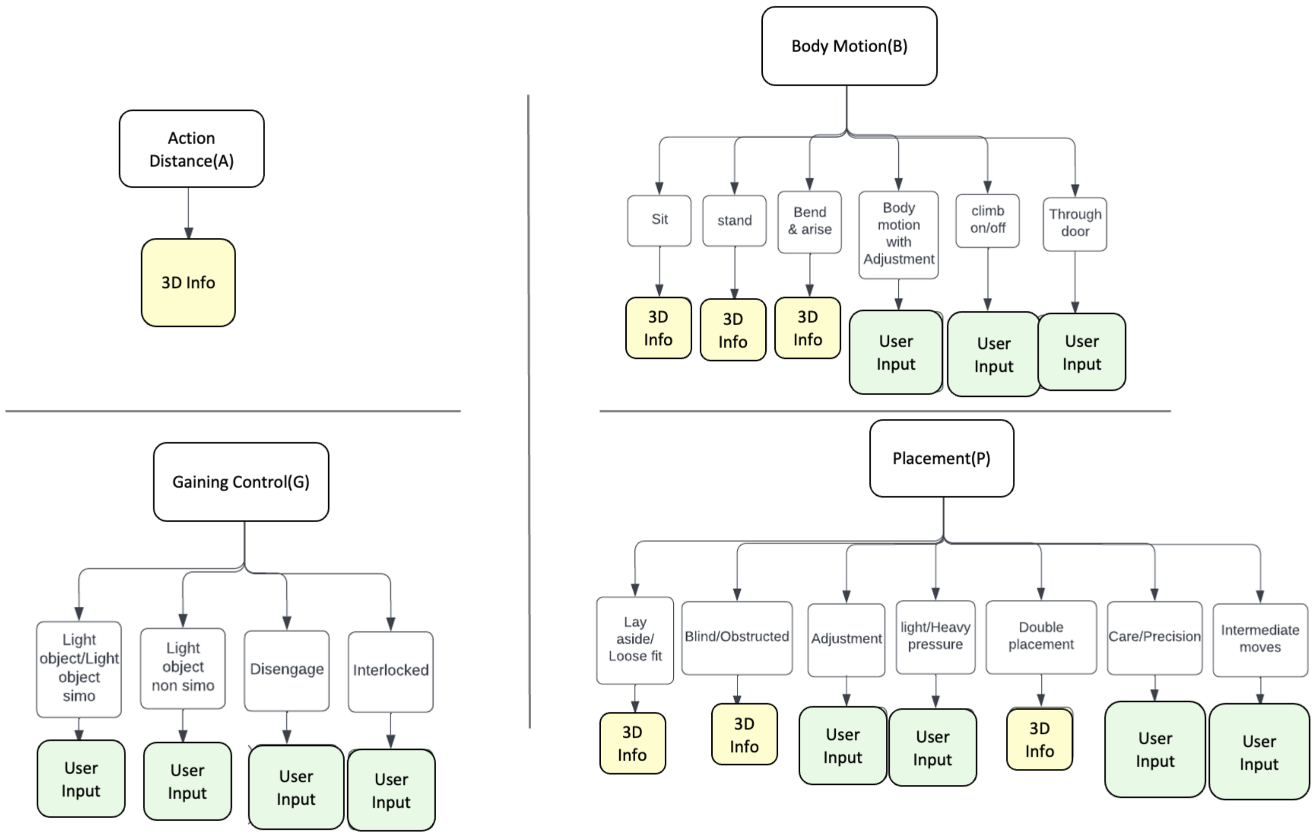


FIGURE 4.1 Contribution of 3D Data and User Inputs in Determining MOST General move Parameters.

4.4 Case example : Integrated Time and Ergonomic Analysis Application in a DHM System

In collaboration with Dassault Systèmes Canada, the proposed time estimation method has been integrated into the Ergonomic Workplace Design (EWD) software, enabling simultaneous time and ergonomic analyses within this DHM system. This integration is protected under U.S. Patent Application No. 18/390,174, filed by Mazareinezhad et al. [78]. This case study demonstrates the concurrent application of time and ergonomic analyses using the EWD system, focusing on the analysis of a sequence of five actions required to screw a bolt during an assembly task.

The actions are specified through an input interface, as illustrated in Figure 4.2. The sequence begins with picking up a bolt from a storage bin (Figure 4.2, Step a), followed by placing it into a thread on the assembly and manually seating the bolt (Figure 4.2, Step b). The next steps involve grasping an air screwdriver (Figure 4.2, Step c), positioning it onto the bolt and operating it (Figure 4.2, Step d), and finally returning the screwdriver to its holder (Figure 4.2, Step e). This figure illustrates the initial steps of the Bolt Screw Operation as implemented in the EWD software.

Table 4.5 provides a detailed breakdown of the time analysis for the initial action of retrieving a bolt from its storage, corresponding to Figure 4.2, Step a.

TABLE 4.5 MOST Analysis for the Task in Figure 4.2, Step a

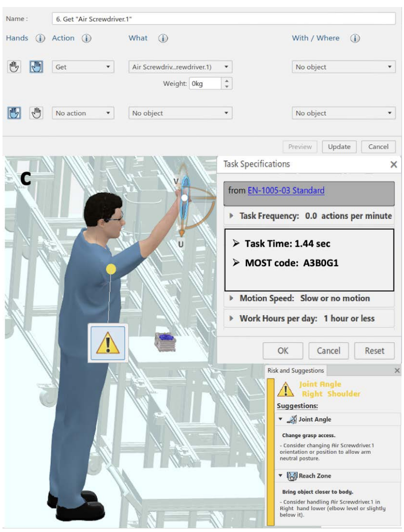
MOST Parameters	**Processing**	**Output**
Motion Category	"GET" is identified as a "General Move."	Code : "ABG-ABP-A" (GET, Put, Return—See Table 4.1).
Action Distance (A)	Determined by the layout based on the mannequin's position.	Classified as A1 (within reach, < 60cm).
Body Motion (B)	Posture-tracking system analyzes the mannequin's movements.	Defined as B6-"bend and arise" (See Table 5.1).
Gaining Control (G)	Assessed by tool/object weight and dimensions.	Light object : G1 (See Table 5.1).
Placement (P)	No placement in retrieval.	Placement : A0B0P0.
Return (A)	No return action in "GET."	Return : A0.
MOST Code	Compiled from parameters.	Code : A1B6G1A0B0P0A0.
MOST Time	Summing indices and converting to seconds.	Total time : 2.88 seconds.

To explain Table 4.5 in more detail, the motion category for "GET" is determined using data from the action verb directory associated with each specific verb. The Body Motion parameter is identified by the posture tracking system, which analyzes the torso's tilt as it retrieves the bolts and returns to a neutral posture. This analysis classifies the movement as B6, corresponding to the "bend and arise" body motion level.

The Gain Control parameter is evaluated based on the weight and dimensions of the objects or tools, as well as the hands involved in performing the movements, using user-provided data. To calculate the task time with the MOST code, the index values for all parameters are summed and multiplied by 10 to convert them into Time Measurement Units (TMUs). The total TMU value is then converted into seconds by multiplying it by 0.036, providing the total time required to complete the task.

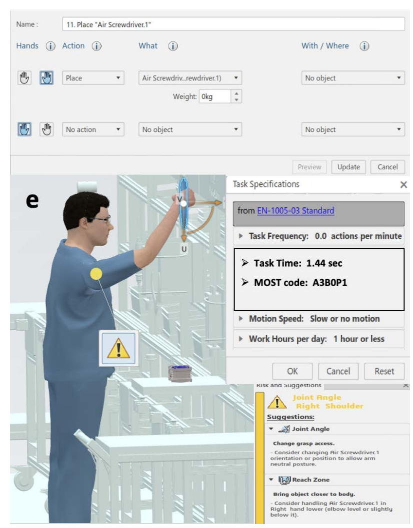
(a) Grasping the bolt from the storage bin (Initial design).

(b) Placing the bolt on the assembly and screwing it manually (Initial design).



(c) Grasping the air screwdriver (Initial design).

(d) Placing the air screwdriver and screwing the bolt (Initial design).



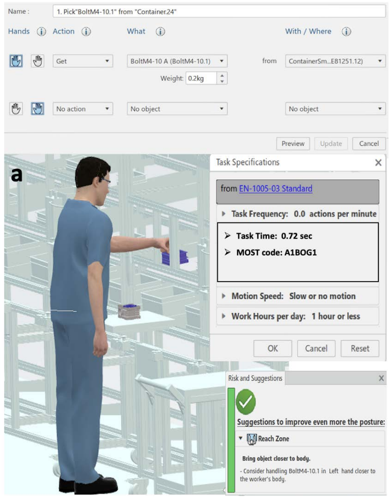
(e) Placing the air screwdriver in its first place (Initial design).

FIGURE 4.2 Steps in the initial design for the bolt screwing operation : (a) Grasping the bolt from the storage bin, (b) Placing the bolt on the assembly and screwing it manually, (c) Grasping the air screwdriver, (d) Placing the air screwdriver and screwing the bolt, (e) Placing the air screwdriver in its first place.

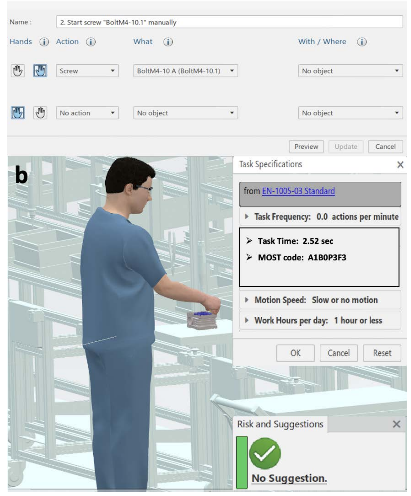
Figure 4.2 depict the initial design of this operation, showing the human model, estimated times, and ergonomic assessments for each task. In the DHM system, ergonomic analyses help designers identify potential risks and recommend design improvements. The interface automatically flags ergonomic issues and suggests adjustments to enhance safety and efficiency. Task durations are influenced by the model's design and its interaction with tools and workstation components, which can be modified during the design phase. Adjusting the workstation layout or human model updates the parameter indices, altering the MOST codes and predicted task durations.

In this case, the DHM system's recommendations led to reorganizing the workspace by repositioning the storage bin and screwdriver. These design changes, illustrated in Figure 4.3, impacted Action Distances and Body Motions, resulting in updated MOST codes. Ergonomic risk assessments confirmed that the redesigned layout reduced ergonomic risks. Notable improvements were observed in steps a, c , d , and e, as shown in Figure 4.3, during the Bolt Screw Operation, where high- and medium-risk motions were minimized to no-risk motions. Consequently, the total time estimation for the sequence decreased.

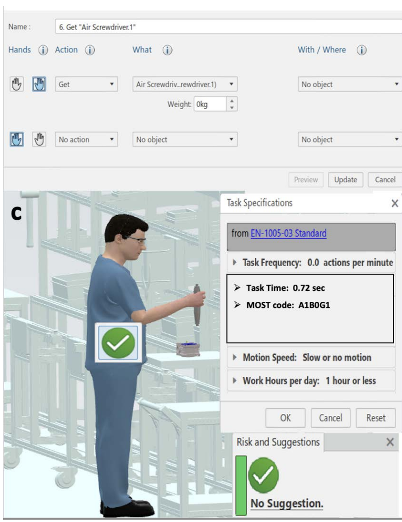
This reduction in time and ergonomic risks highlights the value of integrating ergonomic considerations into the design process, demonstrating the advantages of DHM systems in optimizing efficiency and enhancing worker safety.



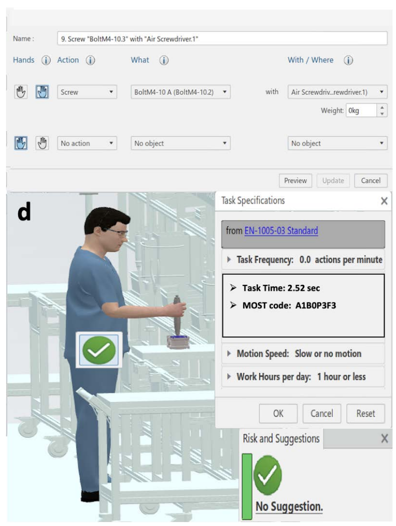
(a) Grasping the bolt from the storage bin (Revised design).



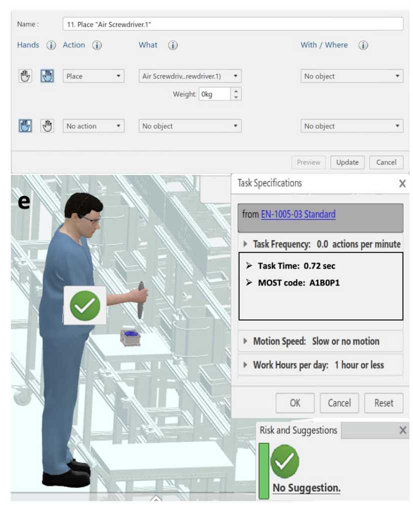
(b) Placing the bolt on the assembly and screwing it manually (Revised design).



(c) Grasping the air screwdriver (Revised design).



(d) Placing the air screwdriver and screwing the bolt (Revised design).



(e) Placing the air screwdriver in its first place (Revised design).

FIGURE 4.3 Steps in the Revised design for the bolt screwing operation : (a) Grasping the bolt from the storage bin, (b) Placing the bolt on the assembly and screwing it manually, (c) Grasping the air screwdriver, (d) Placing the air screwdriver and screwing the bolt, (e) Placing the air screwdriver in its first place.

4.4.1 Key Findings

Each design alteration resulted in changes to time-relevant motion characteristics. For instance, Step a in Figure 4.2 illustrates the mannequin reaching for a bolt, initially assigned the MOST code "A1B6G1." This action was flagged for ergonomic risk due to an inappropriate neck posture, prompting design adjustments to address the issue and reduce the identified risk.

The updated design, shown in Figure 4.3, step a, reflects these changes with a new MOST code "A1B0G1," demonstrating how repositioning the storage bin impacted time estimates. Similarly, the interaction with an air screwdriver, originally coded as "A3B0G1" in Figure 4.2, step c, was reassessed for moderate ergonomic risks related to shoulder strain. Adjustments to the screwdriver's position improved access and eliminated the need for trunk and arm lift during execution. The resulting design, depicted in Figure 4.3, step c, reduced the A index value, with the updated MOST code "A1B0G1," indicating enhanced efficiency and reduced risk.

The automation enables real-time recalculations of time estimates as workspace constraints or task parameters are modified, such as changes in tool positioning, action distances, or worker movements. These updates ensure that time analysis remains consistent with the latest design changes.

These examples highlight the dynamic nature of design and the extensive range of operations requiring evaluation, emphasizing the importance of automated time estimation tools. Such tools significantly expedite design modifications by automating adjustments, risk assessments, and recalculations. Without automation, manually performing these processes for each design iteration could take hours or even days, depending on the complexity of the task and the level of precision required for ergonomic evaluations. By contrast, the automated DHM system reduces this effort to mere minutes, allowing for rapid iterations and continuous optimization.

This case study demonstrates the value of integrated analysis in a DHM environment, revealing the interplay between task design and ergonomics. It underscores how design modifications influence both time estimates and ergonomic suitability. The ability to quickly assess and update designs using automated tools not only accelerates the design process but also enhances the capacity for iterative improvements, making this approach an invaluable asset for design engineers.

4.5 Validation Study

To evaluate the proposed method and its integration of the MOST system into DHM environments, a field study was conducted in a real-world industrial setting. The study focused on an automotive assembly line and included a variety of task complexities, such as component installations in confined spaces, precise alignments, and repetitive motion tasks. Tasks analyzed included screwing, clipping, and applying electrical contacts, reflecting a diverse range of industrial actions performed by real workers under typical workplace conditions. A total of 26 workstations were evaluated, encompassing 633 tasks and over 5000 MOST parameters.

Data collection involved recording actual task durations using high-resolution video to ensure precise measurements. These durations were compared with time estimates generated by the MOST system and the proposed DHM time estimation algorithms. Statistical analyses were performed to assess agreement between time estimates and actual durations, identify differences across datasets, and explore the factors contributing to deviations.

The results demonstrate strong alignment between the estimates of the proposed method and actual task durations, validating its accuracy and reliability. While detailed findings will be presented in a separate publication, this study underscores the method's applicability across diverse industrial contexts. These outcomes highlight its contribution to integrating time analysis within DHM environments.

4.6 Discussion

Time analysis within DHM systems has traditionally been a manual, labor-intensive process requiring significant expertise to achieve reliable results [79]. The proposed automated time estimation method reduces dependence on manual input, streamlining the design process and enabling simultaneous ergonomic and time evaluations. This integration allows for early identification of ergonomic and productivity issues, minimizing the risk of costly redesigns and saving significant resources [80, 81]. Although the method's automation suggests significant time and effort savings, a dedicated study is needed to quantify these benefits through comparative analyses across diverse tasks and contexts.

The method balances the complexity of time analysis with the reliability of results, making it particularly valuable during the early design stages, where approximate estimates are sufficient [82]. By leveraging basic assumptions—such as categorizing objects by weight and dimensions or using joint angles to define Body Motions—the method achieves user-friendly automation while maintaining accuracy. Additionally, automatic measurements within a 3D environment eliminate errors caused by subjective biases, ensuring standardized and consistent results [7].

It is important to note that the framework calculates time estimates based on the parameters provided during the design process. However, ensuring that the designed task accurately aligns with its intended purpose relies on the expertise of the designer, as highlighted by Kuhlang (2023) [7].

Integrating time estimation into DHM systems also enhances ergonomic risk assessments by enabling dynamic evaluations of cumulative fatigue and musculoskeletal disorder risks. Tools like the OCRA index rely on detailed temporal data—task duration, frequency, recovery times, and cycle structure—to effectively quantify worker exposure to ergonomic risks [68]. This transition from static to dynamic evaluations facilitates early detection of prolonged or poorly sequenced tasks that could lead to chronic injuries or decreased productivity [67]. Future advancements, such as incorporating fatigue failure models [69], could further optimize task design by predicting fatigue thresholds more precisely based on task durations and biomechanical stress.

While the method provides the necessary time factors as input for specific ergonomic evaluations, such as OCRA, other ergonomic assessment methods, including RULA and REBA, can be performed independently and concurrently.

The proposed method demonstrates adaptability across various PMTSs, such as MTM and MODAPTS, due to the shared consistency of fundamental movement parameters in these systems [6]. By utilizing fundamental inputs commonly available in DHM environments—such as actions performed, human interactions, object characteristics, and 3D layouts—the method provides a practical framework for time estimation and facilitates integration into diverse DHM platforms. Advanced systems like Delmia Ergonomic Workplace Design (EWD) or Siemens Jack can leverage automation and less inputs, whereas simpler systems may rely on more manual data entry. Regardless of platform complexity, the method ensures compatibility by extracting essential MOST parameters from 3D models and aligning them with the MOST framework. This process involves adjusting parameters to match the system's data capture capabilities and incorporating manual inputs when necessary.

The method has potential applications across various industries. In manufacturing, it aids in analyzing task sequences and tool interactions, providing valuable insights for optimizing workflows. In the automotive sector, it supports the evaluation of seated postures, reach distances, and ergonomic considerations during vehicle assembly. Similarly, logistics and warehousing operations can benefit from its ability to assess repetitive tasks like picking and placing, contributing to improved efficiency and reduced worker fatigue.

While challenges persist, the proposed method establishes a solid foundation for integrating time estimation into DHM systems. Future developments could focus on standardizing cross-platform directories and parameter thresholds to enhance interoperability. Additionally, exploring AI-based tools for automating motion prediction and parameter adjustments could simplify integration processes, reduce manual inputs, and improve scalability. These advancements would further strengthen the method's utility and broaden its industrial applications.

The proposed method, while effective, highlights areas for improvement. Its reliance on joint angles and positions for defining body motion parameters simplifies initial analyses but underscores the need to integrate broader biomechanical aspects, such as muscle activations and joint torques, to improve accuracy. Accounting for individual variances, including unique joint mobility or physical impairments, could enable more personalized assessments [83]. Incorporating these elements would refine posture categorizations and advance the methodology into a more comprehensive framework.

Worker performance variability presents another challenge, as the method does not fully address factors such as skill, motivation, fatigue, or working conditions [84]. Conventional time systems often rely on generalized averages, overlooking individual differences in efficiency [6]. Developing adaptive models that incorporate a broader range of human factors would enhance the method's applicability across diverse workplace environments. The proposed method provides a foundation for such advancements, paving the way for more nuanced and realistic models.

Another limitation lies in the lack of uniformity across DHM platforms and software compatibility. Variations in action directories, data formats, and interface requirements necessitated preprocessing and adjustments to align DHM outputs with the algorithm's input needs. Establishing standardized action directories and parameter thresholds would simplify these adaptations, improving interoperability across platforms and ensuring consistency in application.

Despite these challenges, the method's adaptability and modifications made during this study highlight its potential for broader application. Future research should focus on developing cross-platform standards and automation techniques to streamline integration, reduce manual adjustments, and support usability across different DHM systems. These refinements would further enhance the method's robustness and scalability in industrial settings.

4.6.1 Limitations and Future Studies

One limitation of the proposed method is its reliance on predefined boundaries and thresholds to define MOST parameters. While these thresholds ensure consistency and enable automation, they can introduce variability in time estimates, particularly when parameters fall near category boundaries. Minor discrepancies, such as small variations in joint angles or action distances, may result in misclassifications, affecting the accuracy of time estimations. This issue was observed in the validation study, where the DHM-based method slightly overestimated task durations compared to MOST. Unlike traditional methods that allow analysts to apply subjective adjustments, automated systems lack this flexibility, underscoring the need for more robust strategies to address such challenges. Furthermore, the use of uniform thresholds across all anthropometric profiles fails to account for individual variability, potentially leading to deviations from real-world conditions.

To address these limitations, future refinements should focus on dynamic adjustments that account for anthropometric variability by tailoring thresholds to individual characteristics. For example, systems like Delmia Ergonomic Workplace Design (EWD) already offer ergonomic assessments customized for specific anthropometric profiles, such as the 5th and 95th percentiles for male and female workers. Incorporating advanced motion capture technologies, as demonstrated by Kan and Chen [85], could further enhance the method by dynamically calibrating thresholds using real-time data. This approach would reduce misclassifications and improve predictive accuracy, aligning the method more closely with real-world scenarios.

Although the validation study demonstrated the reliability of the proposed method under current thresholds, further research is needed to refine these thresholds to better account for individual variability and near-boundary parameters. Building on insights from the existing validation results, future studies should aim to enhance the method's robustness by addressing these limitations. Comprehensive empirical validation across diverse industries and task scenarios is essential to improve adaptability and predictive alignment with real-world conditions. Methodologies employed by Mazareinezhad et al. [86], Finsterbusch et al. [87], and Faber et al. [40] provide valuable references for systematically refining thresholds. These include investigating factors such as distances, joint angles, weights, and dimensions, along with their acceptable variances. Adopting this approach would not only mitigate potential sources of variability but also enhance the method's accuracy and reliability across a broader range of industrial applications.

Adapting the method to other time systems, such as MTM or MODAPTS, introduces additional challenges due to the unique terminology and coding structures of each system. While the proposed method demonstrates compatibility with other systems by leveraging shared fundamental parameters, translating and customizing it to meet the specific requirements of each system requires significant effort. Future research could focus on developing a unified framework capable of integrating multiple PMTSs, providing a generalized approach that is applicable across various time systems and further broadening the method's utility.

A further limitation of current DHM systems is their dependence on manual input for tasks involving machine interactions and detailed tool-use actions. Simulating complex motions, such as intricate grasps or crawling postures, remains a challenge, underscoring broader technological constraints in achieving full automation. Addressing these limitations requires advancements in DHM systems through the integration of motion capture technologies, such as OptiTrack, and machine learning algorithms trained on extensive datasets. These innovations could automate the classification of complex tasks, minimize the need for manual inputs, and enhance scalability. Developing advanced 3D models capable of precisely capturing human movement and behavior, as demonstrated by Zhang et al. [88], would further improve the predictive accuracy and applicability of DHM systems. Such advancements would not only streamline simulation processes but also expand the practical use of DHM systems across diverse industrial contexts, enabling more accurate and efficient task analysis.

4.7 Conclusion

Integrating the MOST system into DHM systems required adapting the MOST coding framework to accommodate the 3D-specific requirements of DHM environments. These adaptations were carefully applied to various parameters, incorporating assumptions aimed at reflecting the complexities of simulated work environments. This approach ensures that the MOST coding system, traditionally applied in real-world settings, can now be utilized within DHM systems to provide a valid time estimations that align with simulated scenarios.

This integration offers an accessible method for generating rapid and automated time estimations, even for users with limited knowledge of time systems. By streamlining the design process, the method facilitates human-centered design evaluations and improves workflow efficiency. Design engineers can implement design changes without needing to recalculate operation times manually, enhancing adaptability and efficiency in iterative processes.

Beyond supporting design modifications, integrating time analysis within DHM systems provides a valuable means to monitor motion patterns over time and evaluate task dynamics. This functionality supports the identification of ergonomic risks using methods like the OCRA index, which depend on accurate time estimations for manual tasks. By linking time estimation with ergonomic risk assessments, the method enables targeted interventions to reduce risks and enhance manual work performance, contributing to safer and healthier work environments.

Enhancing DHM systems with time analysis capabilities expands their potential across multiple industries, including manufacturing, healthcare, and transportation. While this integration provides opportunities to improve the design and optimization of human work processes, its broader applicability and potential impacts require further exploration to fully realize its contribution to productivity and worker well-being.

CHAPTER 5 ARTICLE 2 : Evaluating the Accuracy of MOST and a MOST-Based Time Method in Digital Human Modeling : Field Study Insights from Advanced Manufacturing Environments.

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5.1 Abstract

Predetermined Motion Time Systems (PMTS) are widely applied in industrial environments to estimate task durations, yet concerns about their accuracy persist. Despite their widespread use, few empirical studies have rigorously validated their reliability, leading to uncertainties regarding their dependability in modern production systems. Accurate time estimation is crucial for strategic production planning, resource optimization, and performance evaluation, particularly in high-demand manufacturing industries.

This study assesses the accuracy and applicability of time estimates generated by the Maynard Operation Sequence Technique (MOST) and a Digital Human Modeling (DHM)-based method grounded in MOST principles. Data were gathered from a field study conducted at 26 workstations in an automotive manufacturing company. Tasks were observed, recorded, and analyzed using both methods, with video recordings providing actual task durations for comparison.

Agreement between estimated and actual times was evaluated using the Bland-Altman test, hypothesizing deviations within 10%. Results showed that MOST had a mean deviation of -7.04%, while the DHM-based method exhibited -5.45%, both within acceptable limits. The 95% limits of agreement ranged from -14.71 to 7.90 seconds for MOST and -13.81 to 8.45 seconds for DHM. Regression analysis identified task duration and action distance as significant factors influencing discrepancies between MOST estimates and actual times ($p < 0.05$).

These findings demonstrate the reliability and applicability of MOST and DHM-based methods for industrial time estimation and highlight their potential for integration into advan-

ced manufacturing workflows to enhance productivity and operational planning.

keywords : Advanced Manufacturing Systems, Predetermined Motion Time System (PMTS), Digital Human Modeling (DHM), MOST (Maynard Operation Sequence Technique), Automotive Workstation Analysis, Validation Study.

5.2 Introduction

Predetermined Motion Time Systems are methodologies that break down tasks into individual motions and assign predefined time values to each. This standardized approach is essential for comparing workstations or tasks and identifying opportunities for improvement within advanced industrial environments [1].

PMTSs have proven effective in sectors such as manufacturing, healthcare, and service industries by improving the efficiency of production planning, scheduling, and resource utilization. These systems streamline operations and contribute to increased productivity through enhanced time accuracy and resource management [10].

Furthermore, PMTSs play a crucial role in predicting product costs by estimating the time required for production across modern industrial setups, including simulated and real-world assembly lines. This allows manufacturers to make informed decisions about pricing, production planning, and resource allocation. PMTSs also help identify production bottlenecks, enabling managers to optimize workflows and reduce non-value-adding activities critical for maintaining competitiveness in advanced manufacturing systems [1].

Notable examples of PMTSs include Method Time Measurement (MTM), recognized for its detailed motion analysis and high precision, and the Maynard Operation Sequence Technique (MOST), a simplified version of MTM that is widely adopted across industries for its ease of use and ability to quickly generate time estimates with fewer data inputs. Additionally, MODAPTS (Modular Arrangement of Predetermined Time Standards) offers a fast and practical method for time estimation, valued for its straightforward approach in diverse manufacturing contexts [1, 6].

DHM systems are advanced software tools that allow users to create virtual human models and simulate interactions within various environments. These systems are crucial in industrial design, enabling engineers and designers to optimize workplace layouts and refine workflows before physical prototypes are built. Beyond ergonomic analyses, DHM systems support time estimation by predicting task durations in virtual environments, facilitating improvements in efficiency, productivity, and operational planning [2, 41].

Several DHM systems, including Jack, RAMSIS, Pro/ENGINEER, and Human-Builder, provide ergonomic analysis capabilities [71,72]. However, only a few focus on time analysis within a virtual 3D environment. Among these, Jack by Siemens enables time analysis using MTM-1 standards and simulation techniques [73]. Additionally, Chen et al. (2020) [89] developed a maintenance time estimation system that combines MODAPTS with Maintenance Action Elements (MAEs) in a virtual 3D environment, improving accuracy by compensating for the differences between simulated and real-world times. Despite these advancements, more rigorous validation in the context of complex manufacturing scenarios is still needed to ensure their practical applicability.

Accurate time estimation through PMTSs is essential for optimizing industrial productivity, enhancing operational planning, and supporting resource efficiency in advanced industrial environments [6, 90]. However, PMTSs often face challenges in maintaining accuracy, particularly in dynamic and complex work environments. As organizational structures evolve, technology advances, and workforce demographics shift, ongoing validation and updates are crucial to maintaining their reliability in manufacturing contexts [6].

Several studies have highlighted limitations in PMTSs. Harari et al. (2018) [17] pointed out that PMTSs often overlook key physiological and biomechanical factors, such as lifting height and object weight, which are essential for accurate time predictions. Genaidy et al. (1989) [6] found that PMTS accuracy can vary significantly based on the specific motions and tasks being analyzed. Turk et al. (2018) [18] also noted that the MTM method tends to underestimate the time needed for handling boxes of different sizes and weights, leading to discomfort and unrealistic time expectations. Schmidtke and Stier (1961, as cited in Genaidy et al., 1989 [6]) observed that PMTSs often ignore the effect of movement frequency on time estimates, which can result in overly optimistic productivity assessments and increased risk of worker overexertion [17]. Therefore, refining PMTSs to address these factors is necessary to ensure their applicability in evolving industrial environments [6, 91].

Empirical research has shown discrepancies between PMTS estimates and actual times. Bahcivancilar (2012) [46] reported an 8% difference between MTM-1 estimates and actual times for tasks such as grasping, moving, and reaching, with durations ranging from 25 to 35 seconds. Similarly, Bures and Pivodova (2013) found that MTM-1 and Basic-MOST underestimated actual times by -3.66% and -2.05%, respectively, for motions lasting between 5 and 29 seconds across 21 workstations. Kurkin and Bures (2011) [56] also observed that actual times were 17% and 9% longer than MTM-1 and MTM-UAS estimates.

Two key factors—action distance (distance traveled during a motion) and task duration—have been identified as critical in influencing discrepancies between predicted and actual movement times. Bahcivancilar (2012) [46] found higher discrepancies for shorter action distances (1 to 3 inches) in MTM systems, suggesting that shorter movements increase variability in time estimates. Similarly, Mazareinezhad et al. (2024) [92] observed that shorter action distances led to greater variability in MOST estimates, concluding that MOST lacks sufficient precision for tasks involving small, nuanced movements within the operator's reach.

Task duration is another critical factor affecting time estimation accuracy in different systems. Bures and Pivodova (2013) [93] found that the MOST system consistently underestimated shorter-cycle tasks, highlighting its limitations in accurately predicting short-cycle task durations. However, this issue has not been fully explored across a wide range of task types and settings, limiting the broader application of PMTSs in advanced industrial environments.

Despite increased interest in DHM systems for workplace design, there is still a notable gap in empirical studies comparing the performance of time estimation methods in 3D environments, especially within DHM systems [71]. Addressing these gaps is critical to ensuring DHM systems meet the demands of modern manufacturing applications.

A study by Turk et al. (2018) [18] compared time estimates from the JACK DHM system to those produced by the MTM-1 method, analyzing how key parameters influenced time estimation accuracy. Their findings demonstrated strong agreement between the times generated by JACK and those observed in practical experiments. However, there remains a need for further research on how specific variables impact the accuracy of time estimation methods, particularly when comparing DHM systems to real-world data.

In this study, we had three main objectives. The first was to compare actual field data with time estimates generated by the MOST system. Since MOST is widely used in industrial settings, validating its accuracy in predicting task durations through real-world comparisons in manufacturing environments is essential.

The second objective was to evaluate the performance of a newly developed time estimation method for DHM systems based on MOST principles. This method integrates PMTS concepts with 3D modeling tools, facilitating time analysis in advanced industrial design workflows. This system, as described in Mazareinezhad et al. (2024) [78], is designed to estimate task durations in a 3D virtual environment. We aimed to assess how accurately the DHM-based system predicts task times compared to both actual field data and MOST estimates, with the expectation that discrepancies between methods will remain within the 10% margin. Bures and Pivodova (2013) [93] suggest that discrepancies between time estimations and actual measured task times typically fall within a 10% margin, which serves as the benchmark for this study.

Lastly, we aimed to investigate how two key variables—action distance and task duration—affect the discrepancies between measured times and MOST estimates. By including these factors in a regression model, we sought to provide deeper insights into their impact on the accuracy of time estimation systems, helping to identify limitations and potential areas for improvement in time estimation techniques for manufacturing applications.

5.2.1 Time Estimation with MOST and Its Integration into DHM Systems

MOST provides a systematic approach to breaking down tasks into standardized actions and quantifying the time required for each. It uses a coding scheme where predefined codes represent specific motions in manual tasks, allowing for the calculation of total task time by summing the associated predetermined time values [1]. MOST covers a broad range of activities, including walking, machine operation, and tool use.

The time estimation process starts by observing tasks and assigning the appropriate MOST codes to each part of the actions. These codes are then used to compute the total task time. MOST categorizes motions into three primary groups : General Move, Controlled Move, and Tool Use. Each sequence is defined by parameters such as Action Distance (how far an object is moved), Body Motion (the worker's physical movement), Gain Control (how the object is handled), and Placement (the precision needed for positioning the object). These parameters directly influence the time assigned to each action. For example, longer distances result in higher time values for Action Distance, while more precise placements, such as fitting an object into a confined space, increase the time allocated for the Placement parameter [1].

Table 5.1 presents the General Move coding scheme, showing how different motion characteristics influence the time required for each action. The integration of this coding scheme into DHM systems enables automated time analysis, enhancing the applicability of MOST in virtual simulations of tasks.

To conduct a time analysis using the General Move coding scheme, parameter values are determined based on the specific task characteristics. These values are then summed and converted into Time Measurement Units (TMUs), where 1 TMU equals 0.036 seconds [1].

In the DHM time estimation method investigated in this study, MOST principles are applied to analyze tasks modeled in 3D space. This integration bridges the gap between traditional time estimation methods and virtual simulations, enabling design processes to benefit from automated analyses. Time estimation in DHM systems differs significantly from traditional observation-based methods, which typically rely on observing workers' activities and assigning predetermined time values to motion sequences [94]. In contrast, DHM systems require

Table 5.1 General move coding scheme (Adapted from Zandin [1])

BasicMOST System : General Move (ABGABPA)					
Index × 10	**Action Distance (A)**	**Body Motion (B)**	**Gain Control (G)**	**Placement (P)**	**Index × 10**
0	≤ 2 Inches (5 cm)	–	–	Pick up, Toss	0
1	Within reach distance	–	Light Object/Light Object Simo	Lay aside, Loose Fit	1
3	1-2 steps	Sit, Stand, Bend and Arise 50% occurrence	Light Object non-simo, Heavy/Bulky, Blind/Obstructed-Disengage, Interlocked, Collect	Loose fit blind/Obstructed Adjustment, Light pressure, Double placement	3
6	3-4 steps	Bend and Arise	–	Care/Precision, Heavy Pressure, Blind/Obstructed, Intermediate Moves	6
10	5-7 steps	Sit & Stand with adjustment	–	–	10
16	8-10 steps	Bend and Sit, Climb on/off, Stand and Bend, Through Door	–	–	16

more detailed inputs, along with specific rules and assumptions, to estimate time in a virtual 3D environment. DHMs offer the advantage of simulating tasks in a controlled environment, facilitating the optimization of industrial workflows before real-world implementation.

The first step in implementing MOST within a DHM system is aligning the industry-specific language used to represent actions in the DHM with predefined MOST actions. Next, using data from task simulations, including user inputs and CAD data [78], the appropriate MOST motion type (e.g., General Move or Controlled Move) is defined, and time values are assigned to each MOST parameter for the task being simulated. This process ensures compatibility between MOST coding structures and the virtual task models, making it particularly relevant for applications in precision-driven manufacturing environments.

This DHM time estimation method is based on assumptions to account for the limitations of virtual environments, where detailed real-world data may be lacking. Table 5.2 summarizes the key differences between applying MOST in a DHM system and its real-world counterpart, highlighting distinctions in parameters such as Action Distance, Body Motion, Gain Control, and Placement as detailed in Mazareinezhad et al. (2024) [78].

Table 5.2 Comparison of MOST in a DHM System and MOST in Real-world Analysis

Parameter	**MOST in a DHM System**	**MOST in Real-world Analysis**
Action Distance	- Precisely calculates distances using 3D coordinates - Predefined numerical thresholds for each level (e.g., reach distances/steps converted to numerical values) - Consistent distance thresholds across different anthropometric profiles	- Distance estimation based on visual observation - No precise calculations required - Distances vary with workers' step length or reach capacity
Body Motions	- Each motion category (e.g., "sit", "stand") corresponds to specific numerical ranges - CAD-based joint angle calculation and body positions categorize postures - Compares neutral vs critical postures	- No numerical data or algorithm used for classification - Posture levels (e.g., "bend", "stand") are defined based on visual observation, not precise calculations
Gain Control	- Factors in object weight/dimensions from 3D model - Clearly defined weight and dimension thresholds (e.g., <2 kg = "light", >2 kg = "heavy", bulky if any dimension exceeds 90 cm or if two dimensions have at least one exceeding 40 cm) - User-defined input data for complex actions (e.g., "disengage", "collect")	- Subjective assessment based on observation - No precise measurements or set thresholds - Relies on visual approximations
Placement Accuracy	- Utilizes predefined workstation layouts from DHM - Incorporates detailed geometric data - User-defined input data for precision actions (e.g., "blind placement")	- Based on rough observation - No geometric data used - Subjective assessment

Achieving reliable time estimation in DHM systems is challenging due to limited data for time analysis, the complexity of simulating human interactions, and the need for precise task and movement modeling. To ensure the applicability of PMTS within the DHM context, it is essential to establish equivalencies between real-world conditions and their virtual counterparts. Determining each MOST parameter within a DHM system requires precise thresholds as mentioned in Table 5.2, but these must be carefully validated to ensure realism and applicability in real-world industrial environments.

The automated features of the DHM time system provide a user-friendly solution for non-experts, allowing for rapid time estimation of work sequences modeled in the system. This capability is particularly valuable in the early stages of workplace design and operational planning, where accurate time estimates can significantly enhance both design efficiency and effectiveness. Therefore, the DHM time system must be rigorously tested to confirm that it produces realistic time estimates, enabling efficient integration and functionality within the DHM.

5.3 Methods

This field study was conducted at an automotive assembly line in Canada during the summer of 2023, ensuring compliance with industry-relevant conditions. Ethical considerations were strictly followed, including obtaining informed consent from all participants, who agreed to be recorded for research purposes. The study adhered to Polytechnique Montréal's ethical guidelines and received approval under certificate number CER-2223-38-D. Data collection began with video recordings of workers performing various tasks in an industrial setting, providing a source of actual time data for validating PMTS.

5.3.1 Samples

The sampling strategy was aligned with established research protocols [40, 43, 93] that evaluated PMTS-based time estimation in real-world manufacturing environments.

A total of 26 operations were examined across 26 workstations in the automotive assembly line, focusing on tasks such as screwing, clipping, checking, applying electrical contacts, and assembling standard parts. These operations reflect common manual tasks in advanced manufacturing, where time efficiency and ergonomic considerations are essential. The task cycle durations ranged from 38 to 60 seconds, aligning with the range specified by Basic-MOST [1]. In total, 633 tasks were analyzed, encompassing 5,411 Basic-MOST parameters, with key parameters—Action Distance (A), Body Motion (B), Gain Control (G), and Placement (P)—accounting for approximately 90% of the time codes.

5.3.2 Video Recording and Data Analysis

Motion analysis was conducted through high-resolution video recording. Video footage of the entire assembly process was captured using an iPhone X, chosen for its ease of use and ability to consistently capture high-quality motion data. Videos were recorded at 30 frames per second, a standard frame rate suitable for detailed motion analysis in industrial time estimation [95]. IINA software, a media player capable of providing precise temporal information down to the millisecond, was used to analyze the videos frame-by-frame. Each task was segmented into specific sub-tasks, and the duration of each was calculated by identifying the start and end points of the motions.

The analysis process involved assigning MOST codes to the observed task sequences. Initially, the MOST codes and motion sequence descriptions were based on the work processes defined by the company's MOST experts. However, in some cases, the actual worker motions deviated from these predefined descriptions. To ensure accuracy, a detailed review of video footage was conducted, and the codes were revised to align with the actual observed sequences.

Simultaneously, DHM-based time estimation algorithms [78] were applied to analyze the same tasks. These algorithms automate time estimation in simulated production environments, facilitating process optimization in virtual 3D workspaces. Although DHM time estimation is typically automated, in this study, the process was manually simulated to ensure alignment with real-world task execution.

Since DHM systems require precise inputs for time estimation, accurately determining the MOST parameters was essential. This manual simulation replicated the automated process but introduced challenges in precisely measuring MOST parameters such as action distances, body motions, gain control, and placement as defined in Table 5.2. By systematically analyzing these factors, the study ensured a reliable comparison between DHM-based estimations and traditional MOST-derived times.

To address these challenges, specific procedures were implemented. For example, in defining Action Distance (A), the layout of the assembly lines was used, and distances traveled were estimated from video footage and workspace layouts. This method provided precision comparable to automated DHM estimation. However, as mentioned in Table 5.2, in traditional observational methods, MOST analysts typically rely on rough estimates for the Action distance (A) parameter, often disregarding exact distances. In this study, there were cases where the MOST analysis initially assigned lower Action Distance levels. However, after precise measurements were taken, the 'A' parameter was reassigned to a higher level when the distance exceeded the thresholds defined by the DHM time system. More details on the

Action Distance levels are provided in Table 5.1.

Defining the Body Motion (B) parameter was straightforward, as all tasks were performed in a standing position, eliminating the need for complex joint angle calculations. The Gain Control (G) parameter, typically determined through the observation of objects or tools in typical MOST analysis, was assigned using the bill of materials. This provided detailed information about the weight and dimensions of the objects, enabling the use of DHM algorithms. These algorithms adhere to predefined boundaries for weight and dimensions to accurately categorize the Gain Control parameter. For instance, G1 was initially assigned for a task, but after verifying the exact dimensions or weights, G3 was applied to reflect the more precise boundaries defined by the DHM time estimation algorithms. Refer to Table 5.1 for more detail on G parameter levels.

Similarly, for the Placement (P) parameter, which is determined through rough observation in MOST analysis, predefined task descriptions were initially used. In some cases, the initial MOST analysis assigned P3, categorizing the motion as "placement with adjustment." However, after reviewing the task description, a more accurate classification of P6—"placement with precision"—was determined. This discrepancy between MOST and DHM assessments was also noted in other parameters.

The process continued until all motion sequences were analyzed using the DHM method. Time estimations were converted from Time Measurement Units (TMUs) to seconds (1 TMU = 0.036 seconds). The dataset includes one set of time measurements from video timestamps and two sets of time estimations : one from MOST and one from the DHM time system.

5.3.3 Statistical Analysis

Descriptive statistics were used to summarize the three sets of time data : measured times, MOST estimates, and DHM estimates. The data were compiled in Microsoft Excel, and statistical analyses were performed using SPSS (version 23). In addition to the mean and standard deviation, the following key metrics were calculated :

$$\text{Bias} = \frac{1}{n}\sum_{i=1}^{n}(\text{Estimated time} - \text{Measured time}) \tag{5.1}$$

$$\text{rBias} = \frac{\text{Bias}}{\text{mean Measured time}} \times 100 \tag{5.2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Estimated time} - \text{Measured time})^2} \tag{5.3}$$

$$\text{rRMSE} = \frac{\text{RMSE}}{\text{mean Measured time}} \times 100 \tag{5.4}$$

An Analysis of Variance (ANOVA) was performed to assess statistically significant differences among the three sets of time data. Pairwise t-tests were then conducted to examine specific differences between each pair of time methods. Additionally, Tukey's Honestly Significant Difference (HSD) post-hoc test was applied to identify any significant differences between the time methods. The significance threshold for all tests was set at $p < 0.05$.

Bland-Altman Agreement Test

The Limits of Agreement (LoA) analysis, based on the method by Bland and Altman (1986, 1995, 1999) [96–98], was used to evaluate the agreement between estimated and measured times, with 95% LoA calculated as the mean difference ± 2 times the standard deviation of these differences (SDdiff). The normality of the differences was assessed visually using distribution histograms and through a Shapiro-Wilk test, which confirmed no significant departure from normality across all 26 operations ($p < 0.05$).

Regression Analysis

A regression analysis was conducted using JMP statistical software, Version 17.0.0 (SAS Institute Inc., 2023), to examine the effects of two key variables—"action distance" (total distance traveled during a work sequence) and "task duration"—on the deviations between MOST-estimated times and actual measured times for each workstation (n=26). The dependent variable was the deviation between the measured and MOST times, while action distance and task duration served as the independent variables.

A standard least squares regression model was used to assess the relationships between the variables. Model fit was evaluated using the coefficient of determination (R^2), which indicates the proportion of variance explained by the predictors. The significance level was set at $p = 0.05$, and 95% confidence intervals were calculated for the parameter estimates.

To ensure model reliability, diagnostics were performed to assess the normality of residuals with the Shapiro-Wilk test, which showed no significant deviations from normality. Additionally, Cook's distance was used to check for potential outliers or influential data points, with no significant issues identified.

5.4 Results

The descriptive statistics for time estimations from the MOST system, DHM system, and the actual measured times are summarized in Table 5.3.

Table 5.3 Descriptive Statistics of Time Measurements

Statistics	**Captured Time (Sec)**	**MOST Time (Sec)**	**DHM Time (Sec)**
Mean ± SD [1]	47.76 ± 5.74	44.35 ± 7.47	45.08 ± 7.28
Avg. Deviation from Captured Times (rBias) (%)	–	-7.04	-5.45
Mean Difference to Captured Times (sec)	–	-3.41	-2.68
SD Difference to the Captured Times (sec)	–	5.77	5.68
RMSE (Root Mean Square Error compared to the Captured Times) (sec)	–	2.31	2.21
RMSE (Relative Root Mean Square Error compared to Captured Times) (%)	–	5.22	4.89

The average measured time was 47.76 ± 5.74 seconds, with a range from 38.8 to 60.3 seconds. Descriptive statistics showed that both the MOST and DHM time estimation methods consistently underestimated the actual measured times. The results of Shapiro-Wilk test indicated that the distributions of Measured Time, MOST Time, and DHM Time did not significantly deviate from normality ($p > 0.05$), confirming that the assumption of normality was met.

ANOVA results revealed no statistically significant differences between the Measured Time, MOST Time, and DHM Time, $F(2, 75) = 1.77, p = 0.177$. However, pairwise t-tests were conducted to further explore specific differences between each pair of time estimation methods. The t-tests showed statistically significant differences across all pairs : Measured vs. MOST (Mean difference ± SD = -3.41 ± 5.77 sec, $t(25) = 3.01, p < 0.001$), Measured vs. DHM (Mean difference ± SD = -2.68 ± 5.68 sec, $t(25) = 2.40, p < 0.001$), and MOST vs. DHM (Mean difference ± SD = -0.73 ± 1.28 sec, $t(25) = -2.89, p < 0.001$).

1. Statistically significant differences were observed between the Captured Time and both the MOST and DHM times based on paired t-tests ($p < 0.05$).

5.4.1 Bland-Altman Analysis

The Bland-Altman analysis revealed that the 95% limits of agreement between MOST and DHM time estimates ranged from -3.24 to 1.79 seconds, with a mean difference of -0.73 seconds and a standard deviation of 1.28 seconds, indicating strong alignment between the MOST and DHM systems (Figure 5.1). In contrast, the 95% limits of agreement between DHM and the measured times were -13.81 to 8.45 seconds (Figure 5.2), while for MOST estimates and measured times, the limits were -14.71 to 7.90 seconds (Figure 5.3), showing lower agreement between these estimates and the actual measured times.

A substantial spread in estimation differences was observed for some operations, with average deviations exceeding 20% for both methods. This deviation occurred in tasks involving tool handling, complex body positioning, and fine adjustments. Specifically, operations such as component installations in tight spaces, assemblies requiring precise alignment, and tasks with varied tool access showed the largest discrepancies between estimated and actual times. The narrower limits of agreement between MOST and DHM (-3.24 to 1.79 seconds) compared to the other pairs suggest better agreement between MOST and DHM. The Bland-Altman plots (Figures 5.1, 5.2, and 5.3) visually depict these findings, showing the mean bias (solid lines) and limits of agreement (dashed lines) for each comparison.

5.4.2 Regression Analysis

The regression analysis demonstrated that the model examining the effects of action distance (distance traveled during a motion) and task duration on the deviations between MOST estimates and actual measured times was statistically significant at the 0.05 level ($F = 5.856, p = 0.0088$). The model explained approximately 33.7% of the variance in the deviations (R-squared = 0.337), with an adjusted R-squared of 0.28.

Task duration had a positive and significant effect ($\beta = 0.461, p = 0.026$), indicating that longer tasks were associated with greater deviations between measured and MOST estimated times. In contrast, action distance had a negative and highly significant effect ($\beta = -0.314, p = 0.003$), suggesting that as action distance increased, the deviation between measured and MOST estimated times decreased. The model's assumptions of normality were tested and met, confirming the robustness of these results. The findings are summarized in Table 5.4.

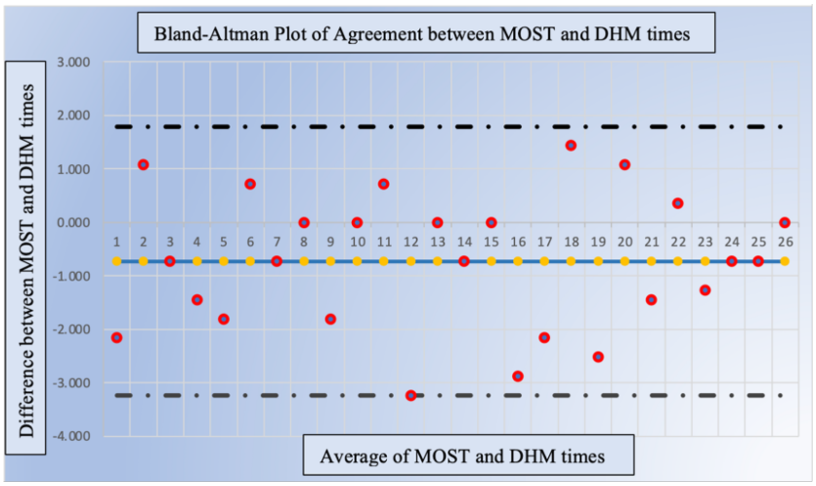

FIGURE 5.1 Comparison of Estimated Times (MOST vs. DHM).

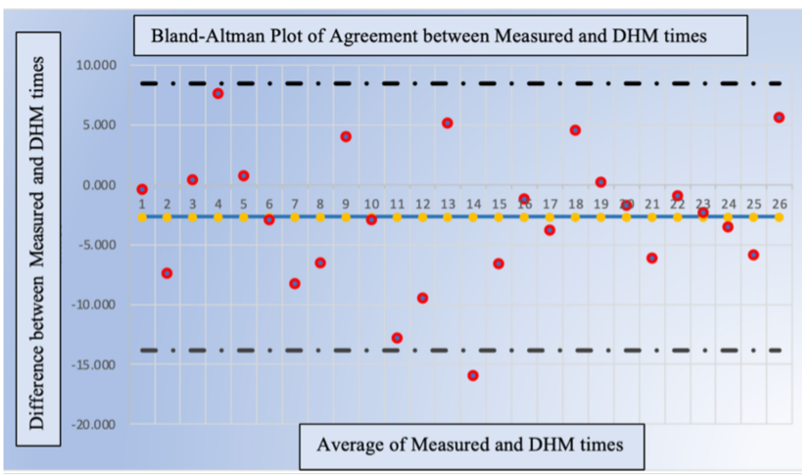

FIGURE 5.2 Comparison of Measured and Estimated Times (Experimental vs. DHM).

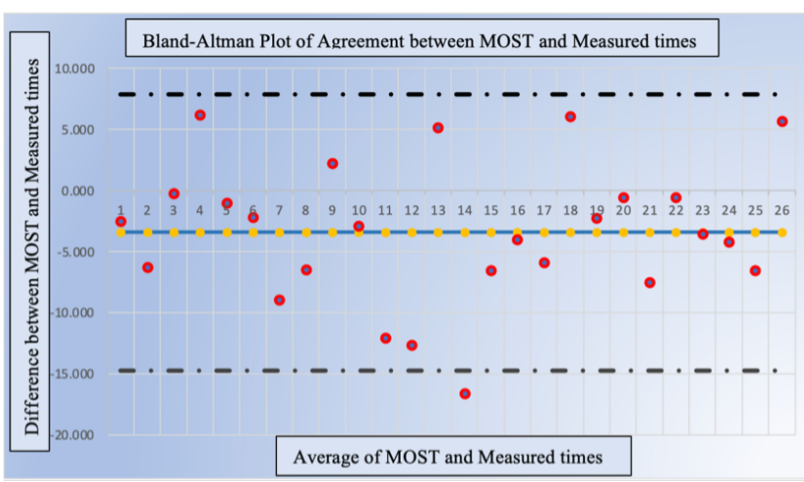

FIGURE 5.3 Comparison of Measured and Estimated Times (Experimental vs. MOST

TABLE 5.4 Fitted Regression Model Analyzing the Effects of Action Distance and Task Duration on the Deviations Between Measured and MOST Estimated Time

Parameter	**Fitted Model (n = 26)**		
	Estimate	**95% CI**	**P value**
Intercept	-7.53	[-24.65, 9.59]	0.37
Action Distance (Distance traveled during a motion)	-0.31	[-0.51, -0.12]	0.003
Task Duration	0.46	[0.06, 0.86]	0.026

5.5 Discussion

The DHM time estimation method showed strong agreement with the MOST system across 26 distinct assembly operations, with limits of agreement ranging from -3.24 to 1.79 seconds. This consistency was further supported by an average deviation of -0.73 seconds, indicating that the DHM method closely approximates MOST results within a 3D environment. However, both the DHM method and MOST tended to underestimate actual measured times, with the DHM showing an average deviation of -5.45% and the MOST system a slightly higher deviation of -7.04%.

Our initial hypothesis suggested that deviations within 10% would be acceptable, based on prior research by Bures and Pivodova (2013) [93], which proposed that acceptable deviations for systems like MTM-1 and BasicMOST fall between 5% and 10%. In this study, the observed deviations were higher than 2.05% for BasicMOST and -3.66% for MTM-1 reported by Bures and Pivodova. These differences may be attributed to the specific context of the assembly operations analyzed. In our study, the operations involved a wide range of task complexities, including component installations in constrained workspaces, precise alignments of multiple parts, and varied tool-handling scenarios. These characteristics add variability to task execution, making it more challenging for the time estimation systems to predict accurate durations compared to standard assembly lines with simpler tasks.

The study findings also align with previous studies documenting the underestimation of actual times by various time estimation methods. For instance, Bahcivancilar [46] and Kurkin and Bures [56] reported discrepancies ranging from 8% to 17% between estimated and actual times, highlighting the ongoing challenges in accurately predicting task durations.

When comparing the two systems, the DHM time method showed a smaller mean difference of -2.68 seconds (SD = 5.68), indicating less underestimation of actual times compared to the MOST system, which had a mean difference of -3.41 seconds (SD = 5.77). Although the DHM method appears to offer more accurate estimations, its closer alignment with actual data is not necessarily due to greater precision. Rather, it reflects DHM's tendency to slightly overestimate certain parameters due to the assumptions built into its algorithms.

As outlined earlier, the DHM system considers factors that MOST does not, such as the precise weight and dimensions of objects. For example, DHM may assign the "Difficult grasp" (G3) parameter instead of "Easy grasp" (G1), based on the actual weight and size of the object. This level of detail can lead to overestimations compared to MOST, where parameters are more loosely determined through observation.

A similar issue occurs with the classification of action distances. DHM uses stricter thresholds for categorizing action distances. For instance, if a task involves reaching slightly more than 60 cm—the threshold for an A1 (short distance) classification—DHM will automatically assign A3 (longer distance), even though the task may still fall within the worker's natural reach distance. This stricter classification can result in overestimated times, as DHM applies uniform thresholds for all anthropometric data and does not account for individual differences in reach capacity. Parameters that exceed a threshold by a small margin may be assigned higher time values, which would not occur in typical MOST analysis. Despite this, the systematic approach employed by the DHM method offers an automated process that reduces subjective bias and enhances the consistency of time analysis. This is particularly valuable in manufacturing environments where automation and digital twin simulations are increasingly integrated into production planning and workflow optimization.

The regression analysis revealed that both action distance and task duration had significant effects on the deviations between MOST estimates and actual measured times ($p < 0.05$). Specifically, longer action distances were associated with reduced deviations ($\beta = -0.31, p = 0.003$), consistent with Bahcivancilar's (2012) [46] findings, which showed higher discrepancies for shorter action distances (1 to 3 inches) in MTM systems, and Mazareinezhad et al. (2024) [92], who noted that shorter distances tend to exhibit greater discrepancies due to MOST's lack of granularity for movements in the A1 zone (reach distances). Conversely, longer task durations were linked to increased deviations ($\beta = 0.46, p = 0.026$), aligning with Bures and Pivodova's (2013) [93] findings that MOST tends to underestimate times for shorter tasks. Our results build on these observations, demonstrating that short action distances and longer task durations challenge the accuracy of MOST time estimates.

These findings highlight the need for further investigation into how time estimation systems like MOST handle such variations, particularly in high-precision manufacturing environments where small deviations can significantly impact production efficiency. Modifications or recalibrations may be necessary to ensure optimal task planning, reduce bottlenecks, and enhance overall productivity in real-world industrial applications.

Potential biases, such as variability in task performance, were minimal in this study. These biases typically arise from differences in skill, technique, or fatigue and can affect task completion times in many work environments [99]. However, the regulated nature of the automotive assembly line, with its fixed pace and controlled task durations, minimized these effects. Similarly, the Hawthorne effect, where workers alter their behavior because they are being observed [100], was unlikely to influence the results. The strict pace of the assembly line leaves little room for workers to change their speed or behavior without disrupting the production process. While these biases were unlikely to impact our study, they could pose challenges in more flexible work environments. In such cases, advanced motion-capturing technologies, such as unobtrusive sensors or wearable devices, could help mitigate observation-related influences [85].

5.5.1 Study Limitations

One limitation of this study is the lack of automated DHM time estimation. We manually estimated the necessary parameters using DHM time algorithms, video observations, the bill of materials, and the assembly line layout, which are less precise than calculations based on CAD data from a DHM. Although we took steps to ensure the accuracy of these estimates, the manual process may have introduced some variability. Future research should focus on fully simulating each task in the DHM system, relying on precise CAD data and automated determination of MOST parameters to reduce bias and improve the accuracy and reliability of time estimates.

Typically, in DHM, virtual tasks are created based on task descriptions, with time estimation beginning once the task is modeled. In contrast, MOST analysis involves real-time observation, where the analyst estimates task durations as the tasks are performed. In this study, however, both MOST and DHM estimations were derived from video recordings of the tasks. Without the support of video footage, there is a higher risk of missing critical task elements in DHM, which can widen the gap between MOST and DHM estimations. This issue is particularly significant when DHM systems are used to design new operations or integrate new components into workflows, where capturing every task detail can be challenging. As a result, the absence of video support may further increase the discrepancy between time estimates from DHM and traditional MOST estimations, highlighting a key limitation of using DHM systems for estimating operation durations.

5.6 Conclusion

This study compared two time estimation methods against actual field measurements in an assembly environment : the well-established MOST system and a newly developed DHM-based time estimation method grounded in MOST principles. Both methods demonstrated good agreement with actual measurements and remained within acceptable margins, with mean deviations of less than 10%.

The DHM method showed slightly higher accuracy than MOST, primarily due to overestimations in certain parameters. These deviations stem from assumptions made to compensate for limited real-world data in 3D environments. However, integrating the DHM-based time estimation system into industrial workflows enhances its practicality, particularly in early-stage production design, by leveraging CAD data and automating motion time definitions. This makes time analysis more accessible and scalable for users unfamiliar with traditional PMTS approaches.

By combining automated time estimation with ergonomic assessments, this study supports a data-driven approach to process optimization, improving both efficiency and worker safety in manufacturing environments. These findings are especially relevant in modern production systems, where automation and digital twin simulations are increasingly used to enhance time planning and resource allocation. As advanced manufacturing technologies evolve, these insights can help organizations streamline workflows, enhance productivity, and maintain a competitive edge in an era of rapid industrial transformation.

CHAPTER 6 ARTICLE 3 : Improving Time Estimation Accuracy in Manufacturing Systems : Experimental Assessment of MOST Predetermined Motion Time System Using Laboratory Data and Fitts' Law.

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6.1 Abstract

Accurate time estimation is critical for process planning, task optimization, and worker safety in modern manufacturing environments. Predetermined Motion Time Systems (PMTSs), such as the widely used Maynard Operation Sequence Technique (MOST), are key tools for time estimation but often lack precision. This study investigates the accuracy of MOST through controlled laboratory experiments, comparing its estimates to direct measurements and predictions using Fitts' law. Twenty participants performed 300 simple movements varying in Action Distance (10–120 cm), Object Weight (0.5–2.26 kg), Motion Level (68–100 cm), Grasp Difficulty (easy/difficult), and Placement Precision (approximate/precise).

Movement times were recorded using an accelerometer and compared to MOST and Fitts' law estimations. Results revealed a 38% underestimation by MOST, with average actual times of 3.83 ± 0.46 seconds (range : 2.97–5.13 seconds). Bland-Altman analysis showed significant discrepancies (95% LoA : -2.37 to -0.063 seconds) with a mean bias of -1.5 seconds (SD = 0.44). Regression analysis identified significant effects of variables like Object Weight and Motion Level, which are not accounted for in the MOST system ($p < 0.0001$). These findings highlight the importance of refining MOST by incorporating overlooked factors, which can significantly improve time estimation accuracy, optimize task performance, and promote

safer working conditions in manufacturing systems.

keywords : Process Planning, Task Optimization, MOST Time Estimation System, Workplace Ergonomics, Manufacturing Efficiency, Worker Safety.

6.2 Introduction

Production is the cornerstone of every industrial enterprise, with meticulous management and strategic planning being key determinants of success. Essential resources, such as materials, human capital, and financial assets, are deeply interlinked and have evolved significantly. This evolution highlights the importance of monitoring time consumption within production processes, particularly in advanced manufacturing systems, where time estimation plays a central role in process optimization, and maintaining efficiency [6, 91].

To enhance production efficiency and resource allocation, many industrial companies rely on Predetermined Motion Time Systems (PMTSs). These systems estimate the time needed for tasks by breaking them down into specific motions and assigning a time value to each. This approach offers a standardized framework for time estimation, helping evaluate product costs, compare different tasks or workstations, and identify opportunities for improvement [1]. PMTSs have proven effective in various fields, including manufacturing, healthcare, and services [10].

Prominent examples of PMTSs are Method Time Measurement (MTM), recognized for its detailed motion analysis, and the Maynard Operation Sequence Technique (MOST), a simplified adaptation of MTM that is widely employed across various industrial fields [1, 6].

MOST, known for its ease of use, simplifies the estimation of task durations in manufacturing environments. This time system employs a coding system with standardized codes that correspond to specific motions. This structured approach facilitates the calculation of parameters such as walking time, machine operation time, and tool usage. To determine the total time for each motion, the predefined time values assigned to each MOST parameter are summed [1].

Fitts' law, a model introduced by Paul Fitts in 1954, predicts movement time based on both the distance to and size of a target. It is a widely recognized standard for estimating time in simple movements, and it offers valuable insights for optimizing manual operations. Fitts' law has been extensively validated in research, from early studies like Crossman Goodeve (1983) [101] to more recent ones by Clark et al. (2020) [102] and Xie et al. (2023) [103], establishing it as a foundational model for time estimation comparisons.

Accurate time estimations from PMTSs are vital for effective decision-making and maintaining productivity within organizations [90]. However, as technology evolves, organizational structures change, and workforce demographics shift, the specific motions and time values used in PMTSs may become outdated. Such inaccuracies can lead to inefficient task assignments, increased worker fatigue, and higher injury risks. This underscores the importance of regular validation to ensure these systems remain aligned with the complexities of real-world manufacturing. [6, 91].

Despite its critical role, PMTS validation has been under-researched. Bahçıvancılar (2012) [46] found an 8% discrepancy between actual times and MTM-1 estimates for actions like grasping, moving, and reaching, which took between 25 and 35 seconds. Similarly, Bures and Pivodova (2015) [47] observed that MTM-1 and Basic-MOST underestimated actual times by about -3.66% and -2.05%, respectively, for motions lasting 5 to 29 seconds across 21 workstations. Further, Kurkin and Bures (2011) [56] reported that actual times were 17% and 9% longer than estimates from MTM-1 and MTM-UAS, respectively.

Harari et al. (2018) [17] pointed out that PMTSs often overlook physiological and biomechanical factors, especially in manual object-handling tasks. They stressed the need to consider workplace design elements like lifting height, object weight, and worker measurements for more precise time predictions. Genaidy et al. (1989) [6] suggested that PMTS accuracy varies with the specific motions and tasks analyzed. Turk et al. (2018) [18] found that the MTM method typically underestimates the time needed for handling boxes of different sizes and weights, leading to potential discomfort due to unrealistic time expectations. Additionally, Schmidtke and Stier (1961, as referenced in Genaidy et al., 1989 [6]) noted that PMTSs frequently overlook the influence of movement frequency on time predictions. Such overly optimistic predictions can cause errors in productivity estimates and risk assessments, potentially leading to worker overexertion and increased injury risk [17]. Addressing these gaps requires detailed validation studies to refine PMTSs, ensuring alignment with ergonomic design principles, process efficiency, and worker safety in advanced industrial settings.

Despite its wide application, the MOST system has notable limitations when applied to modern industrial contexts, particularly for short, repetitive tasks involving variable weights, distances, and heights. These shortcomings can lead to inaccurate time predictions, resulting in inefficient task planning, underestimated workloads, and increased worker fatigue or injury risk [6], [90]. Therefore, improving the precision of time estimation systems like MOST is critical for optimizing task design, reducing ergonomic risks, and contributing to more informed operational decisions in advanced manufacturing environments.

This study is an extension of our earlier work presented at a conference and published in the proceedings (Mazareinezhad et al., 2024 [86]). In this study, we assessed the accuracy of the MOST system by comparing its time estimates with both direct measurements and predictions based on Fitts' law. While MOST is effective for estimating time for complex movements, Fitts' law is particularly well-suited for simpler ones. We hypothesized that for simple movements, the time estimates derived from Fitts' law and MOST would be closely aligned, with deviations from actual measurements not exceeding 10%, as suggested by Bures and Pivodova (2015) [47].

Additionally, we examined the impact of specific workplace design features and motion characteristics on task completion times. The features analyzed included Action Distances (the distances covered by hands during movements), Object Weight (the weight of the object being moved), Motion Level (the height of hand movements relative to shoulder level), Grasp Difficulty (the complexity of grasping actions), and Placement Precision (the accuracy required for placing objects). This detailed analysis aimed to underscore how existing PMTSs might overlook the nuanced challenges of real workplaces, potentially leading to inaccuracies that affect process planning, task execution, and overall operational efficiency.

6.3 Methods

The experiments were carried out at the motion capture laboratory at Dassault Systèmes headquarters in Montreal, Canada, in the summer of 2022. All ethical standards were upheld through informed consent from participants, following the ethical guidelines of Polytechnique Montréal. The study was approved under ethics certificate number CER-2223-38-D.

6.3.1 Participants

Twenty employees at Dassault Systèmes volunteered to participate in this study. The sample consisted of individuals aged 27 to 59 years (mean ± SD : 43 ± 10.9 years, range : 27–52 years), as detailed in Table 6.1. Participants provided informed consent and confirmed their ability to handle objects weighing up to 5 kg before the experiment began.

TABLE 6.1 Participant characteristics (N = 20)

Variable	**Mean ± SD (range)**
Age (years)	43 ± 10.9 (27–52)
Weight (kg)	74.1 ± 12.3 (52–110)
Height (cm)	169.8 ± 10.5 (155–199)
Arm length (cm)[1]	70.7 ± 6.1 (59–82)

6.3.2 Variables

The study design was inspired by previous research that compared estimated times with actual measured times in controlled settings. Kurkin and Bures (2011) [56] compared the estimated times of MTM-UAS with actual measured times in a simulated context, while Bahçıvancılar (2012) [46] evaluated the estimated times of MTM-1 against actual measured times of different motions in a laboratory setting. In our study, we specifically compared the time estimates generated by the MOST system and Fitts' law with the actual measured times in a laboratory environment.

Three experiments were designed to examine the effects of five independent variables (Action Distances, Object Weight, Grasp Difficulty, Placement Precision, and Motion Levels) on task completion times for different motions, focusing specifically on seated "Get and Place" actions. These experiments aimed to assess the transfer of objects over set distances from a defined origin to a precise destination. The tasks were designed to simulate manual operations commonly encountered in assembly lines, such as object retrieval, precise placement, and handling weighted items, ensuring practical relevance to industrial workflows.

The experimental setup included two types of tables to assess the effect of Motion Level (Table Height) on task completion times. A standard fixed-height table (70 cm high) and an adjustable table, with heights ranging from 68 cm to 120 cm, were used. The first experiment was conducted on the fixed-height table (Figure 6.1), while the subsequent experiments utilized the adjustable table (Figure 6.2).

Each table had a pair of black storage bins containing colored markers and rubber bands, positioned directly in front of the participants. Four destination bins and three pads were arranged in a curved configuration on the table. Additionally, three weights—2.26 kg, 1 kg, and 0.5 kg—were placed on the right side of the table, as shown in Figure 6.1. Following the experimental instructions, participants were required to move one of three objects—a marker, a rubber band, or a weight—from its starting position to the appropriate destination bin or pad.

Four tasks, each with specific subtasks, were outlined for the three experiments, with clear instructions provided for each subtask. For example, Task 2, Subtask 3 involved placing a marker in the third destination bin (labeled as number 11 in Figure 6.1), while Task 4, Subtask 1 required moving the first weight (labeled as number 4 in Figure 6.1) to the first pad (labeled as number 8 in Figure 6.1).

1. Note. Measured from the acromion (the bony projection at the top of the shoulder) to the tip of the middle finger with the arm extended along the side of the body [104].

The time taken to complete each subtask was meticulously recorded. These measurements, referred to as "Experimental time," captured a total of 45 movements throughout all experiments for each participant. The tasks were designed to assess various motions—such as reaching, grasping, and placing—while also considering factors influencing these motions, including Action Distance and Object Weight. Table 6.2 summarizes each experiment and the associated tasks.

Table 6.2 Experiments and Corresponding Tasks

Experiments	**Task 1 (Four Subtasks)**	**Task 2 (Four Subtasks)**	**Task 3 (Four Subtasks)**	**Task 4 (Three Subtasks)**
(1) Distances adjusted to each participant's maximum reach (2) Standardized distances for all participants (3) Customized table heights to simulate different movement levels	Moving markers from storage to destination bins	Moving markers with precise placement in bins	Moving blue rubber bands from storage to destination bins	Moving weights from the table's right side to the destination pads

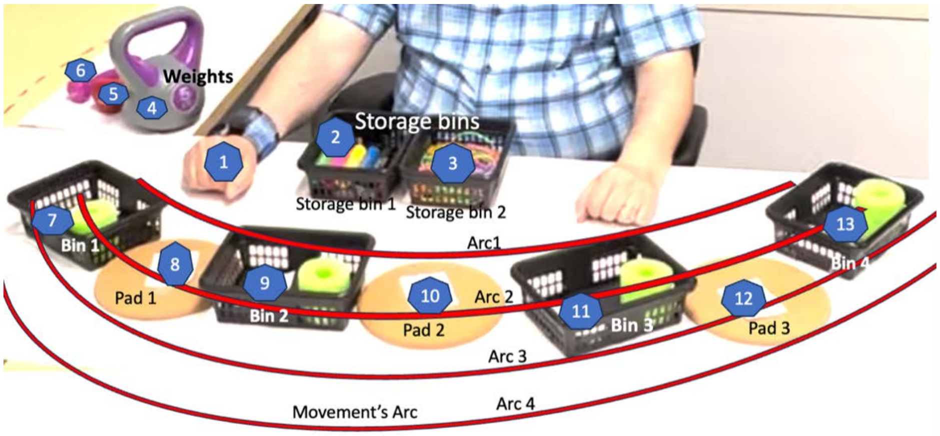

FIGURE 6.1 Experiment 1 Layout.[1]

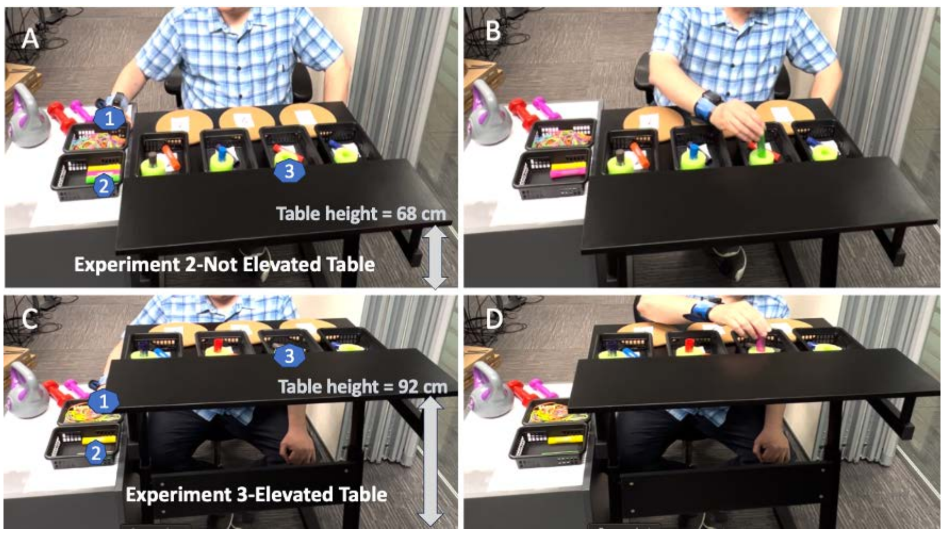

FIGURE 6.2 Participant Performing Movements in Experiment 2 (A, B) and Experiment 3 (C, D).[1]

Action Distances and Motion Levels

In Experiment 1, the destination bins and pads were positioned within the participants' maximum comfortable reach zone, arranged in four distinct movement arcs (Figure 6.1). Arc 4, the outermost reach, was designed based on ergonomic standards for seated operations, which specify a distance not exceeding 49.4 cm from the arc's apex to the table edge. This standard, based on the 5th percentile of female arm length/reach (The Eastman Kodak Company, 2003 [104]), ensures ergonomic compliance by allowing full arm extension without

1. Note. Figures 6.1 and 6.2 are adapted from "Evaluating the Accuracy of the MOST Predetermined Motion Time System Through Lab Experiments," by by Mazareinezhad et al., 2024 [86], in Human Aspects of Advanced Manufacturing, Production Management, and Process Control, p. 118.

requiring back bending, thereby promoting operator comfort and safety.

Three critical Action Distances characterized the subtasks. Initially, participants retrieved objects from storage, moving between point 1 and points 2 to 6 (Figure 6.1). The next Action Distance involved transporting objects to the destination bins and pads, requiring movements from points 2 to 6 to points 7 to 13. In the final Action Distance, participants returned their hands to the starting position by moving from points 7 to 13 back to point 1. Variations in setup and bin/pad positions across subtasks resulted in diverse Action Distances in the first experiment. Figure 6.3 depicts these distances : the hand's path from point 1 to point 3 for object retrieval (B), to point 11 for object placement (C), and back to the starting position at point 1 (D).

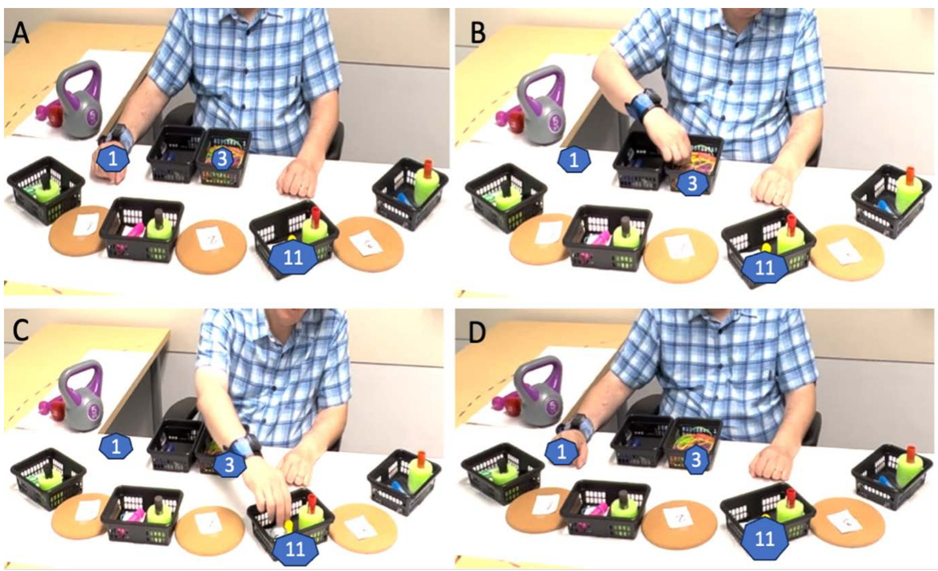

Figure 6.3 Three Action Distances involved in a sub-task

Experiments 2 and 3 shared the same setup for the positioning of storage bins, destination bins, and destination pads for all participants. The key difference between the experiments was the table height during tasks. For Experiment 2, a consistent table height of 68 cm above the ground was maintained, ensuring uniform Action Distances for all participants.

Experiment 3 involved adjusting the table height to match each participant's maximum reach, resulting in variability in Action Distances due to the differing table heights. This setup, following ISO 14738 ergonomic standards, aimed to evaluate how table height (Motion Levels) affected experimental times. These standards recommend that seated work should be performed at or below shoulder level to minimize shoulder strain and that movements should not exceed eye level (ISO 14738 :2008 [105]). To meet these guidelines, table heights were adjusted between 89 cm and 100 cm, based on each participant's reach and comfort.

Figure 6.2 shows the varied movements at different table heights in Experiments 2 and 3, with panels A and B depicting Experiment 2, and C and D depicting Experiment 3.

Throughout the study, 112 distinct Action Distances were measured, reflecting the diversity among participants and subtasks, with distances ranging from 10 cm to 120 cm. The shortest distance was 10 cm between point 1 and point 2, while the longest was 120 cm between point 6 and point 13 (see Figure 6.1). This design allowed for a detailed analysis of the Action Distance segmentation, effectively covering the breakpoints specified in Basic-MOST's coding system. Variations between Experiments 2 and 3 also enabled an investigation into how changes in motion levels affect movement time.

Object Weight

Task 4 in each experiment aimed to assess the impact of object weight on motion completion time. Participants completed tasks using objects of three different weights (0.5 kg, 1 kg, and 2.26 kg), moving them to destination pads at various distances along a curved path. The sequence of moving weights was varied to explore the combined effects of Action Distance and Object Weight on Experimental times.

Placement Precision

Task 2 examined the effect of placement precision on movement times by introducing two levels : precise and approximate. Participants were required to insert markers vertically into green plastic tubes within destination bins, demanding a precision of less than 3 millimeters to simulate precise placement conditions. This task was compared with Task 1, which involved approximate placement, allowing for a comparative analysis of movement times under different precision requirements.

Grasp Difficulty

Grasp difficulty was manipulated to examine its impact on movement time, with two levels : difficult and easy. Task 3 evaluated the effect of difficult grasps by requiring participants to manipulate colored rubber bands, specifically identifying and moving a blue rubber band among others. This task simulated the complexity of grasping interlocked objects. The setup allowed for comparison with Task 1, where grasping was easy, facilitating an analysis of how grasp difficulty affects movement times.

6.3.3 Measures and Apparatus

Participants wore a wrist-mounted accelerometer (GCDC USB Accelerometer, model X16-mini ; 51x25x13mm, 17g) on their dominant hand to capture kinematic data. The accelerometer provides high-precision motion tracking, that recorded acceleration across three axes at a 50 Hz sampling rate. Forearm orientation and alignment with the trunk were monitored through Y-axis and Z-axis measurements, respectively. A simple algorithm was developed to pre-process the data, identifying the start (acceleration) and end (deceleration) of a movement to estimate movement time. The movement time estimations were validated by visually inspecting the accelerometer data profiles. Additionally, the experiments were video recorded using an iPhone 13 Pro, which aided in identifying outliers and improving the quality of the data collected.

6.3.4 MOST and Fitts' Law Time Estimations

The movements were selected from the samples featured in "MOST Work Measurement Systems" by Zandin (2002) [1], which offers detailed time estimations for each move. This approach eliminated subjective judgments and reduced potential bias. MOST estimations, originally given in Time Measurement Units (TMUs), were converted to seconds for uniformity, with 1 TMU equating to 0.036 seconds.

Movement times were also estimated using Fitts's law, as defined by Equation (6.1) [106] :

$$MT = a + b \cdot \log_2\left(\frac{2D}{W}\right) \tag{6.1}$$

where :

- **MT (Movement Time)** : The time required to complete the task.
- **a** : Represents the initial reaction time or delay, also known as the y-axis intercept.
- **b** : Describes the rate of change of MT with respect to the Index of Difficulty (ID = $\log_2(2D/W)$).
- **D** : The distance from the starting point to the target's center, measured in centimeters (measured from the object's center to the average center of the placement area).
- **W** : The width or diameter of the target, defining the precision required for the task, measured in centimeters.

The parameters 'a' and 'b' are empirical constants that depend on the specific task type and the participants' performance, and they can vary across different experiments. In this study, we conducted regression analyses across different motion types using separate datasets, totaling 6,000 data points, and selected the values of 'a' and 'b' based on the best-fitting models for the observed data. The resulting constants were 100 milliseconds for 'a' and 150 bits per millisecond for 'b'. This analysis achieved an R-squared value of 0.88, signifying a strong fit. This approach is consistent with the methodologies outlined by MacKenzie (1992, 1995) and MacKenzie and Buxton (1992) [107–109] for establishing these values.

6.3.5 Procedure

To help participants familiarize themselves with the experiment's layout and required motions, they completed five training sessions before the actual experiments. After these sessions, a 5-minute rest was provided to alleviate any fatigue before commencing the experiments. Additionally, a 2-minute break was given after each experiment to further reduce fatigue effects.

To minimize test-retest variability, all experiments were conducted on the same day. The first experiment was repeated ten times, while the second and third were each repeated five times. This approach aimed to account for the inherent variability in movement. Experiments were scheduled during both morning and afternoon sessions to control for any time-of-day effects. The order of the experiments was also randomized for each participant to minimize fatigue and order effects.

6.3.6 Data Preparation and Processing

A manual review was performed to detect and eliminate missing or anomalous data, leading to the exclusion of 11 outliers, primarily due to extended movements caused by distractions. Additionally, four cases of missing data were handled using mean imputation based on the same participant and experiment [110].

6.3.7 Statistical Analysis

The study analyzed a total of 6,000 movement samples collected from 20 participants across three experiments (300 movements per participant). This analysis included measured experimental times, as well as time estimates obtained from the MOST system and Fitts' law, providing a comprehensive evaluation of movement times.

Descriptive Statistics and Paired t-Test

Descriptive statistics were calculated for all $N = 6000$ motions to summarize both the estimated times and the actual measured (Experimental) times. Beyond mean and standard deviation, additional descriptive metrics were used :

$$\text{Bias} = \frac{1}{n}\sum_{i=1}^{n}(\text{Estimated time} - \text{Measured time}) \tag{6.2}$$

$$\text{rBias} = \frac{\text{Bias}}{\text{mean Measured time}} \times 100 \tag{6.3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Estimated time} - \text{Measured time})^2} \tag{6.4}$$

$$\text{rRMSE} = \frac{\text{RMSE}}{\text{mean Measured time}} \times 100 \tag{6.5}$$

A paired t-test was conducted to determine whether the differences between the means were statistically significant, with the significance level set at $P < 0.05$.

Bland-Altman Test

The Bland-Altman agreement test was utilized to evaluate the agreement between estimated and measured times. Given the presence of repeated measurements for the same subjects, we averaged the measurements for each subject under each condition. This approach mitigates the issue of within-subject correlation, ensuring the validity of the 95% Limits of Agreement (LoA). The LoA was derived from the mean differences ± 2 times the standard deviation of these differences (SDdiff), as described by Bland and Altman (1986, 1995, 1999) [96–98].

The Bland–Altman plot was chosen over conventional methods such as scatterplots, as it offers a more informative representation of agreement. Specifically, it illustrates both the mean bias and the spread (LoA) between the two measurement methods. This is particularly valuable when assessing the accuracy of time estimation systems like MOST, where the objective extends beyond correlation to include the closeness of estimates to actual measured values across the full range of observations.

Regression Analysis

Regression analysis was performed using JMP statistical software, Version 17.0.0 (SAS Institute Inc., 2023 [111]), to explore the impact of five independent variables on Experimental time. The three continuous variables were Action Distance, Object Weight, and Motion Height Level, while the two ordinal variables were Placement Precision (two levels : Precise and Approximate) and Grasp Difficulty (two levels : Difficult or Easy). The relationships were modeled using a standard least squares approach. The model's fit was evaluated using the R-squared value and Root Mean Square Error (RMSE), with statistical significance set at $P < 0.05$.

Five distinct regression models were developed to isolate the impact of different variable combinations on Experimental time, providing a comprehensive understanding of the experimental dynamics. Table 6.3 outlines the variables examined in each model and the corresponding datasets used.

Table 6.3 Overview of Regression Models

Regression Models	Variables	Data Source
1	Action Distance, Object Weight	Experiments 1&3, Task 4
2	Action Distance, Table Height	Experiments 2&3, Task 1
3	Action Distance, Grasp Difficulty	Experiments 1&2, Tasks 1&3
4	Action Distance, Placement Precision	Experiments 1&2, Tasks 1&2
5	Action Distance, Object Weight, Table Height, Grasp Difficulty, Placement Precision	The entire dataset, including 6000 motions

6.4 Results

6.4.1 The Comparison of Measured and Estimated Times (Experimental Times vs. MOST and Fitts's Times)

Descriptive Statistics

Table 6.4 presents descriptive statistics for the entire dataset, including time estimates from MOST, Fitts' law, and the actual Experimental times.

A significant underestimation was found in the time estimates by MOST (Mean bias ± SD = -1.5 ± 0.44 sec, $t(44) = -4.01$, $p < 0.001$) and Fitts' law (Mean bias ± SD = -0.74 ± 0.44

1. Statistically significant based on paired t-tests $p < 0.05$.

Table 6.4 Descriptive Statistics of Time Measurements for the Entire Dataset (N=6000)

Statistics	**Measured Time (Sec)**	**MOST**	**Fitts' Law**
Mean ± SD (sec)	3.83 ± 0.46	2.33 ± 0.32[1]	3.09 ± 0.59[1]
Avg. Deviation from Measured Times (rBias) (%)	–	-38.78	-19.44
Mean Difference to Measured Times (sec)	–	-1.50	-0.74
SD Difference to Measured Times (sec)	–	0.44	0.44
RMSE (Root Mean Square Error compared to Measured Times) (sec)	–	1.16	0.75
RMSE (Relative Root Mean Square Error compared to Measured Times) (%)	–	49.95	24.37

sec, $t(44) = -1.979$, $p < 0.001$) when compared to the actual Experimental times.

MOST estimates showed a greater deviation from the measured times (-38.78%) compared to Fitts' law (-19.44%), suggesting a higher degree of underestimation by MOST.

Table 6.5 provides a detailed comparison of the mean times and standard deviations for the measured Experimental times, Fitts' law and MOST estimations across the three experiments for the entire dataset (N=6000).

Table 6.5 Measured and Estimated Times Across Three Experiments

Experiment	**Experimental Time (Mean ± SD)**	**Fitts' Time (Mean ± SD)**	**MOST Time (Mean ± SD)**
Experiment 1	3.56 ± 0.36	3.02 ± 0.61	2.33 ± 0.33
Experiment 2	3.81 ± 0.41[2]	3.10 ± 0.60	2.33 ± 0.33
Experiment 3	4.12 ± 0.43[2]	3.14 ± 0.60	2.33 ± 0.33

Significant differences were observed in the Experimental times between Experiments 2 and 3, which had comparable motions and shared the same table and setup. Experiment 3 recorded significantly longer times than Experiment 2 (Mean bias ± SD = -0.74 ± 0.44 sec, $t(14) = -1.98$, $p < 0.001$).

2. Statistically significant based on paired t-tests $p < 0.05$.

Bland-Altman Analysis

The Bland-Altman analysis was performed on averaged experimental data, where each data point in the plots (Figures 6.4-6.6) represents the average time for a specific sub-task across all subjects. With 45 sub-tasks examined across all experiments, this resulted in 45 data points in the plots. This method ensures that each sub-task is represented by a single data point, reducing the risk of within-subject correlation.

The Bland-Altman analysis revealed that Fitts' law estimates exhibited a mean difference (bias) of -0.74 seconds (SD = 0.44) relative to experimental times, with 95% limits of agreement ranging from -1.59 to 0.11 seconds (Figure 6.4). These findings suggest closer alignment than MOST estimates, which demonstrated a mean difference (bias) of -1.50 seconds (SD = 0.44) and 95% limits of agreement between -2.37 and -0.63 seconds (Figure 6.6).

Comparing MOST and Fitts' law directly, a mean difference of -0.76 seconds (SD = 0.63) was observed, with 95% limits of agreement from -1.99 to 0.47 seconds (Figure 6.5). This suggests a broader range of limits of agreement and lower concordance between these estimation methods.

Bland-Altman plots (Figures 6.4, 6.5, and 6.6) visually illustrate these findings, showing the mean bias (solid lines) and limits of agreement (dashed lines) for each paired comparison.

6.4.2 Influence of Independent Variables on Experimental Time

Linear regression analyses across five models revealed a significant relationship between all independent variables and Experimental Time, with p-values less than 0.001 for each variable in every model.

As summarized in Table 6.6, the R-squared values ranged from 0.15 to 0.26, indicating that the models accounted for a moderate portion of the variance in Experimental Time. The RMSE values, which measure prediction error, varied from 0.51 to 0.77 across the models. Detailed parameter estimates for each independent variable, along with their 95% confidence intervals, provide further insight into their respective impacts on Experimental Time; these intervals reflect the accuracy of the parameter estimates within the models. The Lack of Fit test was statistically significant for all models, as evidenced by p-values below 0.0001.

2. Note. Adapted from "Evaluating the Accuracy of the MOST Predetermined Motion Time System Through Lab Experiments," by Mazareinezhad et.al, 2024 [86], in Human Aspects of Advanced Manufacturing, Production Management, and Process Control, p. 120.

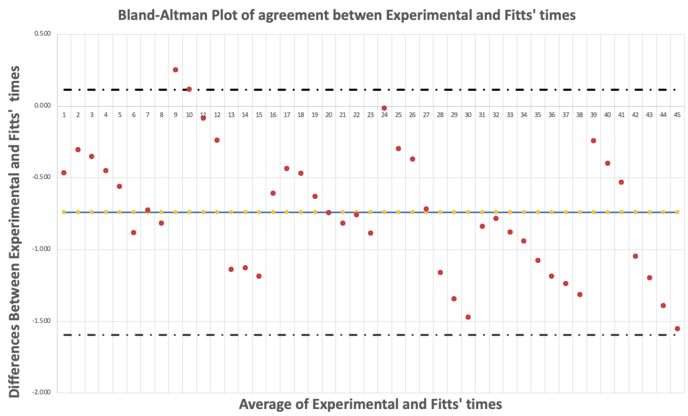

FIGURE 6.4 Bland-Altman Plot of Agreement Between Experimental Times and Fitts' Times.

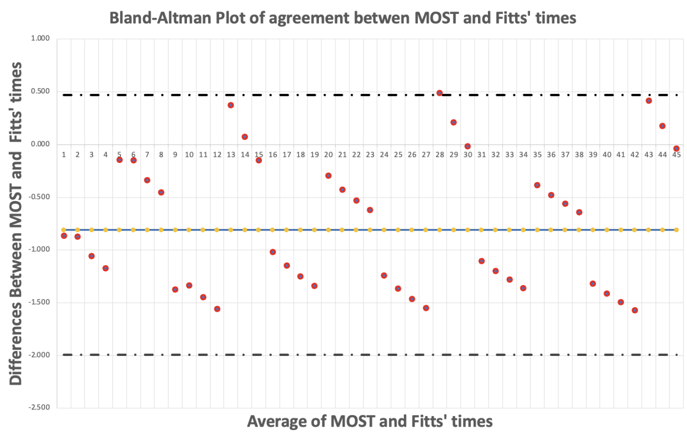

FIGURE 6.5 Bland-Altman Plot of Agreement Between MOST Times and Fitts' Times.[2]

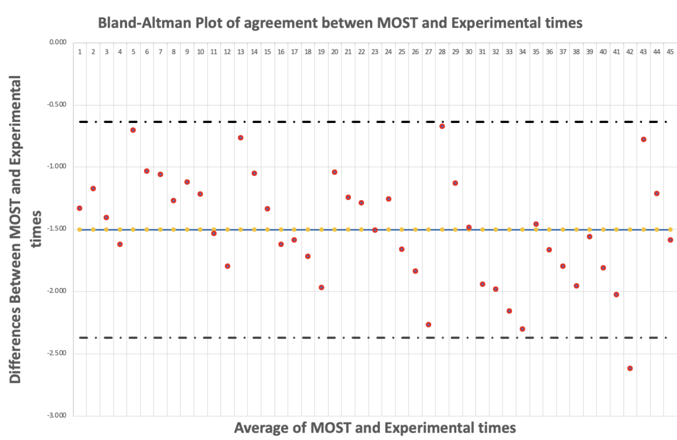

FIGURE 6.6 Bland-Altman Plot of Agreement Between MOST and Experimental Times.

TABLE 6.6 Fitted Regression Models Analyzing Effects of Various Variables on Experimental Time.

Parameter	Fitted Model 1 (n = 900, Exp 1&2, Task 4) Estimate (Sec)	95% CI	Fitted Model 2 (n = 800, Exp 2&3, Task 1) Estimate (Sec)	95% CI	Fitted Model 3 (n = 2400, Exp 1&2, Task 1&3) Estimate (Sec)	95% CI	Fitted Model 4 (n = 2400, Exp 1&2, Task 1&2) Estimate (Sec)	95% CI	Fitted Model 5 (n = 6000) Estimate (Sec)	95% CI
Intercept	2.48	[2.35, 2.62]	2.28	[2.04, 2.53]	2.96	[2.86, 3.07]	2.85	[2.78, 2.93]	2.43	[2.23, 2.62]
Action Distance(cm)	0.011	[0.009, 0.012]	0.008	[0.006, 0.010]	0.015	[0.012, 0.017]	0.012	[0.011, 0.014]	0.016	[0.014, 0.018]
Object Weight(kg)	0.26	[0.21, 0.26]	_	_	_	_	_	_	0.06	[0.02, 0.10]
Table Height(cm)	_	_	0.012	[0.008, 0.015]	_	_	_	_	0.01	[0.007, 0.012]
Grasp Difficulty	_	_	_	_	_	_	_	_	_	_
Easy	_	_	_	_	Ref	_	_	_	Ref	_
Difficult	_	_	_	_	0.38	[0.35, 0.41]	_	_	0.40	[0.37, 0.42]
Placement Precision	_	_	_	_	_	_	_	_	_	_
Approximate	_	_	_	_	_	_	Ref	_	Ref	_
Precise	_	_	_	_	_	_	0.16	[0.14, 0.18]	0.12	[0.17, 0.22]
Lack of Fit F Ratio	5.25	$p < 0.0001$	4.74	$p < 0.0001$	9.75	$p < 0.0001$	7.44	$p < 0.0001$	5.07	$p < 0.0001$
R-squared	0.23	_	0.15	_	0.24	_	0.18	_	0.26	_
RMSE	0.55	_	0.51	_	0.77	_	0.52	_	0.70	_

Model Comparisons

Model 1 analyzed the effects of Action Distance and Object Weight on Experimental time, revealing significant associations ($p < 0.0001$). Specifically, each centimeter increase in Action Distance added 0.011 seconds to Experimental time (95% CI : [0.009, 0.012], $p < 0.0001$), while each kilogram increase in Object Weight added 0.265 seconds (95% CI : [0.21, 0.26], $p < 0.0001$).

Model 2 incorporated Table Height alongside Action Distance. Results indicated that for every centimeter increase in Action Distance, Experimental time rose by 0.008 seconds (95% CI : [0.006, 0.010], $p < 0.0001$), and for each centimeter increase in Table Height, it rose by 0.011 seconds (95

Model 3 examined the effect of Grasp Difficulty, finding that difficult grasps increased Experimental time by 0.381 seconds (95% CI : [0.350, 0.412], $p < 0.0001$). Model 4, which focused on Placement Precision, determined that precise placements raised Experimental time by 0.161 seconds (95% CI : [0.14, 0.18], $p < 0.0001$).

Model 5 provided a comprehensive analysis by integrating Action Distance, Object Weight, Table Height, Grasp Difficulty, and Placement Precision, showing that these variables collectively explained 26% of the variability in Experimental time (R-squared = 0.26). Each variable significantly contributed to the model ($p < 0.005$), highlighting the intricate relationship between these factors and their predictive power for Experimental time. The detailed effect sizes for each variable in Model 5, presented in Table 6.6, underscore their respective impacts on Experimental time.

6.5 Discussion

6.5.1 The Comparison of Measured and Estimated Times (Experimental Times vs. MOST and Fitts's Times)

The results of this study revealed significant discrepancies between the time estimates provided by MOST and Fitts' Law compared to the actual measured times. While a 10% variance between estimated and measured times was anticipated, consistent with the findings of Bures and Pivodova (2015) [47], the analysis showed that MOST underestimated task times by an average of 38%—a deviation far exceeding the 2.05% reported by Bures and Pivodova [47]. This highlights critical limitations in MOST's applicability to tasks commonly encountered in manufacturing environments similar to those investigated in this study.

These larger deviations may result from differences in task duration and complexity examined in prior studies. For instance, Bures and Pivodova (2015) analyzed a wide range of task durations, averaging 12.76 seconds (SD ± 6.81 seconds) with a range from 4.73 to 29.16 seconds. They found that the largest deviations occurred with tasks shorter than 10 seconds. This finding aligns with our study, which focused on shorter tasks with an average duration of 3.76 ± 0.46 seconds and a range from 2.97 to 5.13 seconds, reinforcing the challenge of accurately estimating time for such motions in high-frequency manufacturing processes where short-duration tasks dominate.

Bures and Pivodova (2015) [47] suggested that adopting a more detailed system, such as MTM-1, could improve time estimation accuracy for shorter tasks. However, they also highlighted the practical limitations of MTM-1, including its resource-intensive nature. In contrast, MOST offers a balance of efficiency and simplicity, making it a preferable choice for high-throughput environments despite its accuracy limitations.

Consistent with MacKenzie's (2018) [112] findings, the 19% discrepancy between the time predictions of Fitts' Law and the actual measured times supports its greater accuracy for one-dimensional tasks compared to multi-dimensional ones. Our study included hand movements in three distinct directions, each with varying starting delays and movement accelerations, introducing additional variability. This suggests that while Fitts' Law is a robust model, its accuracy diminishes in complex, multi-directional tasks. MacKenzie (1995) [109] also reported an 18% variance in throughput—a measure of task efficiency—between one- and two-dimensional tasks, further supporting our findings. These results highlight the need for more sophisticated models or the incorporation of additional variables to improve time prediction accuracy for tasks involving multi-directional movements.

Experiment 2 recorded an average experimental time of 3.81 ± 0.41 seconds, while Experiment 3 had the longest time at 4.12 ± 0.43 seconds, with the difference attributable to the increased table height in Experiment 3. This variation underscores the significant impact of ergonomic factors, such as table height, on movement duration and task performance. The uniform MOST times across all experiments (2.33 ± 0.33 seconds) emphasize a key limitation of the system in accounting for such variables, which are essential for optimizing task design and ensuring worker comfort in manufacturing environments. In contrast, Fitts' Law predictions (3.10 ± 0.60 seconds for Experiment 2 and 3.14 ± 0.60 seconds for Experiment 3) mirrored the observed increase, reflecting its better alignment with actual performance.

6.5.2 Influence of Independent Variables on Experimental Time

To address the underestimation observed in the results, the following subsections propose targeted refinements to the MOST system by incorporating key variables—identified through regression analysis—that significantly influence movement time. These refinements include corresponding adjustments to MOST coding, aimed at better integrating these factors into the system and improving its predictive accuracy in real-world applications.

Regression analyses revealed that all examined variables significantly influenced experimental times ($P < 0.0001$). These findings underscore the critical role of factors like Action Distance, Object Weight, and Motion Level in shaping task efficiency and worker performance. Understanding the relative effects of these variables enables the development of more robust time estimation models, which are essential for optimizing task design and improving process workflows in advanced manufacturing environments.

For instance, in Fitted Model 5, a difficult grasp increased movement time by 0.4 seconds, which is comparable to the effects of extending the Action Distance by 25 cm (24.49 cm at the 75th percentile), raising the Table Height by 40 cm (37.63 cm at the 75th percentile), or increasing the Object Weight by 6.7 kg (6.11 kg at the 75th percentile). These comparable effects underscore the importance of integrating these factors into time estimation systems to improve their accuracy and applicability in real-world scenarios.

The observed variability and discrepancies in time estimates emphasize the importance of incorporating the 75th percentile of the population into time estimation systems. By accounting for broader performance variations, such systems can enhance the accuracy and reliability of task planning, particularly in manufacturing environments where diverse worker capabilities and task conditions prevail.

The regression analyses revealed a significant Lack of Fit ($P < 0.001$) and R-squared values ranging from 0.15 to 0.26, indicating moderate explanatory power. These findings suggest that additional factors such as task variability, or interaction effects may influence movement times. Despite improvements to the regression models—such as incorporating participant demographics, anthropometric characteristics, alternative regression frameworks, and outlier adjustments as recommended by Frost (2021) [113]—the lack of fit persisted. This highlights the inherent variability in human performance, which poses challenges to achieving predictive accuracy.

As highlighted by Ozili (2023) [114], R-squared values between 0.10 and 0.50 are considered acceptable in research involving human participants, particularly when the explanatory variables are statistically significant. Similarly, Nau (2014) [115] noted that predicting human behavior or task outcomes often results in lower R-squared values (frequently below 50%) due to the inherent complexity of human responses, which surpass the predictability observed in physical processes. This explains the modest R-squared values observed in the study.

Although the investigated variables significantly influenced movement times, MOST does not account for critical factors like Motion Level and Object Weight. This underestimation of key parameters, particularly for shorter distances, highlights limitations in its coding framework. Further research is essential to refine time estimation systems, ensuring they accommodate these variables to optimize task execution and improve worker safety.

Action Distance

Action Distance was identified as a significant determinant of movement time ($P < 0.0001$), consistent with Fitts's Law, which states that movement time increases with distance. This finding is also in line with Bahccivancilar's (2012) [46] analysis of MTM-1 for distances from 2 cm to 76 cm. Our study extends these insights to movements up to 120 cm, emphasizing the importance of accurately modeling Action Distance to optimize task execution.

The analysis revealed a critical limitation in MOST's accuracy for estimating short-distance task times. The lack of granularity in the A1 zone, which assigns a uniform time value to actions between 5 cm and the maximum reach, fails to capture the nuanced effects of short-distance variations. Addressing this shortfall is essential for improving time predictions in precision-driven manufacturing tasks, where small movements can significantly impact process efficiency.

In practical scenarios, Fitted Model 1 predicts a time differential of 0.495 seconds for movements within the 5 to 50 cm range for a worker with a maximum reach of 50 cm, assuming other factors remain constant (calculated as 0.011 sec $\times$ (50 - 5) cm). For the 75th percentile of the population, this differential increases to 0.526 seconds. Over an 8-hour shift, with an average of 5 movements per minute within this range, the discrepancy amounts to approximately 20 minutes of unaccounted work time per shift. Such inaccuracies can reduce operational efficiency and increase worker strain, particularly in high-throughput manufacturing settings. This underscores the critical need to recalibrate the MOST coding scheme to enhance estimation precision and support worker well-being.

To address these issues, we propose a regression analysis-based refinement of the Basic-MOST coding scheme for the A1 Action Distance zone. Currently, the A1 zone assigns a uniform 0.36 seconds (10 TMU) to all movements starting at 5 cm. Our refinement introduces a base time of 0.36 seconds for 5 cm movements and adds an incremental 0.011 seconds (~0.3 TMU) for each additional centimeter, extending to the maximum reach. This adjustment ensures greater precision, enabling better alignment with real-world task demands.

The proposed refinements divide the A1 zone into four sub-zones, ensuring greater precision in time allocation. Movements between 5 and 15 cm are assigned 0.47 seconds (0.36 sec + 0.11 sec equal to 13 TMU), while movements from 15 to 25 cm are allocated 0.58 seconds (16 TMU). The third sub-zone (25–35 cm) is set at 0.69 seconds (19 TMU), and movements from 35 cm to maximum reach are assigned 0.8 seconds (22 TMU). These calibrated increments transition seamlessly into the subsequent A3 category (1.08 seconds, 30 TMU), thereby ensuring coherence and accuracy in the proposed time estimations within the MOST framework.

Table 6.7 presents the refined values for the Action Distance parameter in the A1 zone, updating the Basic-MOST coding system to improve estimation accuracy. The revised time for the 75th percentile is also calculated to account for a broader range of performance variations. Further research is essential to validate and adjust these boundaries based on new data and the specific context of the study.

Object Weight

The regression analysis revealed that Object Weight significantly impacts movement times ($p < 0.0001$), consistent with findings from Harari et al. (2018) [17], who explored manual material handling of objects up to 23 kg. This relationship highlights the biomechanical and physiological demands of handling heavier objects, which increase muscle exertion and energy consumption. These factors are especially critical in repetitive manufacturing tasks involving objects under 10 kg, where heightened fatigue can compromise worker safety and

Table 6.7 The Proposed Refined Coding Scheme for Basic-MOST's Action Distance Parameter

Index (x10)	**TMU (75th percentile)**	**Action Distance**	**Time (75th percentile) (seconds)**
0	0	5 cm	0 (0)
1.3	13 (14)	5 - 15 cm	0.47 (0.48)
1.6	16 (17)	15 - 25 cm	0.58 (0.60)
1.9	19 (20)	25 - 35 cm	0.69 (0.71)
2.2	22 (23)	35 - 50 cm	0.8 (0.82)
3	30 (31)	1 - 2 Steps	1.08 (1.11)
6	60 (62)	3 - 4 Steps	2.16 (2.23)
10	100 (104)	5 - 7 Steps	3.6 (3.73)
16	160 (166)	8 - 10 Steps	5.76 (5.98)

productivity [116, 117].

Fitted Model 1 indicated that each additional kilogram added to an object's weight increases movement time by 0.26 seconds, assuming all other variables remain constant. However, the MOST system does not account for variations in object weight, assigning a uniform time value regardless of the load being handled. This oversight represents a critical limitation in MOST's time estimation framework, particularly for industries requiring precise workload calculations to optimize task efficiency and ensure ergonomic compliance.

To illustrate the practical implications of this oversight, consider an assembly worker tasked with moving a 10 kg object every minute over an 8-hour shift. Based on the adjustment factor of 0.26 seconds per kilogram, this results in approximately 20.8 minutes of unaccounted work time by the MOST system in a shift. Such discrepancies not only reduce operational efficiency but also increase physical strain on workers, heightening the risk of fatigue-related injuries. This highlights the urgent need for refined time estimation methods that accurately account for object weight.

To address this limitation, we propose incorporating a new 'W' parameter and a coding scheme in the MOST system to represent weight categories. Using regression analysis results from Fitted Model 1, we identified specific weight levels ranging from 'Light' to 'Very Heavy,' each assigned a corresponding time value. Table 6.8 details these categories and their associated time values, offering a simplified framework for estimating the impact of Object Weight on movement time. It is important to note that while the framework includes weights up to 10kg, the experimental validation was limited to a maximum tested weight of 2.66kg. Estimates beyond this range are theoretical and should be interpreted with caution.

Further validation with real-world data is essential to refine these categories and ensure their applicability across diverse contexts.

Table 6.8 The Proposed Object Weight Categories and Associated Time Values for Basic-MOST

Index (x10)	TMU (75th percentile)	Object Weight Category	Object Weight (kg)	Time (75th percentile) (seconds)
1.4	14 (15)	Light	$0 \leq W < 2$	0.52 (0.54)
2.9	29 (31)	Moderate	$2 \leq W < 4$	1.04 (1.11)
4.3	43 (46)	Medium	$4 \leq W < 6$	1.56 (1.66)
5.8	58 (62)	Heavy	$6 \leq W < 8$	2.08 (2.22)
7.2	72 (77)	Very Heavy	$8 \leq W \leq 10$	2.6 (2.77)

Motion Level (Table Height)

The regression analysis revealed that Motion Level significantly impacts Experimental times ($p < 0.0001$). This finding is consistent with Harari et al. (2018) [17], who investigated movement heights ranging from 100 to 120 cm, and Faber et al. (2009) [118], who emphasized the importance of accounting for vertical motion in time estimation. These studies highlight the potential ergonomic and productivity challenges associated with performing tasks at shoulder height or above, particularly in manufacturing environments where repetitive vertical movements are common.

The MOST system currently overlooks the influence of Motion Level on task completion times, highlighting a critical limitation in its accuracy. This gap is especially concerning in scenarios where workers frequently handle objects above standard table height, as seen in seated assembly tasks or high-mix low-volume production lines. Incorporating Motion Level as a factor is essential to improving time estimation reliability and addressing worker well-being in these contexts.

While ISO Standard (ISO 14738 :2008 [105]) considers lifting up to shoulder level ergonomically acceptable, it may not represent the most efficient way to perform tasks. Even within safe ergonomic boundaries, repetitive lifting at shoulder height imposes greater physical demands compared to tasks performed at standard table height. Addressing this inefficiency is critical for optimizing task execution in different workflows and reducing strain-related risks.

Fitted Model 2 shows that each centimeter increase in Motion Level adds 0.012 seconds to movement time. For a 30 cm increase, this results in an additional 0.36 seconds (10 TMU) per movement. Over an 8-hour shift, where workers perform 10 movements per minute at this height for half the duration, this discrepancy accumulates to 14.4 minutes of unaccounted time. Such inefficiencies not only affect production throughput but also elevate fatigue and injury risks, underscoring the urgent need for refining MOST to account for Motion Level as a key factor in task design and time estimation.

To improve MOST's accuracy, we propose introducing a new 'H' parameter and a coding scheme in the MOST system to represent Motion level categories. Using the standard table height as a baseline, the 'H' parameter scales linearly across granular levels up to shoulder height, the ergonomically allowable limit for movements. This refinement ensures greater precision in time estimation and better aligns the system with the demands of ergonomic task optimization.

The proposed refinement adds 0.012 seconds for every centimeter increase in Motion Level, from the table surface to shoulder height. For every 10 cm increment, an additional 0.12 seconds (3 TMU) is incorporated into the estimation. These granular levels range from Low to 'Very High,' as detailed in Table 6.9. By addressing the influence of vertical motion, this approach provides precise time predictions and mitigates risks of musculoskeletal injuries, contributing to safer and more efficient task execution in manufacturing environments. Further validation using diverse industry data is essential to ensure robustness across various contexts.

These refinements not only enhance the accuracy and realism of time estimation but also reflect a human-centered approach to system design. By explicitly accounting for the physical demands associated with lifting heavier objects and performing tasks at varying heights, the system helps reduce fatigue, lower the risk of musculoskeletal injuries, and support ergonomically sound task planning. This shift toward incorporating human physical limits aligns with the principles of Industry 5.0, which emphasize human well-being, sustainability, and the integration of ergonomics into intelligent manufacturing systems.

Grasp Difficulty and Placement Precision

The regression analyses confirmed the significant influence of Grasp Difficulty and Placement Precision on movement times ($P < 0.0001$). Fitted models 3 and 4 revealed that difficult grasps added 0.38 seconds to Experimental Time, while precise placements increased time by 0.16 seconds. These findings underscore the importance of these factors in task execution, particularly in working environments where high levels of precision and dexterity are required.

Table 6.9 The Proposed Motion Height Level Categories and Associated Time Values for Basic-MOST

Index (x10)	**TMU (75th percentile)**	**Motion Height Level Category**	**Motion Height Level (cm above baseline)**	**Time (75th percentile) (seconds)**
0.3	3 (4)	Low	$0 \leq H < 10$	0.12 (0.13)
0.7	7 (8)	Medium	$10 \leq H < 20$	0.24 (0.27)
1.0	10 (11)	High	$20 \leq H < 30$	0.36 (0.40)
1.3	13 (14)	Very High	$30 \leq H <$ up to Shoulder level	0.45 (0.49)

The MOST system accounts for these factors by allocating an additional 0.72 seconds for difficult grasps and precise placements compared to a baseline of easy grasps and approximate precision. However, the difference between our findings and MOST's estimates does not necessarily indicate inaccuracies in MOST ; rather, it suggests that the system may be calibrated for tasks requiring greater precision than those tested in our study. Future research should investigate a broader range of tasks with varying levels of grasp difficulty and placement precision. This would help assess whether MOST's time allocations for these factors are generally overstated or accurately reflect the demands of more complex work scenarios.

Practical Implications

The refined MOST system proposed in this study has important implications for modern manufacturing environments. By refining time estimation through improved precision of key variables such as Action Distance, and by incorporating additional factors like Object Weight and Motion Level, this study enhances the predictive accuracy of motion-based analysis. These improvements support more efficient process planning and resource allocation, ultimately contributing to increased productivity. While the focus is on improving the time system itself, its future integration into advanced Digital Human Modeling platforms lays the groundwork for real-time simulation, automation readiness, and smarter task design—thereby advancing key goals of Industry 4.0, such as digital integration and productivity optimization [119]. In parallel, the system also addresses the goals of Industry 5.0 by promoting human–system collaboration. The integration of physical and task-related variables reflects a shift toward more human-centered and sustainable manufacturing practices, reducing fatigue, minimizing injury risk, and ensuring more realistic and adaptive task design [120]. As such, the proposed refinements not only improve task optimization but also contribute to the development of adaptive and worker-conscious production systems aligned with both emerging industrial paradigms.

6.5.3 Limitations and Future Studies

This study identified key trends related to factors influencing movement times, focusing specifically on short General Move actions. While Zandin (2002) [1] notes that such movements account for about half of all manual tasks during a typical work shift, they represent only a fraction of the tasks performed in manufacturing environments. Consequently, interpreting these findings in broader industrial contexts requires caution. Future studies should expand to include a diverse range of manual tasks with varying complexity, duration, and operational scenarios to enhance the robustness and industrial applicability of the findings.

Additionally, this study acknowledges the limitations of laboratory-based movements, which may not fully replicate the dynamics of actual workplace conditions. To address this, future research should focus on activities conducted in real-world settings, particularly in assembly lines and high-mix, low-volume production systems common in advanced manufacturing. This would ensure that the findings are better aligned with the demands of modern industrial environments, including task variability and worker interaction with automated systems.

Future experiments should include more complex movements of varying durations, improved experimental controls, and an expanded set of variables to capture a broader range of motion characteristics. These efforts would enhance the predictive accuracy of regression models and refine PMTSs, enabling them to better support task design in advanced manufacturing. Improved PMTSs could become more reliable tools for optimizing process efficiency, promoting worker safety, and adapting the MOST system to meet the demands of evolving industrial environments.

6.6 Conclusion

This study evaluated the accuracy of the MOST system against measured times for simple movements, uncovering significant discrepancies. The consistent underestimation of actual times suggests that the MOST system may overestimate human capabilities. While PMTSs like MOST remain valuable for initial planning and resource allocation, addressing these deviations is essential to enhance accuracy and support the demands of advanced manufacturing processes.

Key factors such as Action Distance, Object Weight, and Table Height were identified as significant determinants of movement time, yet they are insufficiently represented in the MOST system. The lack of granularity in the A1 Action Distance zone contributes to inaccuracies, which can be mitigated through the introduction of incremental time values for distinct sub-zones. Additionally, incorporating parameters for Object Weight and Motion Height would address critical gaps, ensuring the MOST system remains relevant for a wider range of tasks in manufacturing environments. These refinements aim to enhance the system's applicability to modern industrial settings, where precision and worker-centric design are paramount.

This study highlights the potential for refining Predetermined Motion Time Systems to close existing gaps, enhance accuracy, and boost their effectiveness for process optimization. By improving time estimation methods, industries can achieve better decision-making, enhanced productivity, and safer work environments. These advancements not only contribute to operational efficiency but also prioritize worker well-being, aligning with the principles of sustainable and human-centered manufacturing practices. These advancements not only contribute to operational efficiency but also prioritize worker well-being, aligning with the principles of sustainable and human-centered manufacturing practices, and reinforcing the broader vision of Industry 4.0 and Industry 5.0 paradigms.

CHAPTER 7 GENERAL DISCUSSION

This chapter provides an in-depth discussion of the research findings, evaluating how the study's objectives were addressed, highlighting their broader implications, and identifying areas for further investigation. The research aimed to develop and validate a time estimation system within Digital Human Modeling (DHM) systems using the MOST framework, focusing on automating time estimation for 3D-modeled tasks, assessing the applicability of the developed DHM-based time estimation method in real-world industrial settings, and refining the MOST system to improve accuracy.

The discussion revisits key experimental results to assess the effectiveness of the proposed methods and their impact on Predetermined Motion Time Systems (PMTS) accuracy, usability, and scalability. By bridging key gaps in traditional approaches, the developed methods lay the foundation for incorporating dynamic ergonomic assessments alongside time analysis. This integration could enable more comprehensive workplace evaluations, supporting proactive design improvements that enhance both efficiency and worker well-being.

Traditional ergonomic assessments in DHM systems have primarily relied on static evaluations, assessing postures at specific moments rather than analyzing how they change over time [8,9]. While effective for identifying posture-related risks, these methods fail to capture sequential task interactions, cumulative strain, and the impact of repetitive motions over extended periods [14]. As highlighted in Chapters 1 and 2, existing research has identified the importance of integrating time-based ergonomic assessments to address this gap [8,9].

By developing a time estimation system within DHM, this study provides a structured approach to modeling task durations and sequential actions, laying the foundation for future dynamic ergonomic assessments over time. This approach offers a more holistic method for workplace evaluations, addressing the limitations of static analyses.

The research addressed the first objective by developing an automated process for time estimation using PMTS to analyze action sequences expressed in natural language and modeled in 3D environments. This process automates the generation of time codes by integrating user inputs and predefined assumptions, enabling real-time task duration analysis with minimal manual intervention. The algorithm presented in Chapter 4 successfully converted natural language task descriptions into time estimates, achieving an average deviation of 5.45% from actual measured times during field validation (Section 5.4). These results highlight the method's reliability within the specific industrial contexts studied and its potential to support task planning and resource allocation.

To address the second objective, the applicability of the DHM time estimation system and MOST was further evaluated using data from an automotive assembly line, specifically focusing on operations at 26 workstations. The analysis showed strong agreement between the DHM method and actual measured times, with deviations of less than 10% (Section 5.3). While this indicates reliability within the studied context, it also underscores the need for further validation to confirm scalability and adaptability in diverse industrial scenarios. Variability in task parameters, such as short-distance and longer-duration tasks, revealed discrepancies between estimated and actual times (Table 5.4). These findings informed recommendations for refining the DHM system to improve its ability to account for such variability.

The third objective was addressed by investigating and refining specific aspects of the MOST system to improve its accuracy and applicability. These refinements included :
Action Distance Coding Scheme : Enhanced granularity for short-distance movements, addressing limitations identified in laboratory experiments.
Object Weight and Motion Level Parameters : The development of new data cards to account for these previously overlooked factors, addressing critical gaps in the original MOST framework.
These improvements, informed by regression analyses of laboratory data (Chapter 6), were validated through controlled laboratory experiments. The findings demonstrated the practicality of these refinements but also emphasized the need for broader validation across diverse industries to establish their generalizability.

The chapter is structured as follows : In section 7.1, the research objectives are revisited to evaluate the extent to which this work addressed its goals. Broader implications of the findings, including their potential applications in industrial contexts and their impact on time analysis and ergonomics, are discussed in Section 7.2. Lastly, Section 7.3 outlines the limitations of this research and proposes directions for future studies to further advance the integration of time estimation and ergonomic assessments in DHM systems, particularly refining the DHM-based time estimation system and expanding its validation across diverse industrial scenarios.

7.1 Interpretation of Key Findings and Their Implications

This section interprets the key findings of the research in relation to the three primary research questions and discusses their broader significance within existing literature. The study aimed to develop and validate a DHM-based time estimation system using the MOST framework, enhancing its applicability in 3D virtual environments while addressing critical gaps in PMTS-based time estimation. The findings contribute to improving automation in time estimation, refining PMTS accuracy, and evaluating its real-world applicability.

A major contribution of this research was the development of an automated framework that integrates process planning data and CAD models into DHM environments, providing a structured and efficient time estimation method. The framework successfully parsed and categorized task descriptions into structured MOST time codes, automating their integration into 3D modeling. While the framework automates the extraction of the majority of MOST parameters from DHM user inputs and CAD data , some elements still require manual input by the analyst, highlighting the current limitations in fully automating complex task interpretation.

Validation results showed that this automated method achieved an average deviation of 5.45% from actual measured times, confirming its accuracy and reliability within controlled environments. These findings align with prior studies highlighting the importance of automation in PMTS estimations [7, 9]. However, the study confirmed that manual adjustments remain necessary for complex tasks, particularly when environmental and ergonomic variations introduce additional time estimation challenges. By providing a structured methodology for automating time estimation in DHM, this research significantly advances previous PMTS integration efforts and lays the foundation for improving automation accuracy in future studies.

The second research question examined discrepancies between the developed DHM time method, MOST, and actual task durations in real-world conditions. A field validation study conducted in an automotive assembly line showed that the DHM-based time estimation method closely aligned with actual task durations, with deviations remaining below 10%. However, two significant trends emerged : short-distance tasks exhibited higher deviations, reinforcing the need for finer granularity in MOST action coding, while longer-duration tasks tended to show deviations, likely due to accumulated worker fatigue, an aspect not explicitly considered in PMTS models. These findings support prior research indicating that traditional PMTS models fail to capture long-term variations in motion and fatigue accumulation [17, 18]. Further investigations are needed to refine MOST models to account for working conditions over extended periods.

The third research question focused on validating and refining the MOST system through controlled laboratory experiments. The study identified previously unaccounted factors affecting time estimations, including short-distance movement underestimation and lack of consideration for object weight and motion level.

Statistical analyses confirmed that existing MOST data cards underestimated the time required for short-distance movements and failed to account for mechanical load effects. This led to the development of enhanced action distance coding schemes and new data cards for weight and motion variability. These refinements align with earlier studies [6, 17, 19], which also identified similar inaccuracies in PMTS frameworks. By systematically validating and refining MOST-based estimations, this study contributes to ongoing PMTS validation efforts, improving time estimation accuracy for simple and repetitive movements.

Positioning these findings within the existing body of research highlights their significance. This study extends existing research on PMTS integration into DHM systems by :
1-Automating structured MOST-based estimation within digital human modeling systems, streamlining task analysis and industrial workflow design.
2-Validating the applicability of the MOST and the DHM MOST-based time system in an industrial setting, bridging the gap between theoretical time systems and real-world implementation.
3-Refining MOST coding schemes to enhance accuracy, particularly for short-distance, weight-based motions and motion estimations at different levels.
These contributions align with prior research emphasizing the need for industry-specific PMTS adaptations [7, 9]. By demonstrating the feasibility of integrating PMTS into digital simulations, this study bridges the gap between traditional time estimation and modern workplace design processes.

By improving automation and accuracy in PMTS-based time estimation, this study enhances the reliability of DHM systems for task planning and process optimization. Future research should focus on further refining PMTS models to integrate ergonomic risk assessments, enabling a more comprehensive evaluation of worker well-being. Expanding validation studies across diverse industries will ensure that these refinements generalize beyond automotive assembly, while the development of adaptive PMTS frameworks capable of dynamically adjusting estimations based on fatigue accumulation and work variability could further improve predictive accuracy. These advancements will optimize industrial design processes, enhance worker safety, and improve predictive accuracy in DHM-based simulations.

7.2 Research Impact

Time and ergonomic analyses are essential for enhancing productivity and safety across industries. To address challenges in time estimation within 3D environments, this research introduces techniques and assumptions to automate the process. Automating time analysis within Digital Human Modeling systems streamlines the design process, making it more efficient and cost-effective. By reducing reliance on time experts, this integration minimizes delays and expenses while optimizing work environments.

Traditional DHM tools focus on static postures for ergonomic evaluations, which limits their ability to capture real-world workflows. Incorporating time analysis allows for more accurate assessments of task sequences and dynamic factors such as fatigue, leading to more precise and comprehensive evaluations. This approach supports the design of safer, more adaptable work environments that better align with actual job demands.

The proposed method enables simultaneous time and ergonomic assessments during the design phase. Designers can optimize ergonomics while leveraging automated time estimation, which updates instantly with each design iteration. This integration enhances efficiency, reduces reliance on multiple experts, and minimizes costs, fostering a more cohesive approach to workplace design. Although precise time savings were not quantified, the automated extraction of the parameters and integration into DHM reduced manual input and analysis time substantially. Future studies should quantify this benefit more formally.

By enabling real-time risk assessments in dynamic work conditions, this integrated approach is particularly valuable for industries like construction, transportation, and manual handling, where conditions frequently change. The ability to quickly analyze risks from workflow or workstation modifications supports proactive interventions, improving safety and operational efficiency. Additionally, it encourages collaboration among interdisciplinary teams, promoting a holistic approach to workplace design.

Traditional DHM systems have primarily focused on static assessments, often overlooking the dynamic aspects of human motion. This research introduces dynamic monitoring of motion patterns, enabling more comprehensive ergonomic evaluations. By analyzing repetitive tasks, force exertion, and awkward postures, this data-driven approach also reduces reliance on subjective judgments and supports proactive workplace interventions.

Field validation studies provided preliminary insights into the applicability of the newly developed DHM-based time estimation method within a specific industrial context. While limited to data from a single factory, this research establishes a foundational framework for future studies. Expanding validation efforts across diverse settings will allow for a more comprehensive assessment of the method's adaptability and relevance, ultimately contributing to safer, more efficient workplaces.

A key contribution of this research is the enhancement of the MOST system's data cards. New data cards address previously overlooked factors, such as short-distance motions and object weight and motion levels. These refinements represent a significant update to the MOST system, offering potential benefits for industries reliant on accurate time assessments.

These refinements are particularly useful in sectors such as assembly lines, quality control, and manufacturing, where precise timing is critical for optimizing workflows, cost estimation, and resource allocation. While these updates demonstrate potential, further validation across diverse contexts is necessary to fully realize their broader applicability.

The advancement of DHM systems, now equipped with enhanced time analysis capabilities, offers opportunities across multiple sectors. Industries such as manufacturing, healthcare, logistics, and transportation can benefit from safer and more efficient work environments. This integration provides a foundation for improving the design and optimization of human work processes, with the potential to enhance productivity and worker well-being.

For example, in healthcare, where patient handling and repetitive movements are common, accurate time estimates combined with dynamic ergonomic assessments can reduce injury risks and improve safety measures. Similarly, in warehouse operations and logistics, where tasks involve handling varying object weights and performing movements at different motion levels, these enhanced methods can improve task planning, operational efficiency, and reduce worker fatigue.

7.3 Limitations and Future Research Directions

While developing time systems for Digital Human Modeling systems, this research relied on certain assumptions to simplify the definition of MOST parameters. For instance, joint angles and body positions were primarily used to define the MOST Body Motion parameter, providing a practical framework for time estimation in 3D environments. However, these simplifications limit the ability to capture the complexities of human movement and physical strain during task performance.

A key limitation is the inability to account for dynamic forces and physiological demands, such as muscle fatigue and joint stress, particularly in tasks involving repetitive high-force exertions or awkward postures. For example, even minor changes in posture, like a slight forward trunk tilt, can increase muscle activity, affecting task difficulty and duration. These dynamic elements are not reflected in the current body motion parameter definition, highlighting the need for more comprehensive modeling.

Incorporating advanced biomechanical elements—such as muscle activations, joint torques, and relative body part orientations—could address these gaps. Previous studies, such as Helmstetter and Matthiesen (2023) [83], have demonstrated the potential of force-based methods to align motion categorization with physiological demands, improving simulation accuracy. Such advancements would enhance posture analysis and time estimation by identifying ergonomic risks associated with suboptimal postures, repetitive tasks, or excessive forces, thereby improving safety and reliability.

While these simplifications were effective within the scope of this study, future research should prioritize integrating biomechanical factors to enhance the adaptability of DHM time estimation systems. This would expand their applicability to industries like construction, healthcare, and agriculture, where task variability and physical demands are significantly higher, ultimately supporting a more robust and ergonomic design framework.

The study utilized predefined thresholds within the MOST system to categorize parameters and levels for time estimation. While these thresholds provided a structured framework and achieved reasonable accuracy, they introduced limitations in flexibility and responsiveness to subtle variations in movement patterns, such as changes in joint angles, distances traveled, or individual differences in motion.

For instance, a 5-degree tilt in a joint angle or a 5 cm variation in action distance could alter the Body Motion or Action Distance parameters, impacting time estimates in DHM systems. These variations, which are accounted for in DHM-based systems, may not influence estimations in observational methods, underscoring the need for more flexible and dynamic threshold systems in future refinements.

Future research could address these limitations by developing adaptive systems capable of dynamically adjusting thresholds based on real-time data from sensors or simulations. Such systems might refine movement categorizations to account for task-specific requirements or worker variability. However, their feasibility depends on advancements in hardware integration (e.g., motion capture technologies) and computational modeling, while balancing complexity against potential sources of inaccuracy, such as variability introduced by analyst experience or sensor precision.

Another limitation of this study was the exclusion of individual variability. Differences in joint mobility, physical impairments, and unique movement patterns can affect task performance and ergonomic assessments. Future research should aim to develop models that account for these individual characteristics to enhance simulation accuracy. This approach is particularly important for assessing risks associated with musculoskeletal disorders (MSDs) and tailoring ergonomic solutions to diverse user populations, improving the inclusivity and precision of DHM systems.

Additionally, factors such as worker skill levels, motivation, and environmental conditions were not considered, despite their influence on task performance. Addressing this gap in future studies would require integrating these factors into adaptive models capable of simulating varying skill levels and external influences. Such models could better represent real-world conditions, enhancing the accuracy of task simulations and increasing the relevance of DHM systems for dynamic work environments.

Another limitation is the potential influence of analyst experience on the accuracy and reliability of time estimates. Expertise in applying PMTS across diverse work environments is crucial for accurately recognizing motion elements and addressing work complications. Prior research highlights that analyst inexperience can lead to significant discrepancies in time estimation and system validation [1].

In this research, steps were taken to standardize time estimates and cross-validate them with validated sources, such as the MOST book, and through consultation with experienced MOST analysts. However, the authors' limited field application experience with MOST may have impacted the method's reliability. Future studies should involve expert MOST analysts to further evaluate the method's robustness and ensure its reliability aligns with results obtained by seasoned professionals. Implementing tailored training modules for analysts using DHM systems could also help bridge the expertise gap, improving the system's accuracy and applicability across diverse practical contexts.

The regression models developed in this study explained between 26% and 33% of the variance in movement time data. While all predictors were highly significant, and this level of explanatory power is considered acceptable in human movement studies [114], it also underscores the presence of unmodeled variability. This unexplained variance may stem from factors such as participant fatigue, biomechanical differences, learning effects, and minor inconsistencies in task execution. To further improve predictive performance, future research could explore the use of broader datasets and complementary modeling approaches or machine learning techniques, which may capture additional sources of variability and enhance model generalizability.

To advance the field, future research should explore the integration of advanced motion capture technology and machine learning techniques to model and analyze complex human movements. These technologies can provide accurate and detailed representations of human anatomy and behavior, potentially enhancing the precision of time estimation methods. By leveraging motion capture data and machine learning algorithms, researchers could develop predictive models capable of simulating human activities more effectively, improving task planning, scheduling, and resource allocation in diverse workplace environments.

Looking ahead, the approach could be extended through the use of AI-driven tools trained on large-scale task data to continuously refine time estimates and reduce reliance on predefined motion rules. These tools can adapt to task variability and automate the classification of complex motion patterns, improving both scalability and predictive accuracy in DHM systems [88]. Additionally, integrating sensors that capture biometric data—such as heart rate or muscle activity—could enable the inclusion of physiological factors such as fatigue or exertion, allowing for more personalized and context-aware evaluations.

Adopting professional motion capture methodologies in both laboratory and field validation studies is essential to ensure unbiased and authentic data collection. Motion capture systems should be utilized across diverse industrial settings to capture realistic performance data and minimize the limitations of controlled environments. Combining motion capture with machine learning could enable the refinement of time estimation methods while verifying their applicability in dynamic real-world conditions, providing a robust framework for improving the accuracy, reliability, and relevance of DHM-based systems.

This research has significantly advanced the integration of PMTS-based time estimation within DHM environments by automating structured time analysis, refining the MOST framework, and validating its applicability in industrial settings. By addressing critical limitations in traditional PMTS methods—particularly in accounting for motion variability, object weight, and task complexity—this study enhances the accuracy and reliability of time estimation systems.

The findings demonstrate that incorporating PMTS into DHM enables more efficient and adaptable workplace simulations, bridging the gap between theoretical modeling and real-world implementation. This research has important implications for both academia and industry, laying the foundation for future advancements in digital human modeling, time estimation methodologies, and ergonomic risk assessments. The proposed refinements improve predictive accuracy in task planning, support proactive workplace design, and enhance the feasibility of integrating automation into time analysis. These contributions not only strengthen the scientific understanding of time estimation in virtual environments but also provide practical tools for optimizing industrial workflows, ultimately improving productivity and worker well-being.

CHAPTER 8 CONCLUSION

In today's industrial landscape, optimizing workplace design with an emphasis on worker safety and efficiency remains a critical challenge. Digital Human Modeling (DHM) systems have emerged as valuable tools for addressing these needs. Automating time analyses within DHM systems is increasingly recognized as an effective approach to designing productive and safe work environments.

This thesis was driven by the need to develop and automate time estimation within DHM environments, a capability currently limited in both knowledge and application. To address this gap, we proposed methods to develop and improve time analysis in the 3D environments of DHM systems by adapting the MOST Predetermined Motion Time System (PMTS).

Integrating MOST into DHM systems required adapting its data cards to reflect the unique demands of 3D environments. These adjustments focused on key parameters to better capture the complexities of simulated work scenarios while ensuring alignment with the original intent of MOST. As a result, the adapted MOST data cards provide a foundation for reliable time estimations in DHM systems. While these adjustments demonstrate potential for improving time analysis, further validation in diverse contexts is necessary to fully assess their applicability and scalability in 3D environments.

The introduction of automated time estimation methods within DHM systems marks a notable step forward in enhancing their usability and functionality. By reducing reliance on manual input and specialized expertise, these methods make time estimation more accessible to a broader range of users. This automation streamlines the design process, enabling early and rapid time estimations that support more efficient, human-centered designs and improved task planning.

Additionally, the integration of time estimation within DHM systems provides a framework for conducting more detailed ergonomic analyses that rely on precise task duration data. Traditional DHM systems often focused on static ergonomic assessments, limiting their ability to capture the complexities of dynamic human motion. By incorporating time analysis, this approach enables dynamic monitoring of motion patterns, facilitating a more comprehensive understanding of task-related risks. For example, advanced ergonomic tools such as the OCRA index, which depend on accurate time estimates, can now be applied more effectively to identify and mitigate ergonomic risks.

This research contributes to the field of time analysis by proposing solutions aimed at enhancing the accuracy and applicability of time estimation methods. Through validation studies, we evaluated the MOST PMTS and tested the newly developed DHM time estimation systems. The refinements introduced for both systems demonstrated potential improvements in their accuracy and applicability in specific real-world scenarios. However, further validation across diverse settings is needed to fully establish their broader relevance and scalability.

Validation in real-world industrial settings provided initial insights into the effectiveness of the developed DHM time estimation method. Conducted at an automotive assembly line, the field study highlighted the method's practical performance in a specific industrial context. The results indicated that the DHM method could estimate operational times with a reasonable degree of accuracy, closely aligning with actual measured times. While these findings suggest the potential of the method as a framework for workplace optimization, further validation across diverse industries and work environments is needed to fully assess its robustness and scalability.

The laboratory validation study examined the accuracy of a critical part of the MOST system and identified key gaps in existing time estimation methods. Key issues included uniform time estimates for varying short distances and the omission of important factors such as object weight and movement height levels. To address these gaps, rigorous regression analyses were conducted using a dataset of 6,000 recorded movement times. These analyses informed the development of new coding systems that incorporate previously overlooked factors and led to refinements in the existing Action Distance coding scheme. The enhanced system now provides improved granularity for short-distance movements and introduces additional data cards that account for object weight and motion levels, contributing to greater accuracy in time estimation.

These enhancements improve the alignment of the MOST time system's estimations with real-world conditions, offering industries more reliable time assessments. This progress represents a step forward in refining the application of this widely used time system within industrial settings, while highlighting the need for further validation across diverse environments to fully establish its broader applicability.

In conclusion, the methods and refinements presented in this thesis contribute to advancements in the fields of virtual ergonomics and time analysis. By addressing key gaps and proposing solutions, this research provides a foundation for improving the accuracy, efficiency, and comprehensiveness of ergonomic and time analyses across various industries. Future studies should build on these findings to further refine time estimation methods and evaluate their broader applicability in dynamic work environments.

The enhanced capabilities of DHM systems, now incorporating improved time analysis methods, offer opportunities for industries such as manufacturing, healthcare, and transportation to optimize workplace design and processes. While the integration of these methods lays the groundwork for advancements in human work process optimization, further validation is essential to fully assess their impact. These contributions aim to support improved productivity and worker well-being, fostering safer and more efficient work environments.

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(54) SYSTEMS AND METHODS FOR ASSESSING DYNAMIC ERGONOMIC RISK

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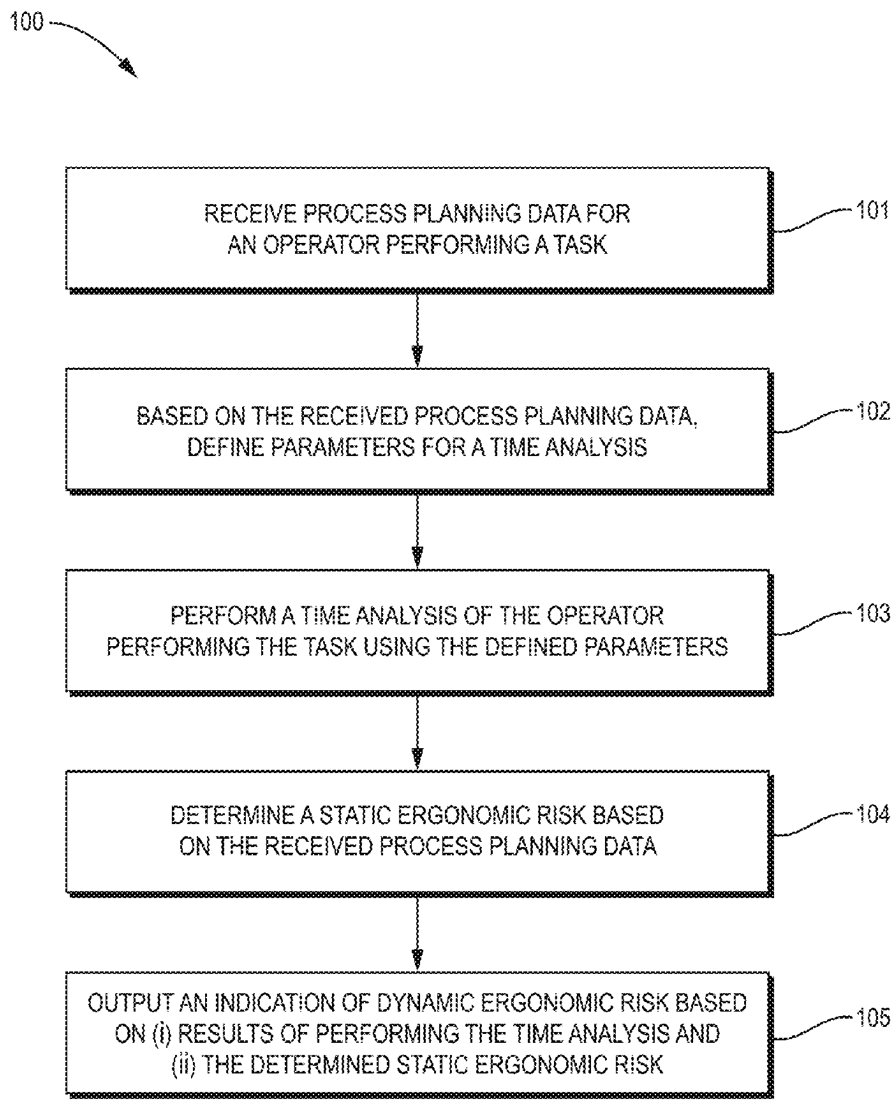
CPC ***G06F 40/40*** (2020.01); ***G06F 11/3612*** (2013.01)

(57) **ABSTRACT**

Embodiments provide functionality to assess dynamic ergonomic risk. One such example embodiment receives process planning data for an operator performing a task. Based on the received process planning data, parameters for a time analysis are defined and a time analysis of the operator performing the task is performed using the defined parameters. In turn, static ergonomic risk is determined based on the received process planning data. Then, an indication of dynamic ergonomic risk is provided based on (i) results of performing the time analysis and (ii) the determined static ergonomic risk.



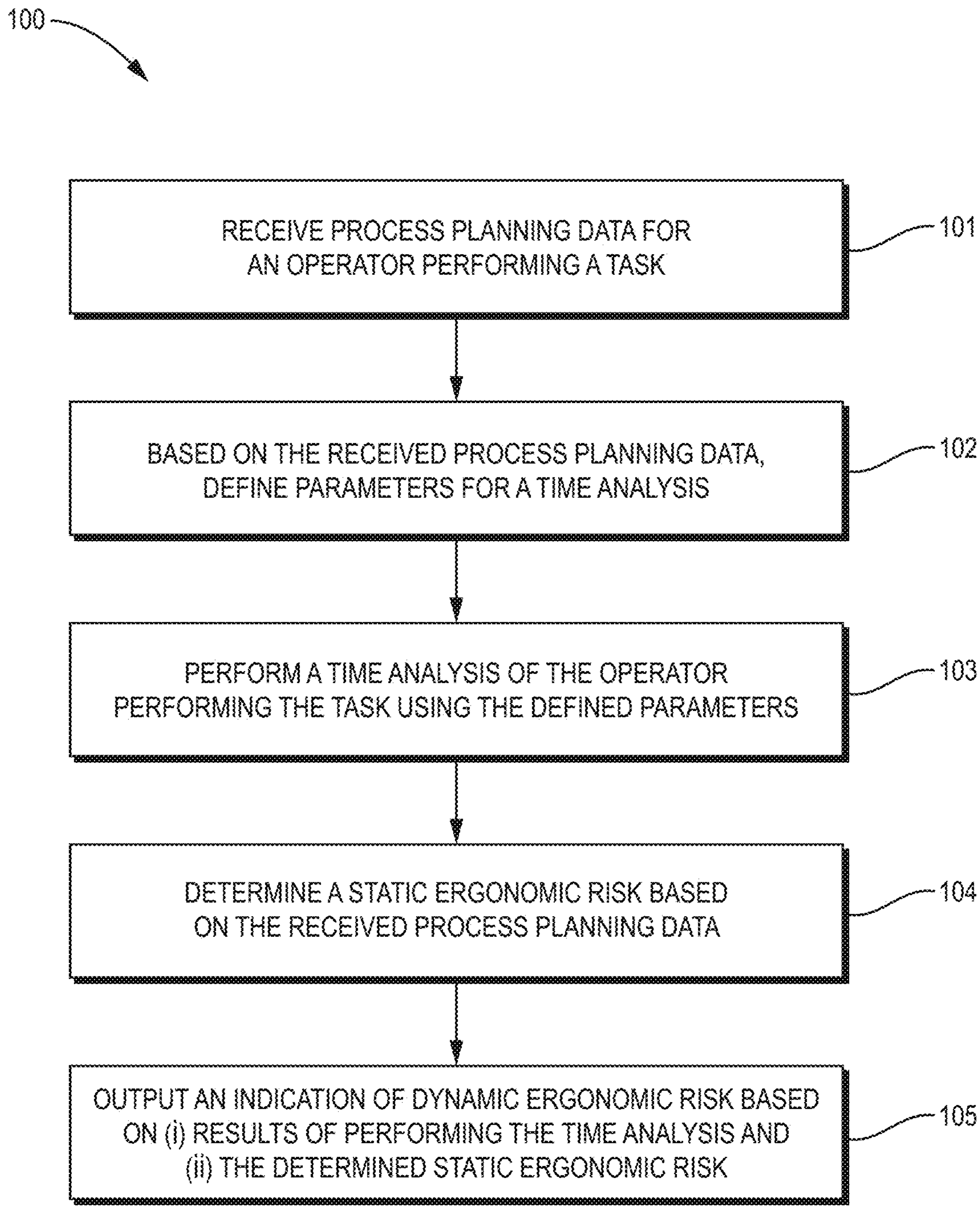

100
RECEIVE PROCESS PLANNING DATA FOR AN OPERATOR PERFORMING A TASK
101
BASED ON THE RECEIVED PROCESS PLANNING DATA, DEFINE PARAMETERS FOR A TIME ANALYSIS
102
PERFORM A TIME ANALYSIS OF THE OPERATOR PERFORMING THE TASK USING THE DEFINED PARAMETERS
103
DETERMINE A STATIC ERGONOMIC RISK BASED ON THE RECEIVED PROCESS PLANNING DATA
104
OUTPUT AN INDICATION OF DYNAMIC ERGONOMIC RISK BASED ON (i) RESULTS OF PERFORMING THE TIME ANALYSIS AND (ii) THE DETERMINED STATIC ERGONOMIC RISK
105

FIG. 1

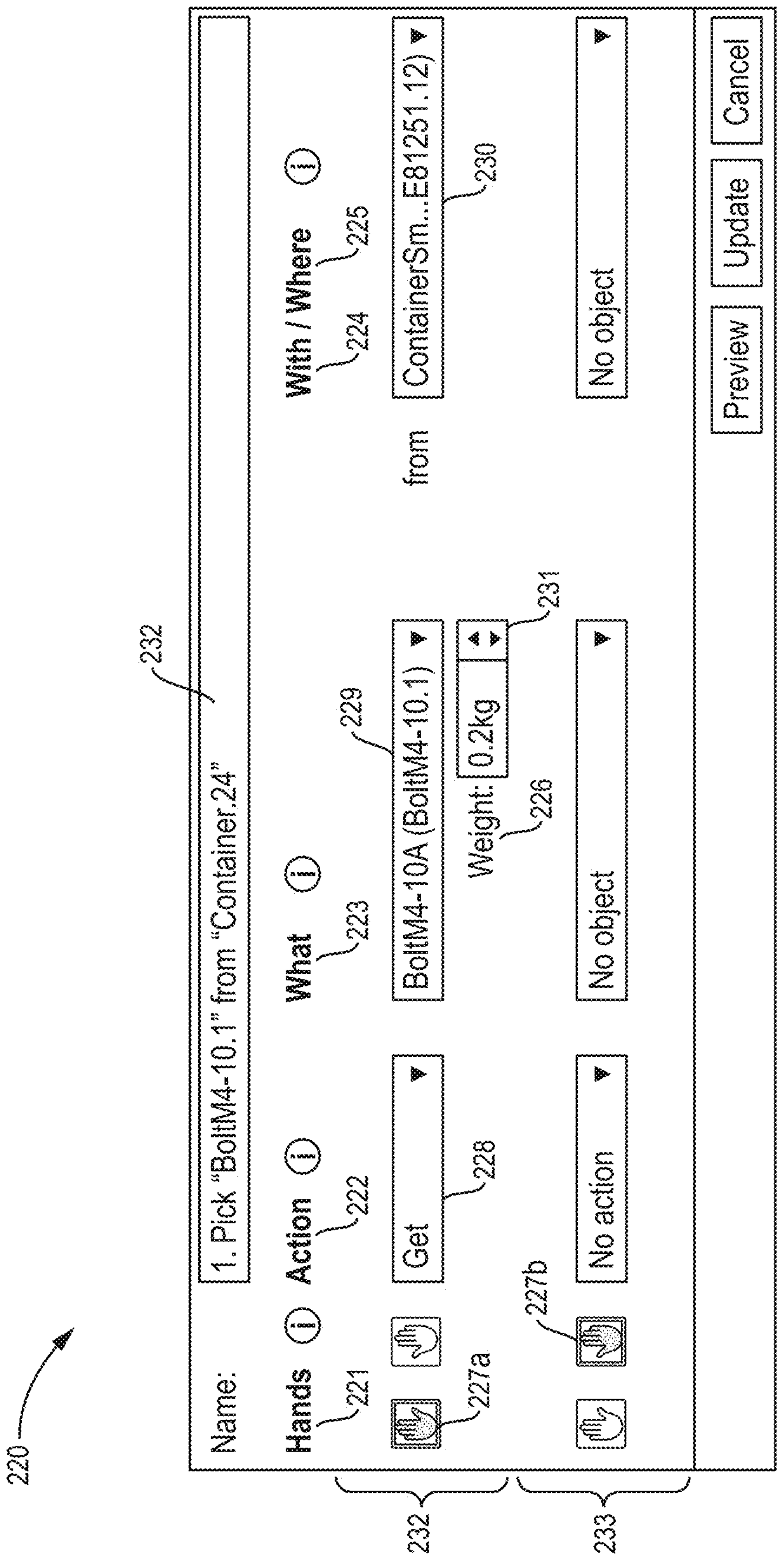

220
Name:
1. Pick "BoltM4-10.1" from "Container.24"
232
Hands
221
Action
222
What
223
With / Where
224
225
227a
227b
Get
228
BoltM4-10A (BoltM4-10.1)
229
Weight: 0.2kg
226
231
from
ContainerSm...E81251.12)
230
No action
No object
No object
Preview
Update
Cancel
232
233

FIG. 2

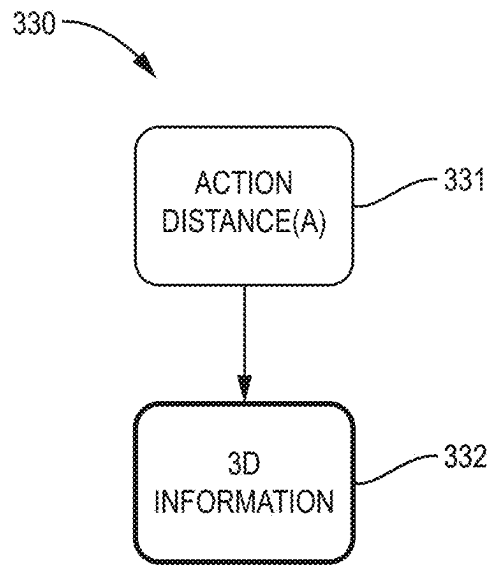

330
ACTION DISTANCE(A)
331
3D INFORMATION
332

FIG. 3

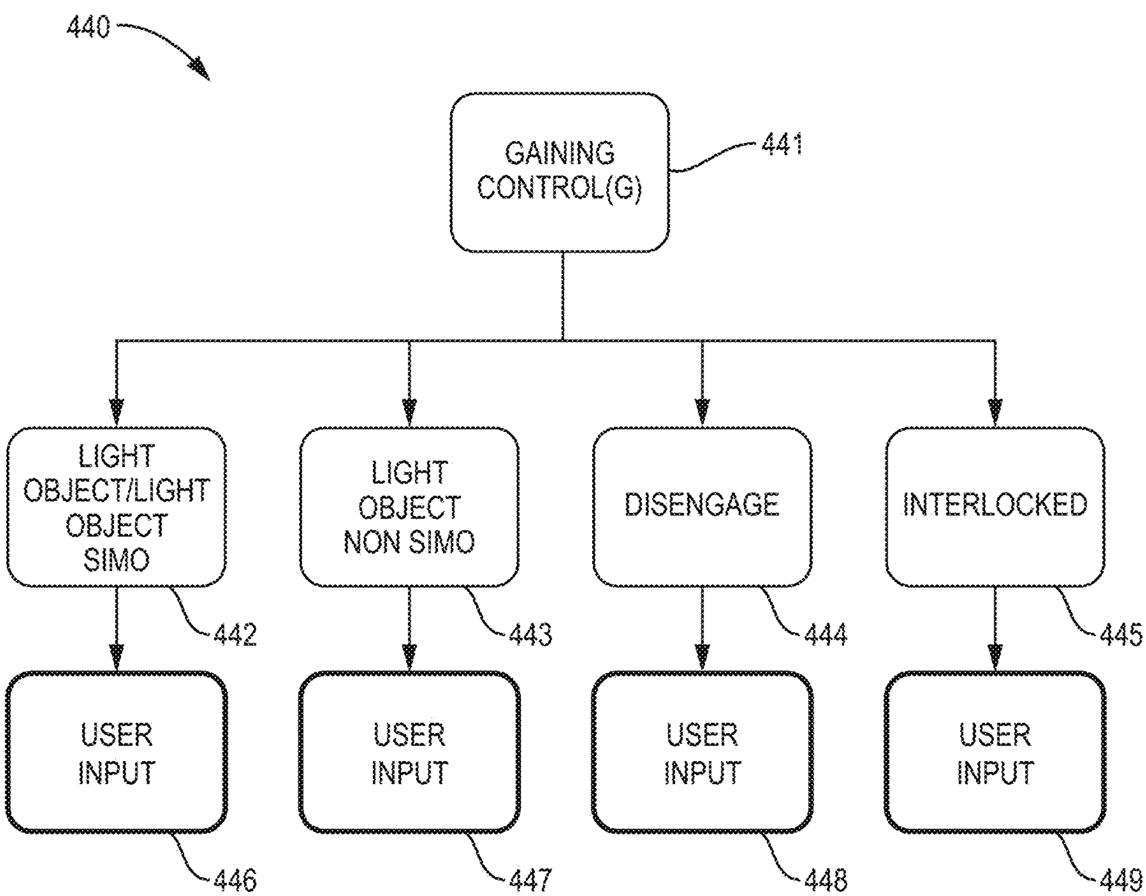

440
GAINING CONTROL(G)
441
LIGHT OBJECT/LIGHT OBJECT SIMO
442
LIGHT OBJECT NON SIMO
443
DISENGAGE
444
INTERLOCKED
445
USER INPUT
446
USER INPUT
447
USER INPUT
448
USER INPUT
449

FIG. 4

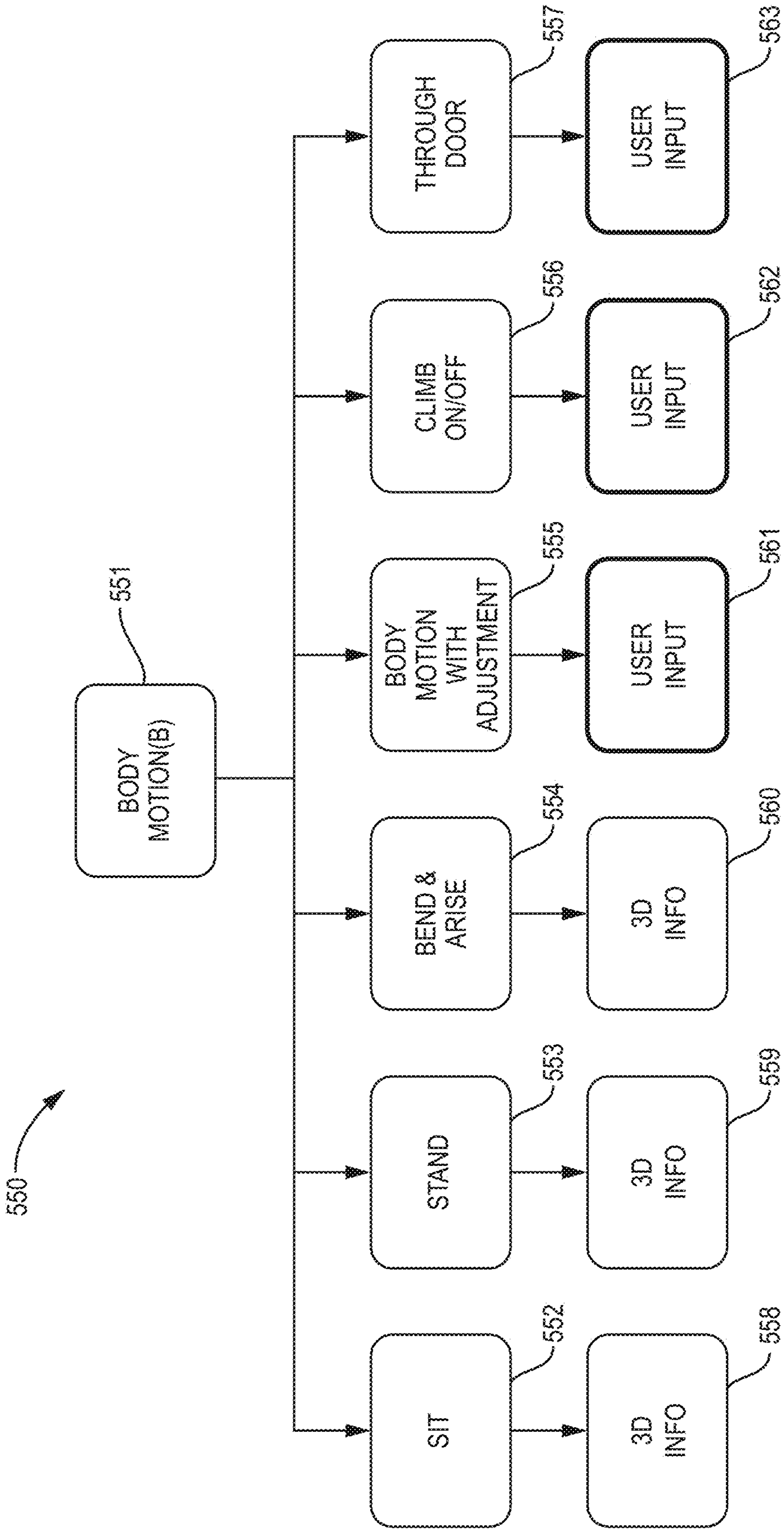
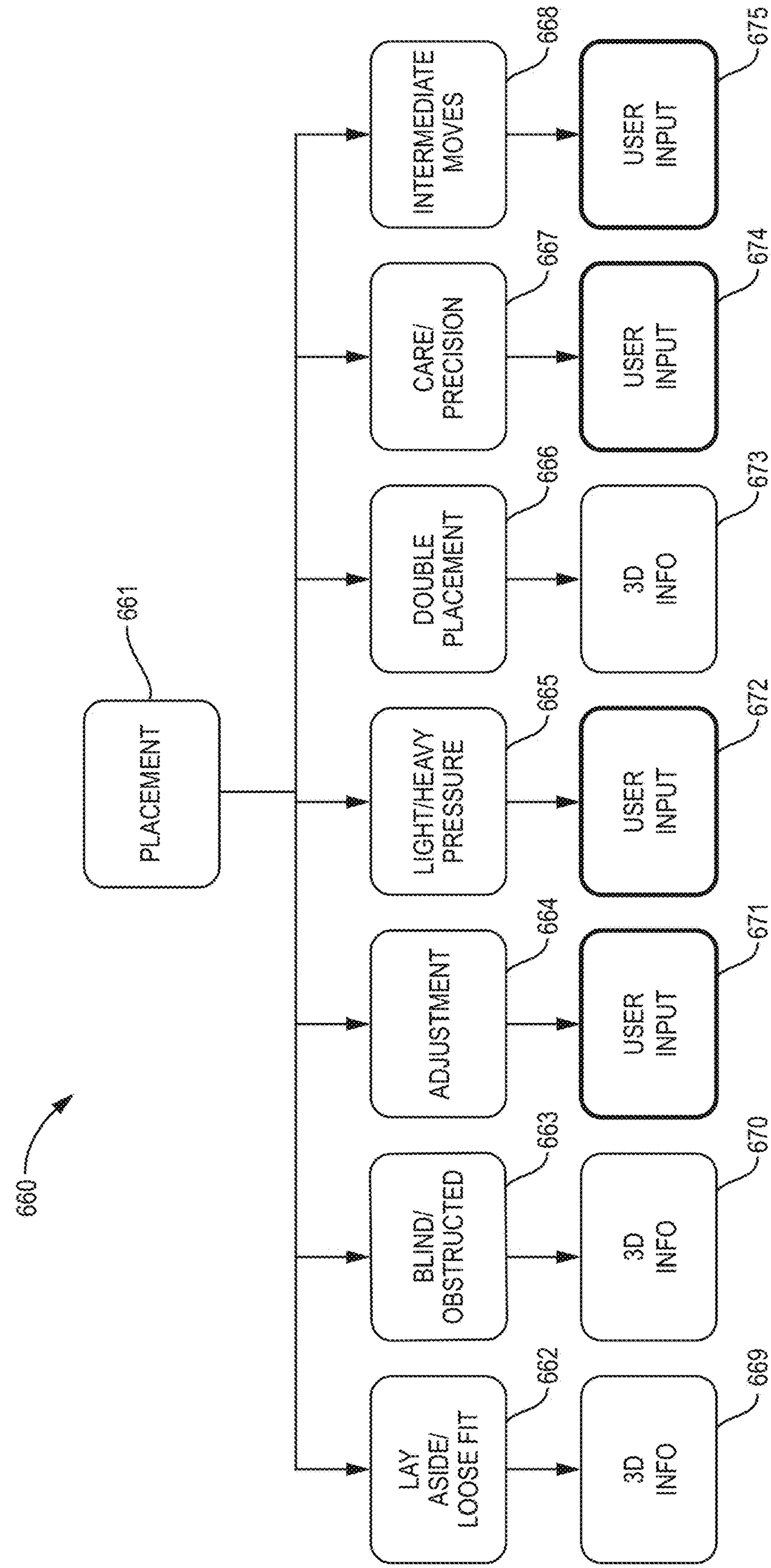

550
BODY MOTION(B)
551
SIT
552
STAND
553
BEND & ARISE
554
BODY MOTION WITH ADJUSTMENT
555
CLIMB ON/OFF
556
THROUGH DOOR
557
3D INFO
558
3D INFO
559
3D INFO
560
USER INPUT
561
USER INPUT
562
USER INPUT
563

FIG. 5


660
PLACEMENT
661
LAY ASIDE/ LOOSE FIT
662
BLIND/ OBSTRUCTED
663
ADJUSTMENT
664
LIGHT/HEAVY PRESSURE
665
DOUBLE PLACEMENT
666
CARE/ PRECISION
667
INTERMEDIATE MOVES
668
3D INFO
669
3D INFO
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USER INPUT
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USER INPUT
672
3D INFO
673
USER INPUT
674
USER INPUT
675

FIG. 6

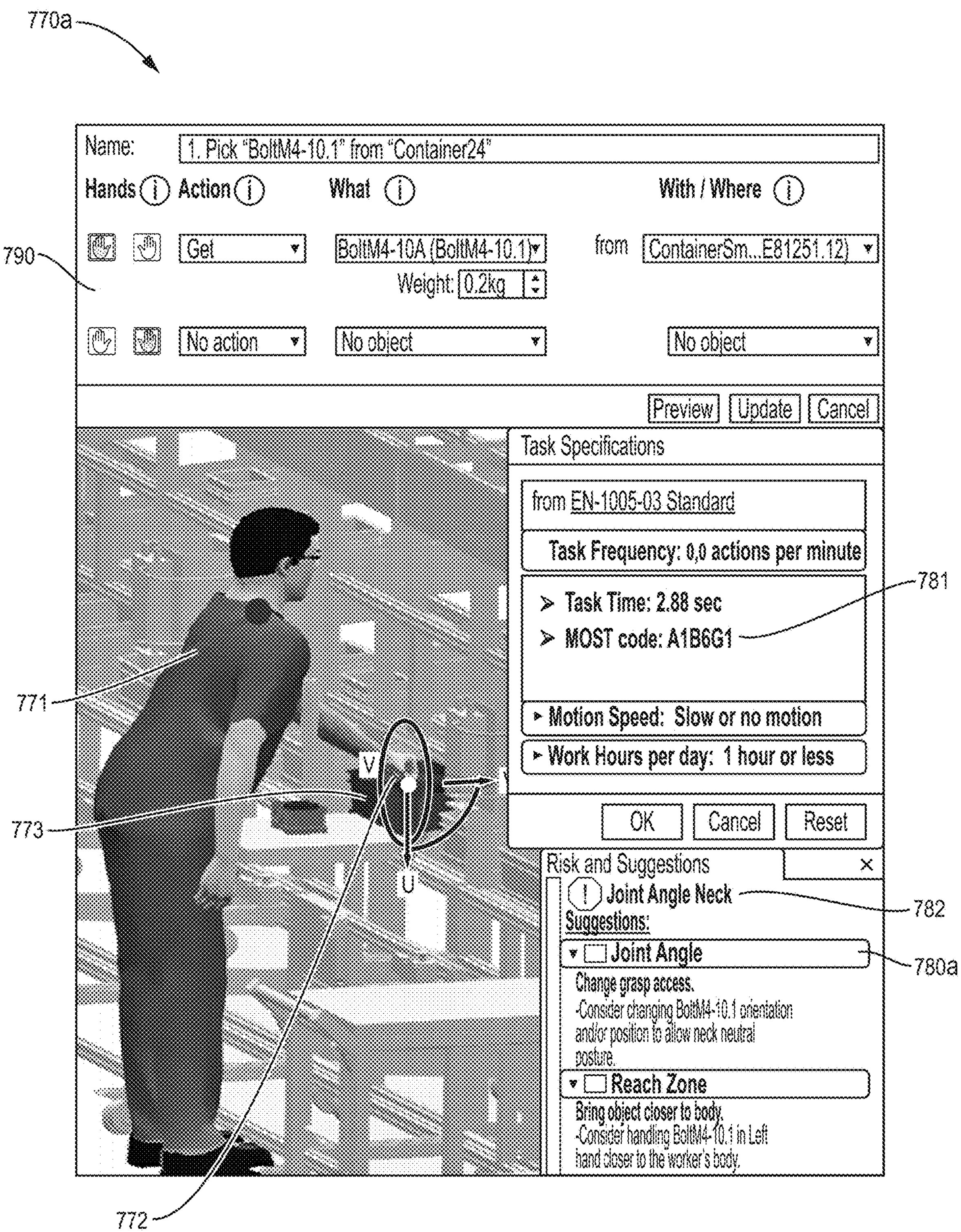

770a
Name:
1. Pick "BoltM4-10.1" from "Container24"
Hands
Action
What
With / Where
790
Get
BoltM4-10A (BoltM4-10.1)
from
ContainerSm...E81251.12)
Weight:
0.2kg
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 2.88 sec
MOST code: A1B6G1
781
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
771
773
V
U
Risk and Suggestions
Joint Angle Neck
782
Suggestions:
Joint Angle
780a
Change grasp access.
-Consider changing BoltM4-10.1 orientation and/or position to allow neck neutral posture.
Reach Zone
Bring object closer to body.
-Consider handling BoltM4-10.1 in Left hand closer to the worker's body.
772

FIG. 7A

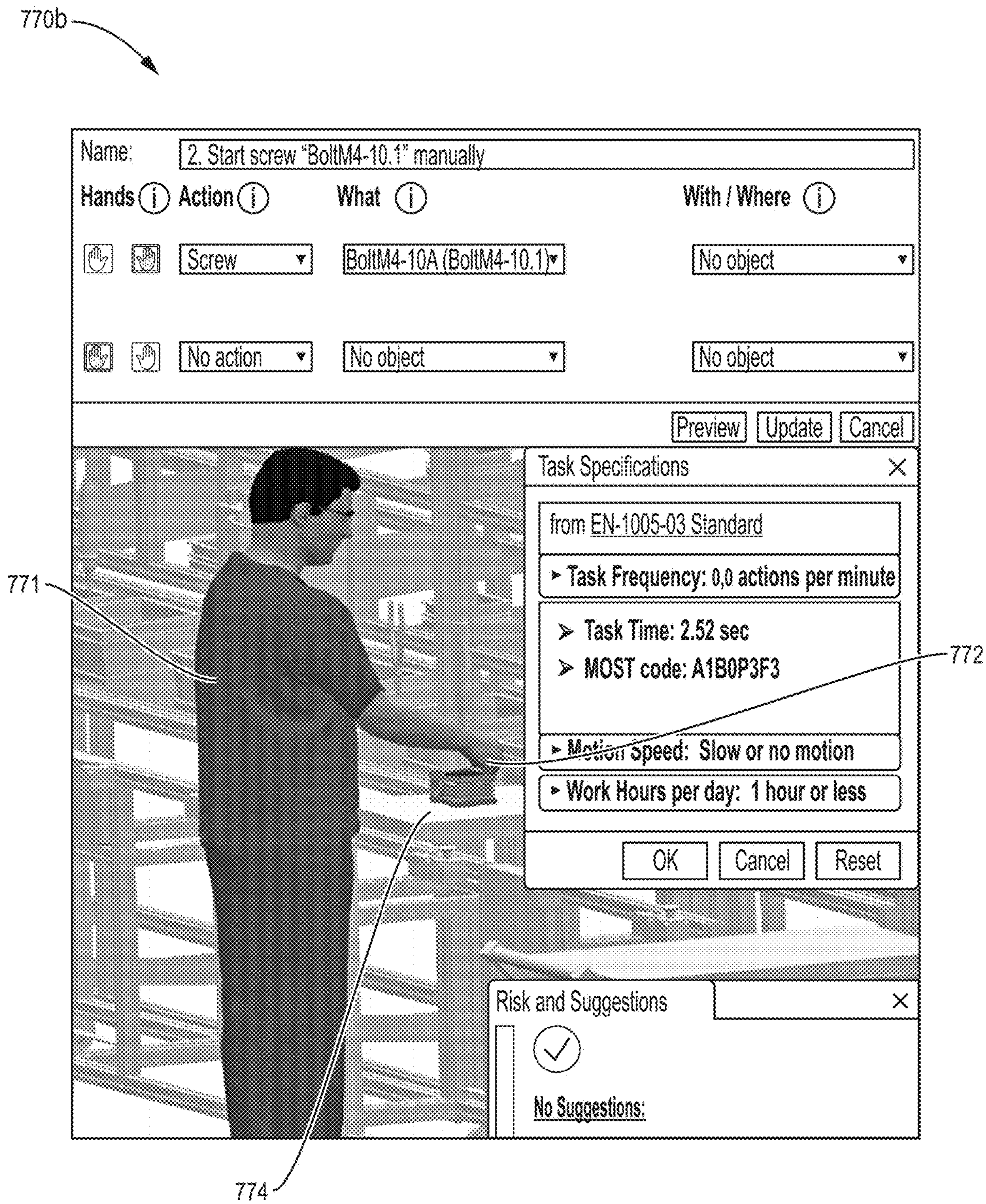
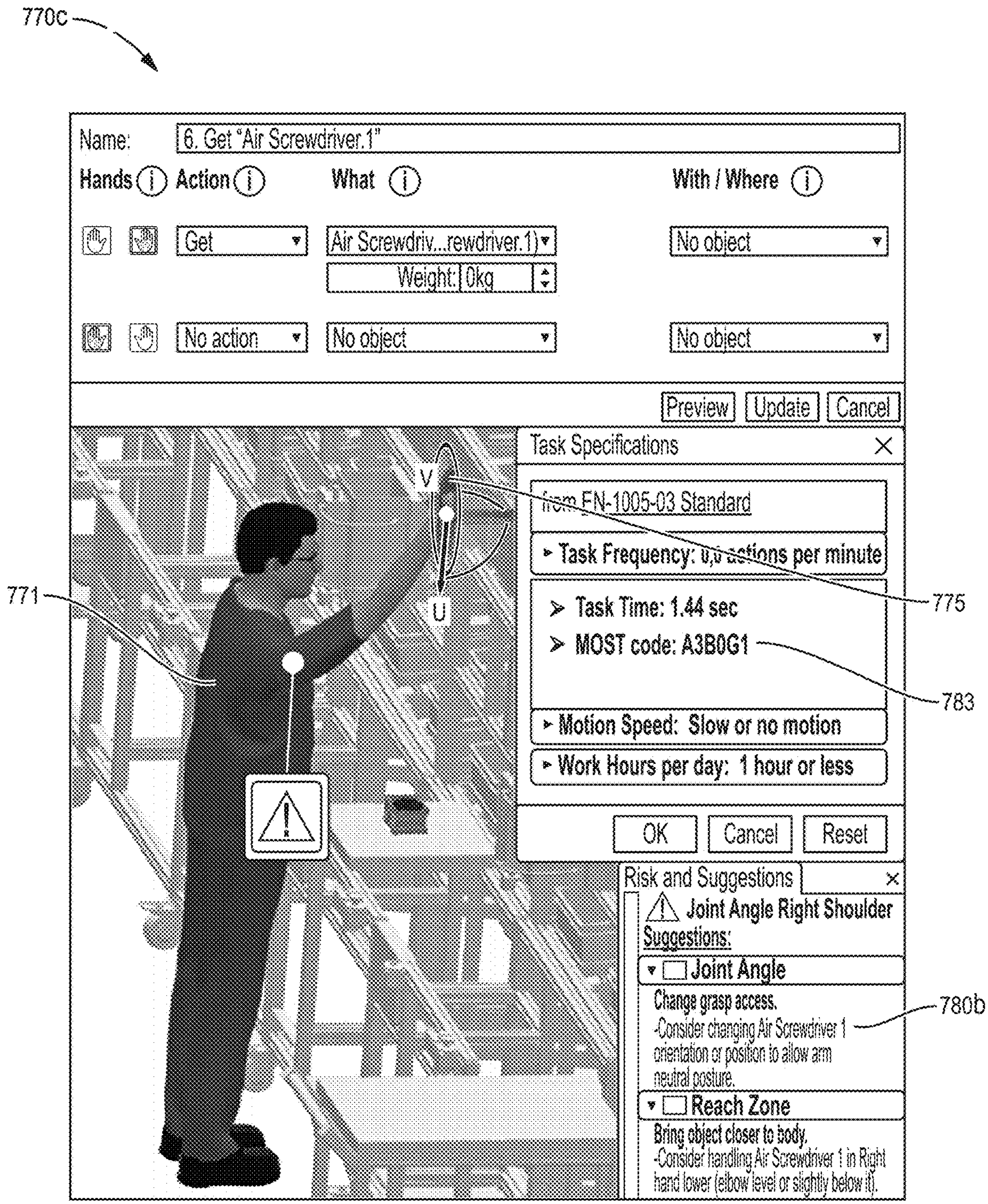

770b
Name:
2. Start screw "BoltM4-10.1" manually
Hands
Action
What
With / Where
Screw
BoltM4-10A (BoltM4-10.1)
No object
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 2.52 sec
MOST code: A1B0P3F3
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
Risk and Suggestions
No Suggestions:
771
772
774

FIG. 7B



770c
Name:
6. Get "Air Screwdriver.1"
Hands
Action
What
With / Where
Get
Air Screwdriv...rewdriver.1)
Weight: 0kg
No object
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 1.44 sec
MOST code: A3B0G1
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
V
U
771
775
783
Risk and Suggestions
Joint Angle Right Shoulder
Suggestions:
Joint Angle
Change grasp access.
-Consider changing Air Screwdriver 1 orientation or position to allow arm neutral posture.
780b
Reach Zone
Bring object closer to body.
-Consider handling Air Screwdriver 1 in Right hand lower (elbow level or slightly below it).

FIG. 7C

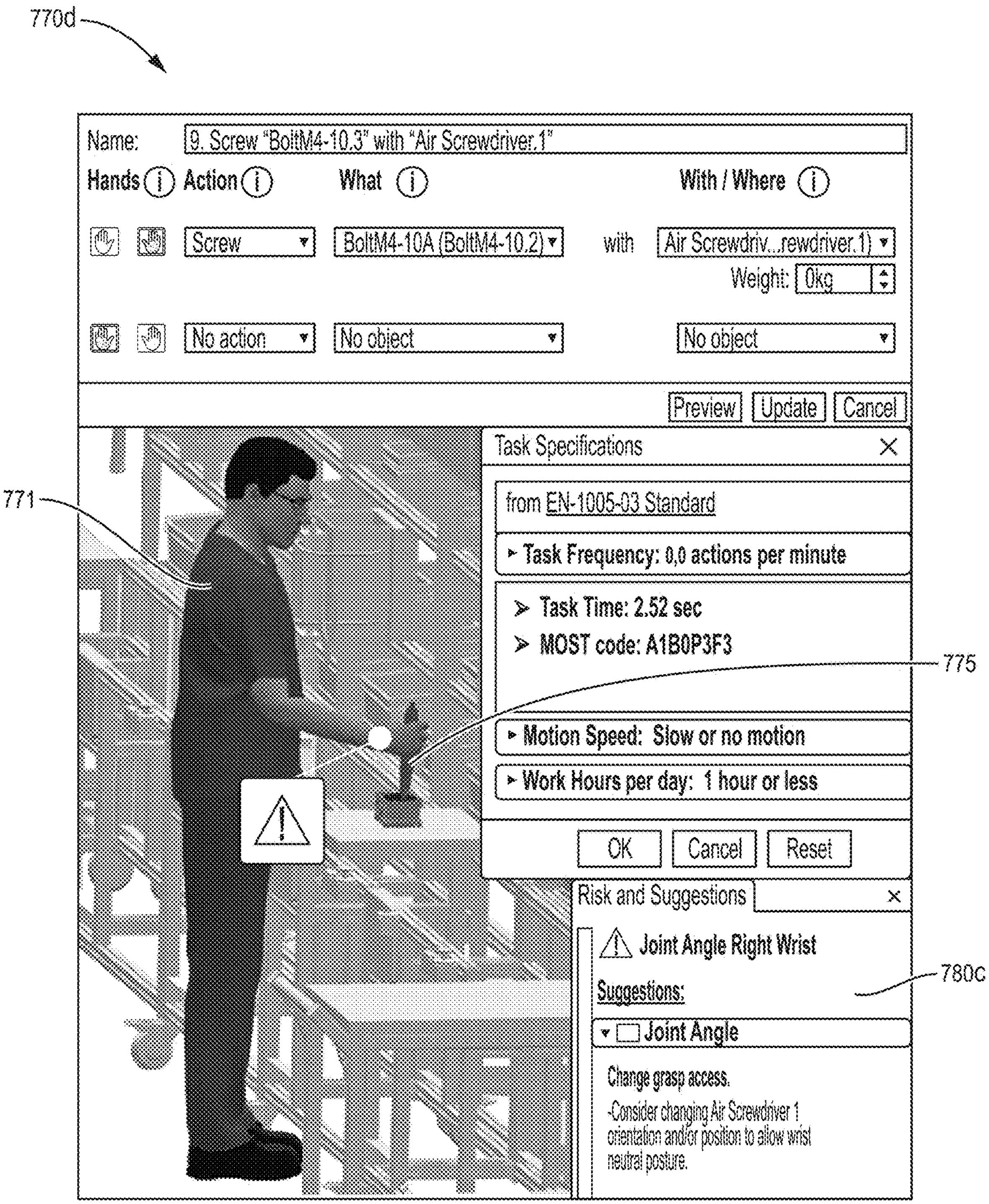

770d
Name: 9. Screw "BoltM4-10.3" with "Air Screwdriver.1"
Hands
Action
What
With / Where
Screw
BoltM4-10A (BoltM4-10.2)
with
Air Screwdriv...rewdriver.1)
Weight: 0kg
No action
No object
No object
Preview
Update
Cancel
771
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 2.52 sec
MOST code: A1B0P3F3
775
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
Risk and Suggestions
Joint Angle Right Wrist
Suggestions:
780c
Joint Angle
Change grasp access.
-Consider changing Air Screwdriver 1 orientation and/or position to allow wrist neutral posture.

FIG. 7D

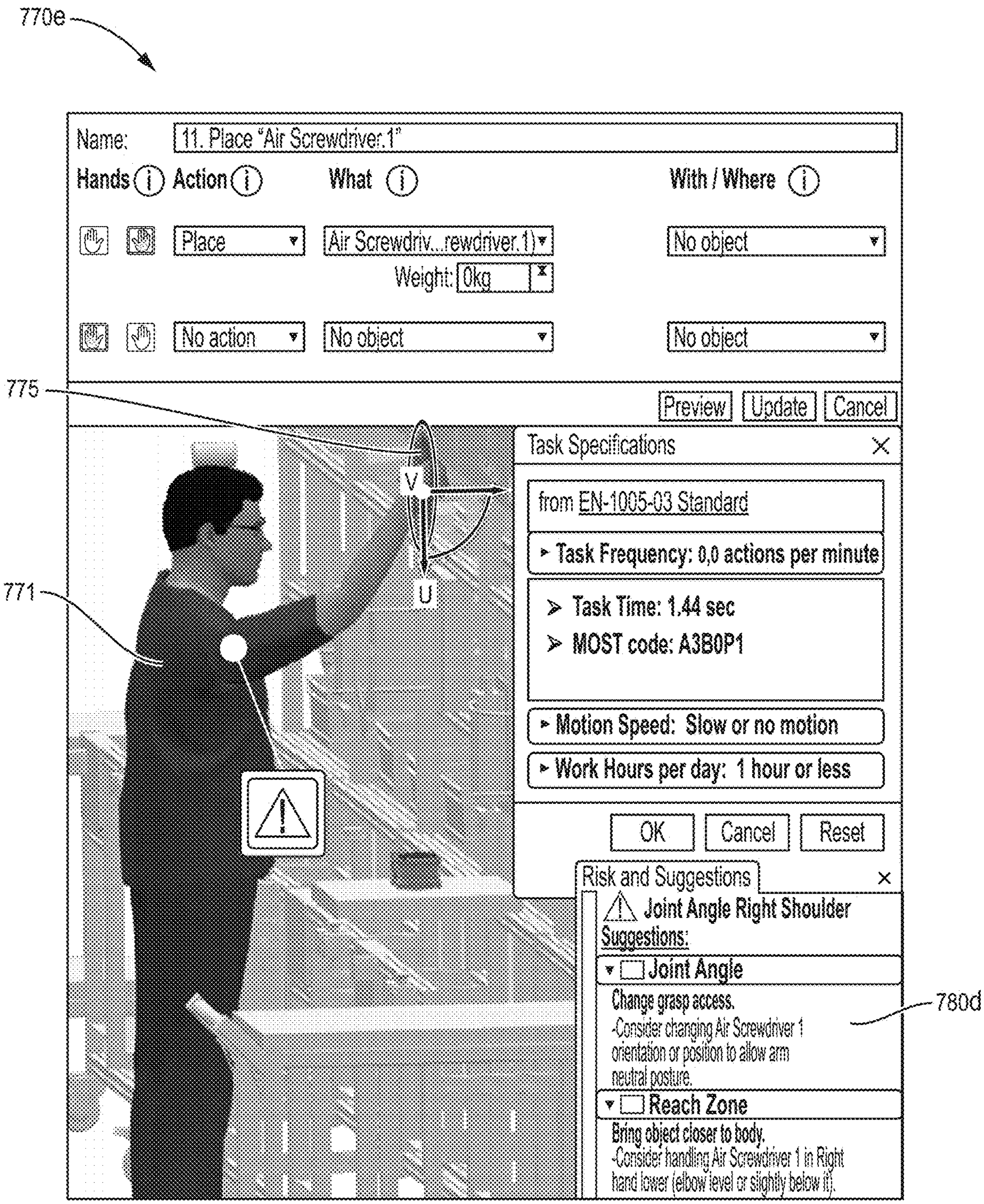

770e
Name: 11. Place "Air Screwdriver.1"
Hands Action What With / Where
Place
Air Screwdriv...rewdriver.1)
No object
Weight: 0kg
No action
No object
No object
775
Preview Update Cancel
771
V
U
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 1.44 sec
MOST code: A3B0P1
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK Cancel Reset
Risk and Suggestions
Joint Angle Right Shoulder
Suggestions:
Joint Angle
Change grasp access.
-Consider changing Air Screwdriver 1 orientation or position to allow arm neutral posture.
780d
Reach Zone
Bring object closer to body.
-Consider handling Air Screwdriver 1 in Right hand lower (elbow level or slightly below it).

FIG. 7E

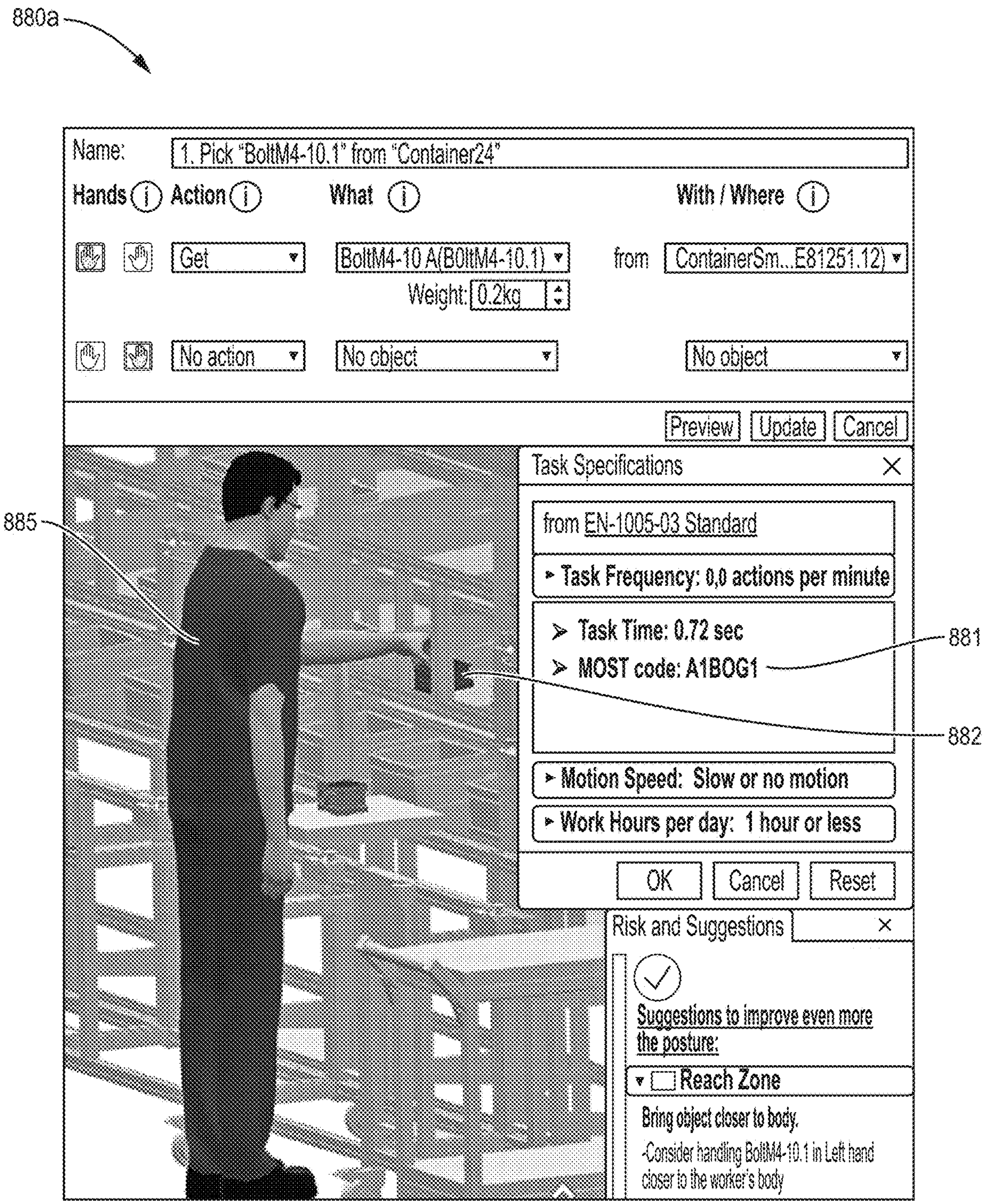

880a
Name:
1. Pick "BoltM4-10.1" from "Container24"
Hands
Action
What
With / Where
Get
BoltM4-10 A(B0ltM4-10.1)
from
ContainerSm...E81251.12)
Weight:
0.2kg
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 0.72 sec
MOST code: A1BOG1
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
Risk and Suggestions
Suggestions to improve even more the posture:
Reach Zone
Bring object closer to body.
-Consider handling BoltM4-10.1 in Left hand closer to the worker's body
885
881
882

FIG. 8A

880b

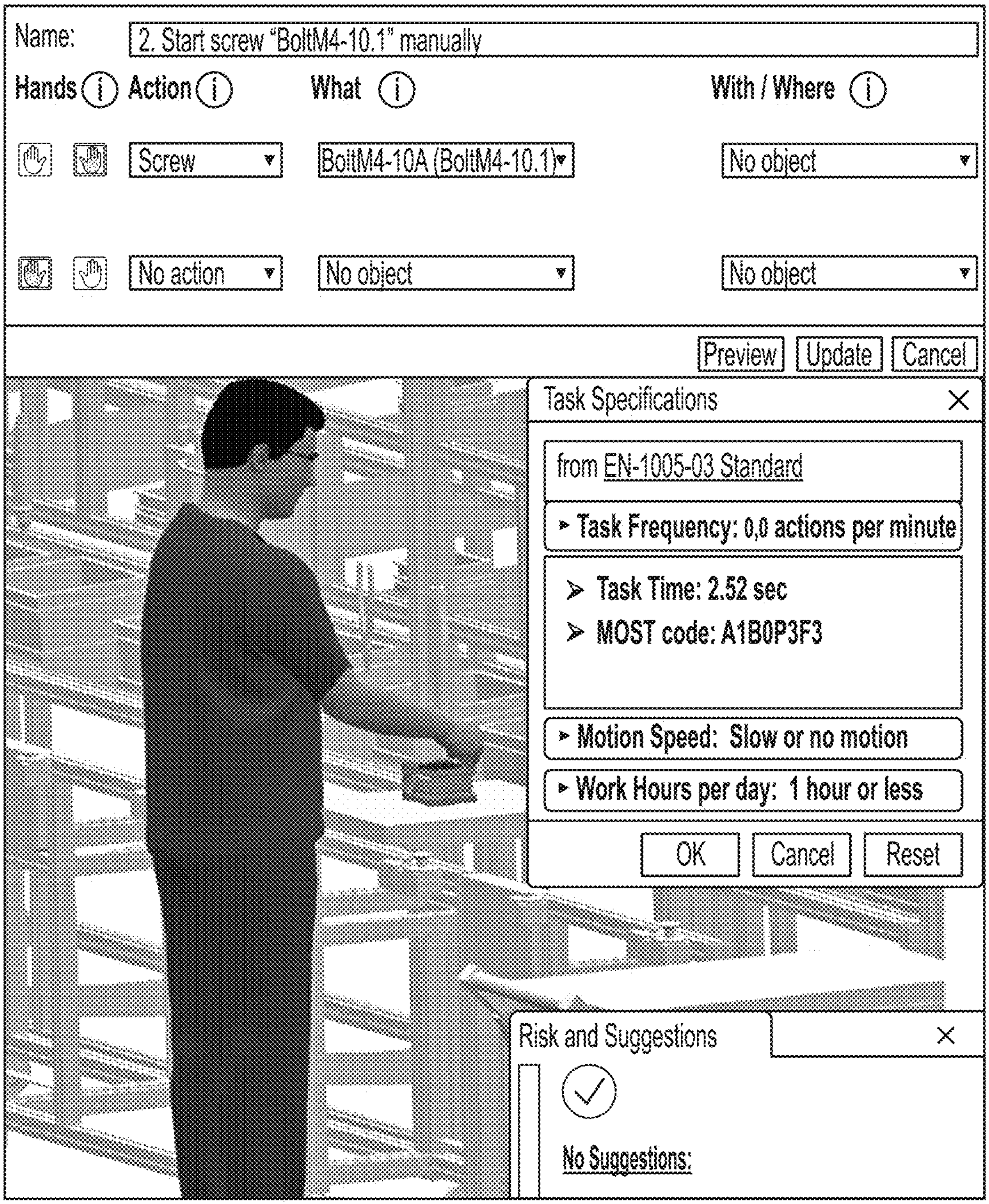

Name:
2. Start screw "BoltM4-10.1" manually
Hands
Action
What
With / Where
Screw
BoltM4-10A (BoltM4-10.1)
No object
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 2.52 sec
MOST code: A1B0P3F3
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
Risk and Suggestions
No Suggestions:

FIG. 8B

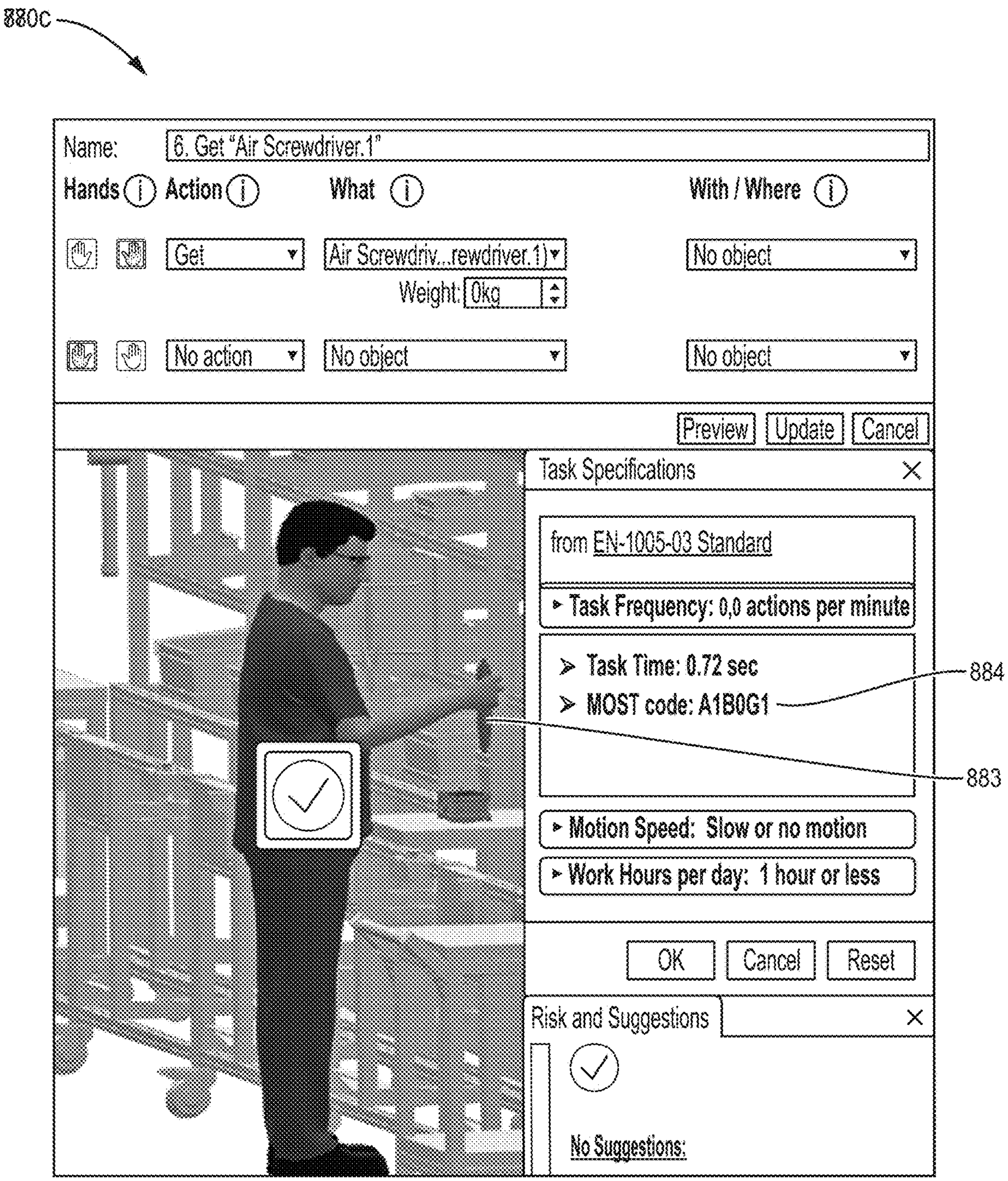

880c
Name:
6. Get "Air Screwdriver.1"
Hands
Action
What
With / Where
Get
Air Screwdriv...rewdriver.1)
No object
Weight: 0kg
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 0.72 sec
MOST code: A1B0G1
884
883
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
Risk and Suggestions
No Suggestions:

FIG. 8C

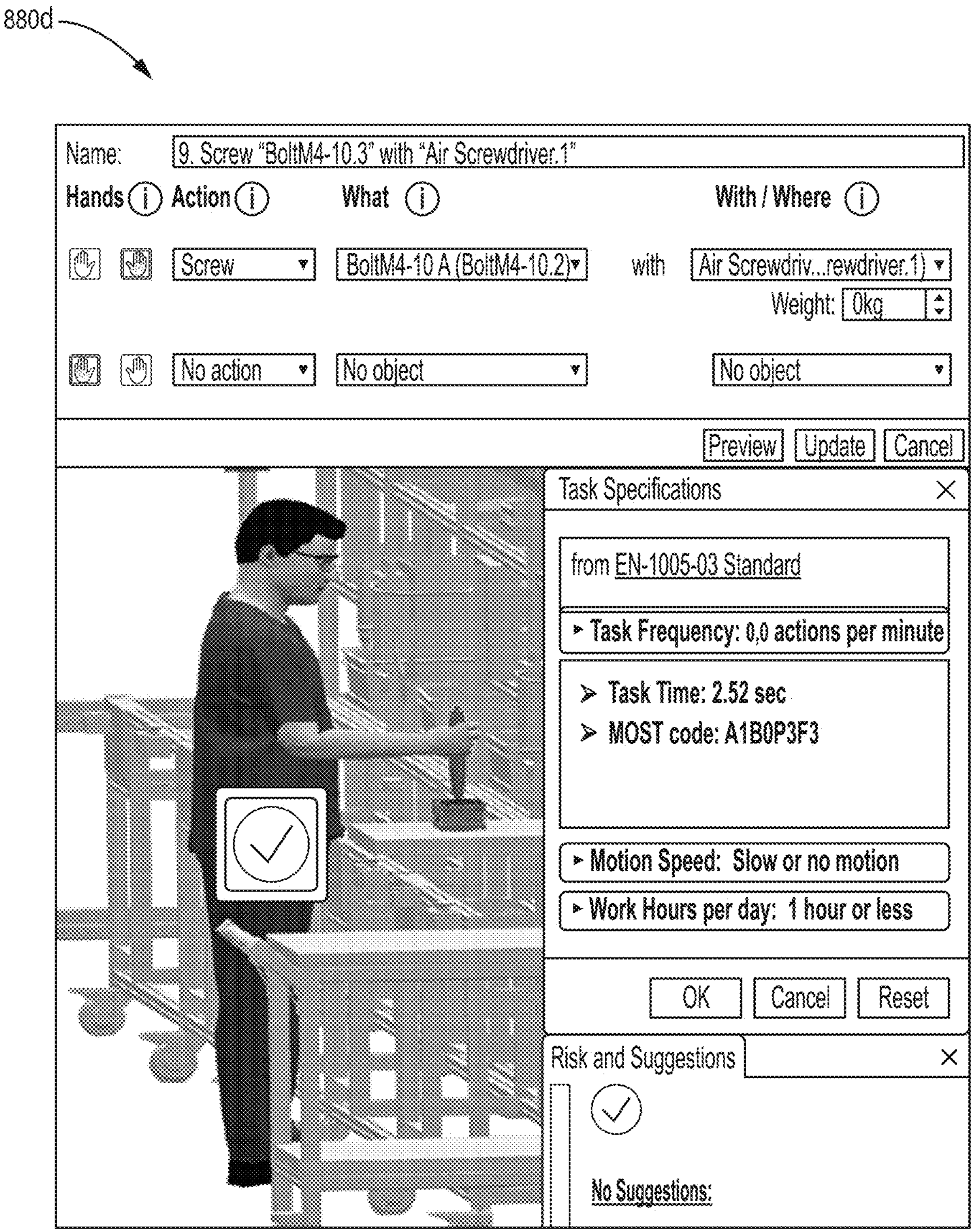

880d
Name:
9. Screw "BoltM4-10.3" with "Air Screwdriver.1"
Hands
Action
What
With / Where
Screw
BoltM4-10 A (BoltM4-10.2)
with
Air Screwdriv...rewdriver.1)
Weight:
0kg
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 2.52 sec
MOST code: A1B0P3F3
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
Risk and Suggestions
No Suggestions:

FIG. 8D

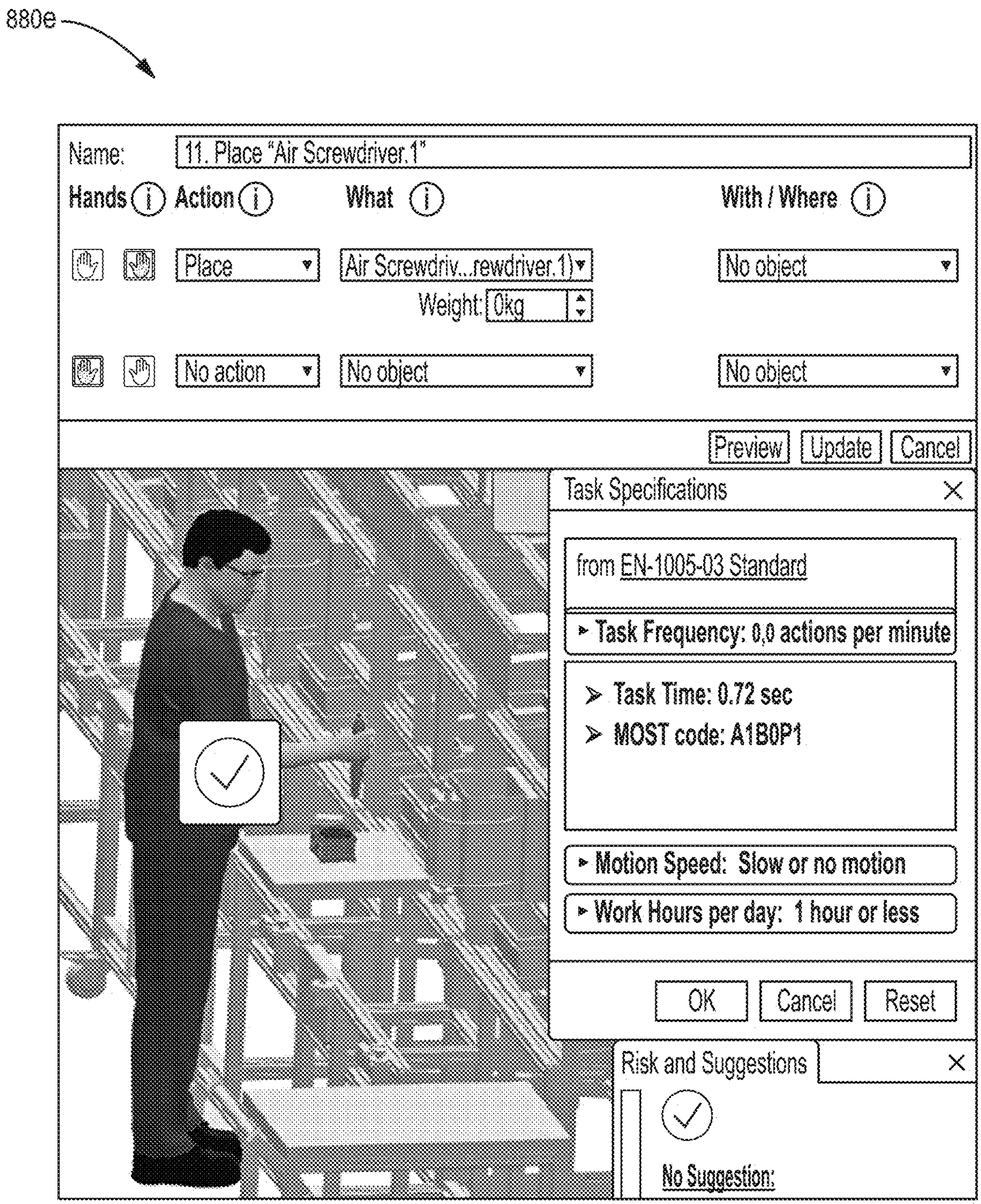

880e
Name:
11. Place "Air Screwdriver.1"
Hands
Action
What
With / Where
Place
Air Screwdriv...rewdriver.1)
Weight: 0kg
No object
No action
No object
No object
Preview
Update
Cancel
Task Specifications
from EN-1005-03 Standard
Task Frequency: 0,0 actions per minute
Task Time: 0.72 sec
MOST code: A1B0P1
Motion Speed: Slow or no motion
Work Hours per day: 1 hour or less
OK
Cancel
Reset
Risk and Suggestions
No Suggestion:

FIG. 8E

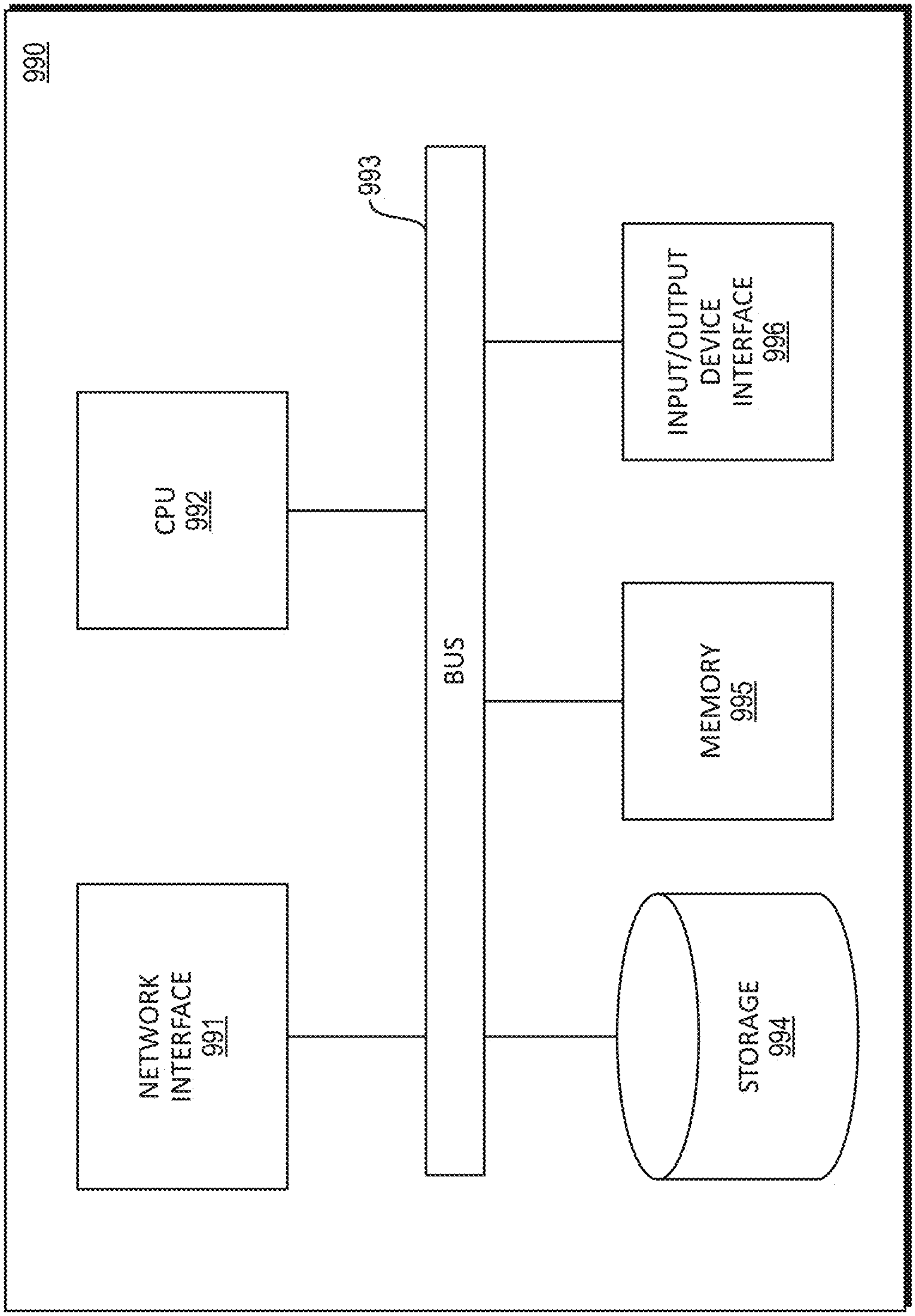

990
993
CPU
992
NETWORK
INTERFACE
991
BUS
INPUT/OUTPUT
DEVICE
INTERFACE
996
MEMORY
995
STORAGE
994

FIG. 9

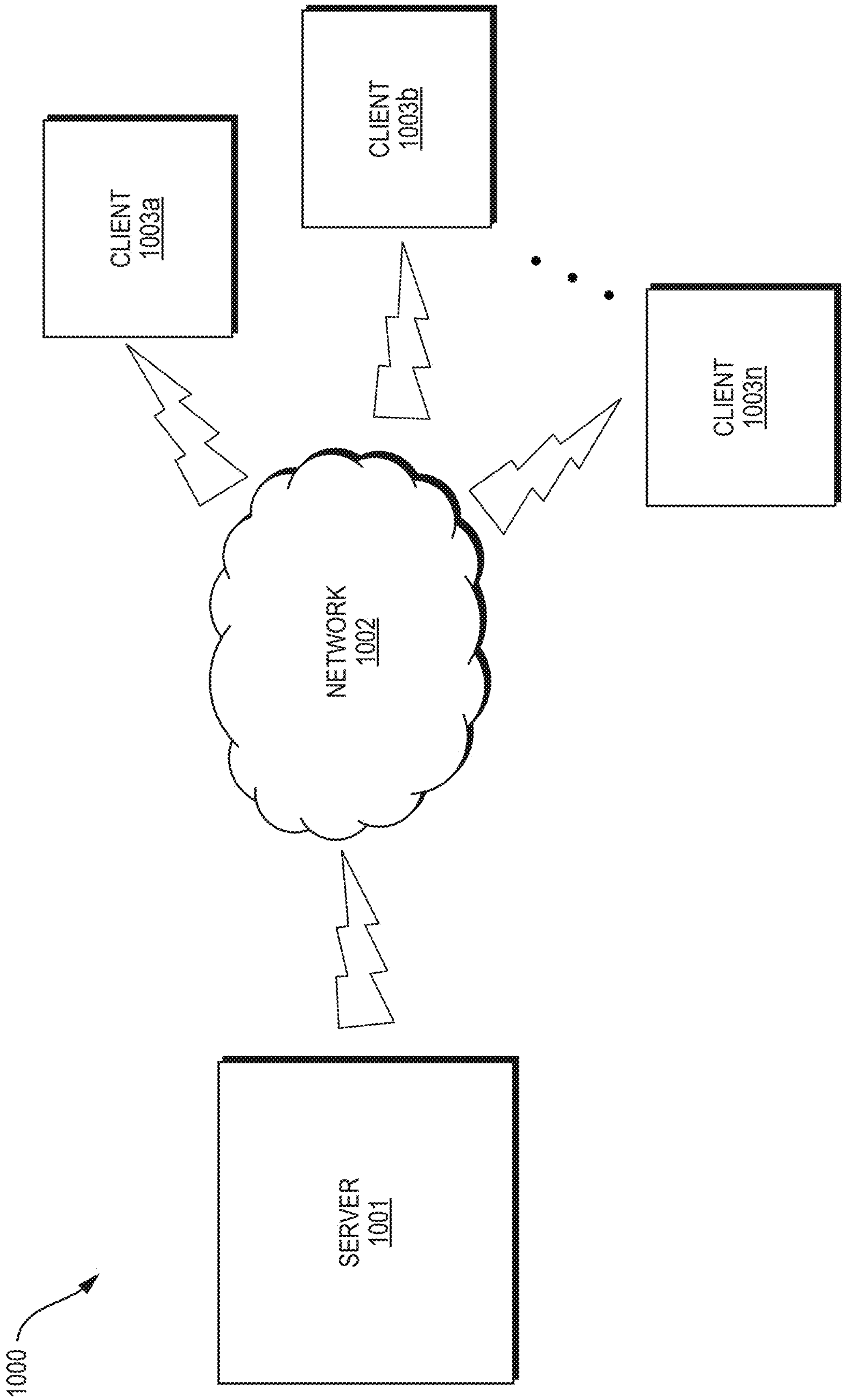

CLIENT
1003a
CLIENT
1003b
CLIENT
1003n
NETWORK
1002
SERVER
1001
1000

FIG. 10

SYSTEMS AND METHODS FOR ASSESSING DYNAMIC ERGONOMIC RISK

RELATED APPLICATION

[0001] This application claims the benefit of U.S. Provisional Application No. 63/476,182, filed on Dec. 20, 2022.

[0002] The entire teachings of the above application are incorporated herein by reference.

BACKGROUND

[0003] A number of existing product and simulation systems are offered on the market for the design and simulation of objects, e.g., humans, parts, and assemblies of parts, and actions, e.g., tasks, associated with objects. Such systems typically employ computer aided design (CAD) and/or computer aided engineering (CAE) programs. These systems allow a user to construct, manipulate, and simulate complex three-dimensional (3D) models of objects or assemblies of objects. These CAD and CAE systems, thus, provide a representation of modeled objects using edges, lines, faces, polygons, or closed volumes. Lines, edges, faces, polygons, and closed volumes may be represented in various manners, e.g., non-uniform rational basis-splines (NURBS).

[0004] CAD systems manage parts or assemblies of parts of modeled objects, which are mainly specifications of geometry. In particular, CAD files contain specifications, from which geometry is generated. From geometry, a representation is generated. Specifications, geometries, and representations may be stored in a single CAD file or multiple CAD files. CAD systems include graphic tools for representing the modeled objects to designers; these tools are dedicated to the display of complex objects. For example, an assembly may contain thousands of parts. A CAD system can be used to manage models of objects, which are stored in electronic files.

[0005] CAD and CAE systems use of a variety of CAD and CAE models to represent objects. Such a model may be programmed so that the model has the properties (e.g., physical, material, or other physics based) of the underlying real-world object or objects that the model represents. Moreover, CAD/CAE models may be used to perform simulations of the real-world objects/environments that the models represent.

SUMMARY

[0006] Simulating an operator, e.g., a human (which can be represented by a digital human model (DHM)), in an environment is a common simulation task implemented and performed by CAD and CAE systems. Here, an operator refers to an entity that can observe and act upon an environment, e.g., a human, an animal, or a robot, amongst other examples. Computer-based operator simulations can be used to automatically predict the behavior of an operator in an environment when performing a task with one or more objects, e.g., target objects. To illustrate one such example, these simulations can determine the position and orientation of a human when assembling a car in a factory. The results of the simulations can, in turn, be used to improve the real-world physical environment. For example, simulation results may indicate that ergonomics or manufacturing efficiency can be improved by relocating objects in the real-world environment.

[0007] Existing simulation methods, e.g., for workplace design, focus on either time analysis or ergonomic analysis. This is both inefficient and cumbersome. As such, functionality is needed that considers both time and ergonomics. Embodiments provide such functionality. In this way, embodiments provide functionality for assessing dynamic ergonomic risk. In other words, embodiments, provide an evaluation of ergonomics while performing a task where the ergonomics evaluation considers the time it takes to perform the task. This provides a significant improvement over existing methods because the comprehensive evaluation of ergonomics hinges on the simultaneous inclusion of time analysis.

[0008] An example embodiment is directed to a computer-implemented method of assessing dynamic ergonomic risk. Such a method receives, in memory of a processor (implementing the method), process planning data for an operator performing a task. To continue, parameters for a time analysis are defined based on the received process planning data, and a time analysis of the operator performing the task is carried out using the defined parameters. Next, such a method determines a static ergonomic risk based on the received process planning data. In turn, an indication of dynamic ergonomic risk is output based on (i) the results of performing the time analysis and (ii) the determined static ergonomic risk.

[0009] In an embodiment, the received process planning data includes a natural language statement. According to one such embodiment, defining the parameters comprises performing natural language processing on the statement to extract an indicator of a movement type. In turn, a category of movement is defined based on the indicator of a movement type. Then, based on the defined category, the parameters (i.e., variables in accordance with a predetermined motion time system (PMTS) model indicating a sequence of sub-activities (i.e., actions, events, etc.) to perform the task) for the time analysis are identified and a value of at least one parameter is set based on the received process planning data. In an embodiment, the parameters form a sequence model that is determined based on the types of motions. The sequence model includes a series of letters organized in a logical sequence. The sequence model defines the events or actions that take place in a prescribed order to perform a task, e.g., moving an object from one location to another. Yet another embodiment defines the parameters by translating an element of the natural language statement into a parameter definition.

[0010] According to another embodiment, the received process planning data includes at least one of: (i) the physical characteristics of a workstation in a certain real-world environment at which the task is performed, (ii) the physical characteristics of the operator, and (iii) characteristics of the task.

[0011] According to another aspect, receiving the process planning data comprises receiving a measurement from a sensor in a certain real-world environment in which the task is performed.

[0012] Embodiments may further include, e.g., prior to defining the parameters, identifying the parameters by searching a look-up table based on an indication of the task in the received data, wherein the look-up table indicates the parameters as a function of the task.

[0013] In an embodiment, the parameters are variables in accordance with a PMTS model (i.e., sequence model) where the variables indicate a sequence of sub-activities to perform a task. According to one such embodiment, the parameters are one of: Maynard Operation Sequence Technique (MOST) parameters, Methods-Time Measurement (MTM) parameters, Modular Arrangement of Predetermined Time Standards (MODAPTS) parameters, and Work-Factor (WF) parameters.

[0014] According to another embodiment, defining the parameters includes automatically defining a first subset of the parameters based on the received process planning data and defining a second subset of the parameters responsive to user input. In an embodiment, automatically defining the first subset of parameters includes (i) using the received process planning data to perform a computer-based simulation of a digital human model performing the task and (ii) defining at least one parameter, from the first subset of parameters, based on results of performing the computer-based simulation. According to another example embodiment, automatically defining the first subset of parameters comprises at least one of: (a) defining a posture parameter based on body position indications from the received process planning data and (b) defining a distance parameter based on an indication in the received process planning data of a start point and end point of the task. In yet another example embodiment, defining a second subset of the parameters responsive to user input comprises: based on the received process planning data, identifying a user prompt; providing the user prompt to a user; and receiving the user input responsive to providing the user prompt.

[0015] In embodiments, the indication of the dynamic ergonomic risk includes at least one of: a risk type, a risk location, a risk level, a suggestion to lower risk, and time to perform the task. Further, in an example embodiment where the indication of the dynamic ergonomic risk includes the suggestion, such an embodiment may determine the suggestion by searching a mapping between risk types, risk locations, and suggestions, wherein the determined suggestion is mapped to a given risk type and a given risk location of the dynamic ergonomic risk. Embodiments may further include implementing the suggestion in a certain real-world environment.

[0016] Another embodiment is directed to a system for assessing dynamic ergonomic risk, e.g., evaluating the probability that performing a task will cause harm to a worker in a workplace. According to an embodiment, the system includes a processor and a memory with computer code instructions stored thereon. In such an embodiment, the processor and the memory, with the computer code instructions, are configured to cause the system to implement any embodiments or combination of embodiments described herein.

[0017] Yet another embodiment is directed to a cloud computing implementation for assessing dynamic ergonomic risk. Such an embodiment is directed to a computer program product executed by a server in communication across a network with one or more clients. The computer program product comprises program instructions which, when executed by a processor, causes the processor to implement any embodiments or combination of embodiments described herein.

[0018] It is noted that embodiments of the method, system, and computer program product may be configured to implement any embodiments, or combination of embodiments, described herein.

BRIEF DESCRIPTION OF THE DRAWINGS

[0019] The foregoing will be apparent from the following more particular description of example embodiments, as illustrated in the accompanying drawings in which like reference characters refer to the same parts throughout the different views. The drawings are not necessarily to scale, emphasis instead being placed upon illustrating embodiments.

[0020] FIG. **1** is a flowchart of a method for assessing dynamic ergonomic risk according to an embodiment.

[0021] FIG. **2** depicts a graphical user interface (GUI) that may be used to input data in an embodiment.

[0022] FIGS. **3-6** are graph diagrams illustrating the contribution of data and user inputs to influencing variables, i.e., parameters.

[0023] FIGS. **7**A-E are interfaces showing data input tools, steps of a task, and results for evaluating, using an embodiment, dynamic ergonomic risk of performing the task.

[0024] FIGS. **8**A-E are interfaces showing data input tools, steps of a task, and results for evaluating, using an embodiment, dynamic ergonomic risk of performing the task.

[0025] FIG. **9** is a simplified diagram of a computer system for assessing dynamic ergonomic risk according to an embodiment.

[0026] FIG. **10** is a simplified diagram of a computer network environment in which embodiments of the present invention may be implemented.

DETAILED DESCRIPTION

[0027] A description of example embodiments follows.

[0028] Work-related musculoskeletal disorders (MSDs) are injuries that affect the human body's movement and musculoskeletal systems, including the muscles, tendons, ligaments, nerves, and other soft tissues (Hales & Bernard, 1996). These disorders can result from various risk factors, including poor posture, repetitive motions, and forceful movements. MSDs are significant public health problems among the leading causes of disability and lost productivity worldwide (Bevan, 2015).

[0029] The economic cost of MSDs is considerable. It is estimated that work-related injuries cost nations 1.2-6.2% of their gross domestic product, comparable to cancer costs (Leigh, 2011). According to a European Agency for Safety and Health at Work report, MSDs account for up to 50% of all work-related illnesses in the European Union and cost an estimated €240 billion per year (Bevan, 2015). In the United States, MSDs account for nearly one-third of all workplace injuries and illnesses, costing employers an estimated $50 billion per year in direct and indirect costs (Silverstein et al., 2002).

[0030] Ergonomics is the scientific discipline concerned with designing products, processes, and systems to optimize human well-being and overall system performance. It aims to ensure that workspaces, tools, and equipment are designed to fit the workers' physical and cognitive capabilities to prevent MSDs and increase productivity. By using ergonomics methods like biomechanical analysis, observation, and self-report surveys, it's possible to identify and mitigate risk factors linked to musculoskeletal disorders (MSDs) (Bernard, 1997).

[0031] Boosting productivity while upholding safety is paramount for any company's success. Enhancing productivity fuels organizational growth and strengthens competitive advantage. Accurately estimating the time required for various operations is a key approach to monitoring productivity. By pinpointing time requirements, companies can streamline processes, optimize efficiency, and ultimately elevate overall productivity levels (Wells et al., 2007).

[0032] Predetermined Motion Time Systems (PMTSs) have been instrumental for many years in estimating the time required for human work sequences, i.e., sequences of sub-activities to perform tasks. Using a PMTS involves breaking down a task into its constituent motions and assigning predefined time values to each of these motions. The primary purpose of PMTSs is to determine the amount of time a worker will need to produce a specific product unit in a simulated future assembly line design scenario. This determination of time holds crucial significance in the computation of the anticipated cost of the product (Zandin, 2002).

[0033] PMTSs encompass several categories, such as MTM, MOST, MODAPTS, and Work Factor. Each PMTS has its own unique attributes, i.e., parameters, and applications, making each PMTS a valuable tool across a range of industrial and manufacturing settings.

[0034] The design of human work processes is a critical task in industrial companies, with productivity and ergonomics being crucial performance indicators. To assess and enhance these indicators, professionals utilize a variety of methods for analyzing and designing work processes. However, most of these methods focus on either productivity or ergonomics considerations separately, rather than addressing both simultaneously. Additionally, the existing methods often require substantial manual effort in terms of data collection and interpretation when performing time and ergonomics analyses (Kuhlang et al., 2023).

[0035] The diverse nature of time and ergonomics analyses necessitates that two groups of people with different expertise, technical language, and perspectives analyze the same design at different times. This makes the process cumbersome and inefficient (Wells et al., 2007). Thus, it is becoming increasingly apparent that effective workplace design requires an integrated approach that encompasses time estimations and ergonomics analysis. This eliminates the need for separate procedures for describing and evaluating work times, and ergonomics aspects, such as postures and force exertions (Laring et al., 2005).

[0036] Digital Human Modeling systems (DHMs) are software solutions that allow users to create virtual models of humans and simulate their interactions with the environment. DHMs have gained increasing popularity in recent years as tools for simulating and analyzing the design of workplaces. DHMs can facilitate ergonomics analysis by integrating various ergonomics methods to evaluate workstations, allowing for the assessment of physical demands on workers and the optimization of work processes before the physical structure is implemented. This, in turn, leads to improved productivity in the design process (Schaub et al., 2012), ultimately reducing the costs and time associated with physical prototyping and testing (De Magistris et al., 2015; Kazmierczak et al., 2007; Falck et al., 2010; Laring et al., 2005).

[0037] Moreover, DHM systems can similarly be used to evaluate existing environments, e.g., a manufacturing line, and determine ergonomic improvements to the existing environments so as to improve worker health.

[0038] One of the primary challenges to the successful application of a DHM is the lack of integration between time estimation and ergonomics analyses for 3D-designed human work (Kuhlang et al., 2023). Ergonomics analysis ensures the safety and productivity of the designed tasks, but feasible times must be assigned to digitally recorded work sequences to achieve design productivity, e.g., the time it takes to perform a task. Additionally, some of the more advanced ergonomics assessment methods, such as Occupational Repetitive Actions (OCRA), require determining the duration of operations. These assessment tools can estimate the MSD risk associated with a worker's movements and postures over a work shift (Colombini, 2002).

[0039] Identifying potential ergonomics related risks and implementing design interventions to reduce fatigue and MSD risks can enhance worker safety and health. Thus, the lack of integration of time estimation in a DHM can limit its effectiveness in analyzing the ergonomics related risks associated with a sequence of events (or sub-activities) that unfolds in time, as it fails to provide the necessary temporal context required for proper risk assessment. This limitation can restrict the modeling, designing, and optimization of human-centric systems and products. Furthermore, it can increase the complexity and cost of the assessment process, as time and ergonomics analysis need to be performed separately with current approaches.

[0040] Efforts have been made to integrate time and ergonomics analysis in approaches such as ErgoSAM (Laring et al., 2005), Ergo-UAS (Vitello et al., 2012), and MTM-HWD (Faber, 2019). However, these existing methods are paper-based and lack integration into automated software solutions, making them time-consuming and challenging to use together with complex in-house integrated software systems.

[0041] Several DHM systems, including Jack, RAMSIS, Pro/ENGINEER, and HumanBuilder, can perform ergonomics analysis of a 3D simulated work sequence. These systems allow the creation of realistic virtual human models, simulate human-environment interactions, and provide a comprehensive approach to ergonomics evaluation (Agostinelli et al., 2021; Miehling et al., 2013). Jack by Siemens is a DHM system for ergonomics analysis that enables integrated ergonomics and time analysis using MTM-1 standards and simulation techniques (Grandi et al., 2021).

[0042] Despite these efforts, there remains a notable deficiency in the availability of virtual ergonomics tools adept at seamlessly integrating predetermined motion time systems (PMTS) with ergonomics analysis within a DHM environment. This insufficiency presents significant challenges in the successful implementation and utilization of DHM tools (Kuhlang et al., 2023). Further research is needed to clearly define the boundaries and research problems and address the gaps in DHM and PMTS integration.

[0043] Embodiments provide such functionality. For instance, an embodiment is directed to a comprehensive framework for conducting time analysis using the MOST (Maynard Operation Sequence Technique) predetermined motion time system within 3D environments of a DHM system. Such an embodiment facilitates automated time analyses on 3D-designed operations of workstations, even by users lacking prior knowledge in the field, resulting in a streamlined and accelerated design process, ultimately leading to increased workplace productivity and safety.

Time Estimation with MOST

[0044] The Maynard Operation Sequence Technique (MOST) serves as a widely adopted time system in various industrial domains. It offers a structured approach for describing and analyzing the diverse actions performed by workers during task execution. These actions encompass a wide range of activities typical of handling objects, such as grasping them, moving them over distances, placing them at precise locations, etc., that is, activities that are typically found in manual assembly tasks. MOST employs data cards containing standardized codes that are used to describe the actions performed by a worker during manual work. The data cards also provide instructions for quantifying additional activities, like walking, machine usage, and tool use that can be part of a work content. To estimate the total time required for a given work content, one simply aggregates the predetermined time values associated with each of the MOST codes that were used to describe the work content, as outlined by Zandin in 2002. The analysis process thus requires, specifying the work content, assigning MOST codes that best describe the work content, and then summing the time values associated with each code. It is noted that while embodiments are described as utilizing the MOST PMTS, embodiments are not limited to utilizing MOST, and any PMTS known to those of skill in the art may be utilized.

[0045] Table 1 shows the three main motions in MOST, along with the corresponding sequence model and parameters (Zandin, 2002). The sequence model specifies the order in which the different parts of motion are performed (e.g., the motion of the hand between two points, to reach an object, grasp it, and then place it at a precise location). The parameters are characteristics of the motion that impact the time it takes to perform it. For instance, if the distance traveled by the hand is large (Action distance), then the motion is expected to take longer and hence a higher time value will be associated with it. To be able to assign time values to all parts of a motion sequence model, one has to characterize all of the parameters, that is, measuring the Action distance in cm in the preceding example. This detailed parameter description is typically done manually while observing a worker performing a work content, and thus it is very time-consuming.

TABLE 1

Sequence models for motions in MOST (adapted from Zandin, 2002).
Motion Sequences in MOST

Activity	Sequence Model	Parameter
General Move	ABGABPAA	A-Action distance B-body motion G-gain control P-placement
Controlled Move	ABGMXIA	M-move controlled X-process time I-alignment
Tool Use	ABGABP*ABPA	F/L-fasten/loosen C-cut S-surface treat M-measure R-record T-think

[0046] Table 2 shows the General move data card, which can help understand how the motion characteristics described by the parameters influence the time it takes to accomplish the motion. For example, the Action distance has up to 6 levels. The higher the level, the higher the index, and the higher the time it takes to travel over the Action distance. In the same fashion, the Placement parameter has 4 levels. At the higher level, if the Placement of the object in its final location requires precision because of a tight fit for instance, then it also requires more time to be performed than at the lower level (pick up or toss). The presence of two identical index columns in Table 2 primarily facilitates ease of use and clarity in recording and analyzing tasks. To utilize the Table 2, e.g., to perform a time analysis in an embodiment, the value for each parameter is identified, e.g., automatically from memory storing the left or right index column of the data card. A higher index value correlates to a longer duration required to execute an action. The basic unit of time measurement in MOST is TMU (Time Measurement Unit). To calculate the time needed for an activity, an embodiment sums up the index values within the sequence model (i.e., the parameters indicating the sub-activities to perform the task). This sum is then multiplied by 10 to convert the sum into TMU, where each TMU equals 0.036 seconds.

TABLE 2

General Move Data Card (adapted from Zandin, 2002)

BasicMOST System		General Move	ABGABPA		
Index ×10	A Action distance	B Body motion	G Gain control	P Placement	Index ×10
0	<=2 Inches (5 cm)			Pick up, Toss	0
1	Within reach distance		Light Object/Light Object Simo	Lay aside, Loose Fit	1
3	1-2 steps	Sit, Stand, Bend and Arise 50% occurrence	Light Object non-Simo, Heavy/Bulky, Blind/Obstructed-Disengage, interlocked, Collect	Loose fit blind/Obstructed, Adjustment, Light pressure, Double placement	3
6	3-4 steps	Bend and Arise		Care/Precision, Heavy Pressure, Blind/Obstructed, Intermediate Moves	6

TABLE 2-continued

General Move Data Card (adapted from Zandin, 2002)					
BasicMOST System		General Move	ABGABPA		
Index ×10	A Action distance	B Body motion	G Gain control	P Placement	Index ×10
10	5-7 steps	Sit& stand with adjustment			10
16	8-10 steps	stand and bend, Bend and sit, climb on/off, Through Door			16

[0047] The MOST codes can be generated once index values are assigned to the parameters based on the characteristics of a motion that influence or impact the time it takes to perform that motion. To estimate the time required for a 3D-designed task in a DHM system, embodiments utilize several sources of information. A significant portion of the MOST building block parameters can be derived from information available in a DHM simulation, such as the inputs used to create a human model or the CAD information accessible within 3D environments. However, some physical data (such as information regarding complex postures like interlocked grasps in the General move category) and mental data (such as information regarding reading or thinking in the Tool use category) is typically not available in a DHM system and, thus, embodiments, cannot identify and extract all of the task characteristics to define MOST parameters in every simulation scenario.

[0048] Embodiments implement techniques to overcome the missing data in these scenarios, e.g., when data needed to define a MOST code is not available or derivable from data in a DHM system. In some embodiments, assumptions are utilized to simplify the extraction of data from 3D models. Additionally, embodiments can obtain supplementary information from DHM users. In this way, embodiments can determine the information to estimate the time for 3D-designed motions.

Application of MOST Predetermined Motion Time System in DHM Systems

[0049] In a real-world work setting, a time analyst typically conducts direct observations of a worker's motions during task performance. The analyst records the fundamental aspects of the worker's movements and subsequently maps these to the relevant MOST codes. Temporal values are assigned based on established empirical data.

[0050] However, in the context of a 3D DHM environment, where a live worker is absent, traditional observation-based methodologies are inapplicable. Instead, to utilize MOST with a DHM system, the data for temporal analysis must be sourced from available resources within the 3D-designed workstation. These available resources include information such as the spatial characteristics and dimensions of manipulated objects, as well as the postures and movements of a simulated worker (DHM), within CAD models.

[0051] To apply MOST in a DHM environment, adjustments to MOST data cards are needed to accommodate the unique characteristics of the simulated workspace and the three-dimensional context of the DHM system. This can include expanding or adjusting the basic elements of the motion sequences and motion characteristics that are described in MOST data cards to reflect the unique aspects of the simulated work/environment and adding new elements to capture information that is relevant specifically in simulated environments. The time values assigned to each element may also be fine-tuned to align with the specific details of the simulated task.

[0052] Currently, DHM systems are capable of analyzing static postures associated with using a tool in a given posture. However, in order to analyze a work sequence or put a time estimate on a work sequence, an embodiment first obtains data indicating the work sequence (i.e., describing the work sequence). Users typically want to use natural/common language terms to describe different actions/activities workers perform in a work sequence. However, there exists a wide range of terminology used to describe work and this wide range of terminology may not correspond directly to the standardized terminology used in PMTSs, e.g., MOST. Therefore, an embodiment translates a user's descriptions of work sequences, expressed in common language terms, into corresponding sequences using PMTS, e.g., MOST, terminology. These modifications and translations enable a PMTS to effectively analyze each activity within work sequences in DHM environments.

Example Solutions

[0053] FIG. **1** is a flowchart of a method **100** for assessing dynamic ergonomic risk according to an embodiment. The method **100** is computer-implemented and may be performed using any combination of hardware and software as is known in the art. For example, the method **100** may be implemented via one or more processors with associated memory storing computer code that causes the processor to implement steps **101**-**105** of the method **100**.

[0054] The method **100** begins at step **101** by receiving, in memory of a processor, process planning data for an operator performing a task. Next, at step **102**, parameters for a time analysis are defined based on the received process planning data and, at step **103**, a time analysis of the operator performing the task is performed using the defined parameters. To continue, at step **104**, a static ergonomic risk is determined based on the received process planning data. In turn, at step **105**, an indication of dynamic ergonomic risk is output based on (i) results of performing the time analysis and (ii) the determined static ergonomic risk.

[0055] The method **100** is computer implemented and, as such, the process planning data may be received at step **101** from any location, memory, or data storage, that can be communicatively coupled to a computing device implementing the method **100**. In embodiments, the received process planning data may include any data known to those of skill in the art that relates to the task being assessed. For instance, in an embodiment of the method **100**, the process planning data received at step **101** includes at least one of: the physical characteristics of a workstation in a certain real-world environment at which the task is performed, physical characteristics of the operator, and characteristics of the task. Amongst other examples, characteristics of objects and/or tools that are utilized in performing, or associated with, the task, may be received at step **101**.

[0056] Further, embodiments of the method **100** may be utilized to assess a real-world environment, e.g., a workstation at a factory, and results can be utilized to modify the real-world environment, e.g., to improve ergonomics. In such an embodiment, receiving the process planning data at step **101** can include receiving a measurement from a sensor in a certain real-world environment in which the task is performed. Amongst other examples, the measurements can include dimensions of a workstation, weights, and dimensions of objects, and locations of objects.

[0057] In yet another embodiment, the process planning data received at step **101** includes a natural language statement. According to an embodiment, the natural language statement is received responsive to user input provided via a graphical interface, such as the interface **220** described hereinbelow in relation to FIG. **2**. In yet another embodiment, the natural language statement is obtained using functionality in U.S. Patent Publication No. 2023/0169225 A1.

[0058] In an embodiment where the process planning data includes a natural language statement, defining the parameters at step **102** includes, first, performing natural language processing on the statement to extract an indicator of a movement type. Examples of indicators of movement type include verbs or phrases that imply actions or movements, such as "get," "move," "grasp," "align," "fasten," or "clean," amongst other examples. These verbs or phrases serve as indicators within the natural language statement. Further, these terms typically align with movement types falling into motion categories such as "General Move," "Controlled Move," or "Tool Use" in MOST. To continue, such an embodiment defines a category of movement based on the indicator of a movement type and, based on the defined category, identifies the parameters for the time analysis. In turn, a value of at least one parameter is set based on the received process planning data. To illustrate such functionality, consider an example embodiment where, for instance, the natural language statement contains the term 'Fasten.' Such an embodiment can define the corresponding MOST motion category which is "Tool use" and, consequently, such an embodiment defines the sequence model for this movement type and identifies the temporal index values for the parameters within this sequence model accordingly. In yet another embodiment of the method **100** where the process planning data includes a natural language statement, defining the parameters comprises translating an element of the natural language statement to a parameter definition.

[0059] According to an embodiment, the parameters indicate the sequence of sub-activities to perform the task. In an embodiment, the parameters indicating the sequence of sub-activities may be parameters from an existing time analysis model, e.g., the sequence of a PMTS model. In other words, in such an embodiment, the parameters are variables in accordance with a PMTS model where the variables indicate a sequence of sub-activities to perform a task. Amongst other examples, in an embodiment, the parameters are one of: Maynard Operation Sequence Technique (MOST) parameters, Methods-Time Measurement (MTM) parameters, (Modular Arrangement of Predetermined Time Standards (MODAPTS) parameters, and Work-Factor (WF) parameters.

[0060] Before defining the parameters at step **102**, embodiments of the method **100** may first identify the parameters to be defined. In one such embodiment, the parameters are identified by searching a look-up table, e.g., Table 1, based on an indication of the task in the received data. In such an example embodiment, the look-up table indicates the parameters as a function of the task. In an embodiment, worker-task actions (as indicated in the process planning data received at step **101**) are used to define a motion category and a sequence model to perform the task, and then, from the sequence model, parameters (e.g., PMTS codes) are defined. To define the parameter values (e.g., codes values) at step **102**, an embodiment investigates objects, tools, distances, posture, etc. Such functionality may include analyzing and/or processing data received at step **101**, and defining the parameters at step **102** based on the results of said analysis and processing.

[0061] In another embodiment of the method **100**, defining the parameters at step **102** includes automatically defining a first subset of the parameters based on the received process planning data and defining a second subset of the parameters responsive to user input. An embodiment of the method **100** utilizes the relationships shown in the graphs **330**, **440**, **550**, and **660**, described hereinbelow in relation to FIGS. **3-6**, respectively, at step **102** to define the parameters. More specifically, such an embodiment can automatically define parameters and define parameters based on user input, in accordance with the graphs **330**, **440**, **550**, and **660** described hereinbelow.

[0062] According to an embodiment, automatically defining the first subset of parameters comprises using the received process planning data to perform a computer-based simulation of a digital human model performing the task and, in turn, defining at least one parameter, from the first subset of parameters, based on results of performing the computer-based simulation. To illustrate, the received process planning data may be used in a DHM system with a 3D model (defined based on the process planning data) that includes a DHM and representations of tools and objects (amongst other examples) to determine properties of the environment being simulated. These properties, e.g., positions of the tools and a posture for the DHM, can be used to define parameters. In an example embodiment, the determined properties are used to calculate the distance between the DHM and a tool when performing a task. In such an embodiment, this distance can be used to define a parameter.

[0063] Further, embodiments of the method **100** may implement a variety of different techniques, alone or in combination, to automatically define parameters at step **102**. For instance, embodiments may define a distance parameter based on an indication in the received process planning data of a start point and end point of the task and/or define a posture parameter based on body position indications from the received process planning data. In an embodiment, posture parameters include "Body Motion" which is a MOST parameter that encompasses vertical movements of the body or actions needed to address obstacles or limitations to body movement. According to an embodiment, defining the posture parameter using indications from the received process planning data includes providing the received process planning data to a Smart Posture Engine™

(SPE™) to determine a posture for the DHM. This determined posture is then utilized in such an embodiment the define the posture parameter.

[0064] In embodiments, automatically defining parameters can also include defining distance, defining body postures, and defining accuracies that are used for time estimations including the accuracies of grasping and placing an object and tools (Gain control and Placement parameters) that can be defined based on the dimensions of the objects or tools. To illustrate, consider an embodiment that is assessing the dynamic ergonomic risk of the action of grasping a cap and placing the cap on an assembly. In such an embodiment, several parameters can be automatically defined based on user inputs and the corresponding 3D model (e.g., through use of a Smart Posturing Engine™ (SPE™)). In such an illustrative embodiment, a user specifies inputs in a user panel, such as the interface **220** described herein. The inputs can include the action, specifics of 'what' and 'where', the active hands, the cap to be picked, and a target assembly for cap placement. In an embodiment, these selections are made from a list of available tools and objects. Subsequently, such an embodiment can automatically determine the following parameters: (1) Action distance: This parameter is automatically determined by the pre-defined layout, specifying distances between the assembly and the cap, the human model, and the cap, as well as the human model and the assembly; (2) Body motion: The embodiment automatically identifies the posture with the help of a SPE™, and a posture tracking system defines the corresponding body motion; (3) Gain control: Based on the dimension of the cap and defined thresholds, the embodiment defines this parameter (for instance, larger caps may require higher control for grasping, resulting in a higher index value for G); (4) Placement: The embodiment, utilizing an expanded action directory, determines the level of pressure needed for assembly and such an embodiment also assesses placement precision by analyzing the cap's dimensions and the cap's fit (play) on the assembly, if the play is more than a threshold, the embodiment can define approximate placement (lower index value), if the play is less than the threshold, the embodiment can define precise placement, leading to a higher index value.

[0065] To define parameters, e.g., the second subset of the parameters, responsive to user input, an embodiment identifies a user prompt based on the received process planning data and provides the user prompt to a user. In turn, the user input is received responsive to providing the user prompt. To illustrate, such an embodiment may analyze the process planning data and, therefrom, identify a parameter that cannot be defined using the process planning data. Such an embodiment will then prompt the user for the data that is needed to define the parameter.

[0066] After defining the parameters at step **102**, the method **100**, at step **103**, performs a time analysis. Performing a time analysis at step **103** may include aggregating the time it takes to perform each operation of performing the task. To illustrate, consider an embodiment where the parameters defined at step **102** each correspond to an operation that make-up a sequence of sub-activities to perform the task. In such an embodiment, each parameter has an associated pre-defined time indicating how long each operation takes. Thus, in such an embodiment, performing the time analysis at step **103** includes aggregating each operation's pre-defined time to determine the total time it takes to perform the task.

[0067] In another embodiment, after defining the parameters at step **102**, the method **100** proceeds to step **103** to complete the time analysis by calculating the total time. Performing time analysis at step **103** may include aggregating the time it takes to perform each sub-activity within the task. To illustrate, consider an embodiment where the parameters defined at step **102** correspond to individual sub-activities constituting a sequence to perform the task. In such an embodiment, each parameter has an associated pre-defined time indicating how long each sub-activity takes. Consequently, the time analysis at step **103** entails summing the pre-defined times for the sub-activities. In such an embodiment, this total is then multiplied by the activity frequency (which may be user defined) and converted into TMU (Time Measurement Unit) by multiplying it by 10. Lastly, the TMU total is converted into seconds by multiplying it by 0.036, thereby determining the overall time required to perform the entire task.

[0068] At step **104**, a static ergonomic risk is determined based on the received process planning data. In embodiments of the method **100**, the static ergonomic risk can be determined using the functionality described in U.S. Patent Publication No. 2023/0177228 and/or U.S. Patent Publication No. 2023/0177437. According to an embodiment, the static ergonomic risk is determined at step **104** using process planning data and/or data that can be generated/determined using the process planning data. An example embodiment utilizes manikin posture, object weight, task frequency, task time, motion speed (which can be based on user input indicating slow/no motion, evident movement, etc.), work hour per day (which can be based on user input indicating 1 hour or less, more than 1 hour up to 2 hours, more than 2 hours up to 8 hours). In absence of user inputs, an embodiment can use default values, such as a frequency of 2 actions per minute, a task time of 0.05 minutes, a speed of slow or no motion, a duration of more than 1 hour up to 2 work hours per day.

[0069] According to an embodiment, outputting an indication of dynamic ergonomic risk at step **105** includes outputting an indication of dynamic ergonomic risk based on (i) results of performing the time analysis and (ii) the determined static ergonomic risk. At step **105**, an embodiment determines a dynamic risk that is a cumulative risk based on the time analysis (e.g., resulting in a determination of total time for performing the task) and the determined static risk, where determined static risk includes risk for each of multiple postures to perform the task. Such an embodiment determines and outputs an indication of the dynamic cumulative ergonomic risk. In such an embodiment, determining the static risk at step **104** includes determining a risk for each of multiple postures to perform the task. Further, at step **105**, an embodiment determines (and outputs) an overall ergonomic score based on both the time analysis and postures for the entire cycle of actions to perform a task.

[0070] According to an embodiment, the indication of the dynamic ergonomic risk includes at least one of: a risk type, a risk location, a risk level, a suggestion to lower risk, and time to perform the task.

[0071] Embodiments of the method **100** may also perform real-world actions to improve efficiency and ergonomics, amongst other examples. For instance, in an embodiment where the indication of the dynamic ergonomic risk includes a suggestion, the method **100** may further include determining the suggestion by searching a mapping between risk types, risk locations, and suggestions. The determined suggestion is mapped to a given risk type and a given risk location of the dynamic ergonomic risk. In turn, such a method implements the suggestion (or causes the implementation of the suggestion, e.g., via providing the suggestion as output) in a certain real-world environment.

[0072] The description of a work sequence can play a vital role in understanding the actions and movements of a virtual mannequin in a DHM system. Natural language processing techniques are utilized in an embodiment of method **100** to extract relevant information from a task description provided by a user. For instance, extracted information may include the types of movements (e.g., reaching, grasping, lifting), the objects involved, and the sequence of sub-activities. Once an embodiment identifies relevant actions, the next step is to analyze the 3D data to determine the MOST parameters (Codes) and each parameter's temporal index values based on the available data in 3D environments. Such functionality may be performed at step **102** of the method **100**.

[0073] It is noted that the work sequence description and the subsequent 3D data analysis are complementary methods for calculating motion times in DHM systems according to an embodiment. While the description provides valuable context and task-related information, the 3D data analysis allows for a more precise measurement of relevant parameters, such as the distances covered during actions.

Information to Create Digital Human Model

[0074] The application of MOST in the realm of a DHM system according to an embodiment utilizes an assessment of DHM-related data to establish the fundamental elements of MOST, e.g., the parameters, and their determining factors. In general, a comprehensive set of data and parameters is utilized to simulate a human work process (task) in a DHM system where a human is represented by a mannequin in a 3D environment.

[0075] A component in an embodiment is user input, which serves as the descriptor for the work sequence, e.g., operations comprising a task. According to an embodiment, the input data encompasses contextual information, such as surrounding resources like objects and tools, as well as a phrase that describes the most likely action that the mannequin's posture partially simulates (action). A mannequin's fixed posture is often associated with force exertion events, such as lifting a component from a jig or applying force on a tool positioned on a component.

[0076] FIG. **2** illustrates an example interface **220** for providing input data. In particular, a user can use the interface **220** to indicate "hand" **221** (e.g., the hand(s) being utilized), "action" **222**, "what" **223**, "with" **224**, "where" **225**, and weight **226**. "Hand" **221** specifies (using the selection buttons **227***a-b*) the actively engaged hand in the action **222** and outlines the role of the passive hand (left **227***a* or right **227***b*), which may assist or hold. In the interface **220**, the row **232** indicates the role of the left hand **227***a* and the row **233** indicates the role of the right hand **227***b*. "Action **222**" (indicated using dropdown **228**) details the specific activities involved in the motion (i.e., task). "What" **223** (indicated using dropdown **229**) identifies the object or tool subject to manipulation during the action **222**. "With" **224** indicates any additional object or tool involved in the action, where applicable. It is noted that the example illustrated in the interface **220** does not involve "with" **224**, but like other input data, the "with" data **224** can be provided using a dropdown. "Where" **225** (indicated via dropdown **230**) describes the place where the action takes place and ends. Weight **226** (provided via selection box **231**) quantifies the weight of the manipulated object or tool, when relevant. Using the interface **220** allows users to provide a significant portion of the foundational elements for time analysis.

[0077] In FIG. **2** the input parameters are illustrated in a simulation scenario where a bolt is retrieved from a container. This scenario delineates the active hand, specifies the type of bolt involved, and provides information regarding the bolt's weight. The natural language sentence **232** created is also illustrated in the interface **220**.

[0078] According to an embodiment, the "Actions" or "Action verbs" **222** are selected via drop down **228** from a directory. In an embodiment, the "actions" **222** are a collection of predefined movements a DHM can perform in an environment being simulated. These actions **222** can range from basic movements, such as "Get," "Place," and "Move," to more complex activities, such as "Screw," "Operate," and performing assembly tasks. However, according to an embodiment, this library is limited by a DHM's ability to create corresponding postures in a 3D environment, which restricts the model's range of movements.

[0079] To accurately represent human work processes within a DHM system, a substantial amount of information and parameters are needed, much like the data required for MOST analysis. This information encompasses details about the objects or tools involved in a task and precise descriptions of the actions that best represent the work process. In essence, much of the foundational information required for MOST (or other such PMTS) analysis is already embedded within the simulation.

[0080] In an embodiment, the DHM information is examined for the presence of each MOST parameter listed in Table 1. In such an embodiment, the initial focus is on defining General move parameters, such as Action distance, Body motion, Gain control, and Placement, which constitute fundamental components of each MOST code. Table 3 presents the parameters and their corresponding motion characteristics that influence the time required for motion execution, as outlined in Table 2, alongside their availability in a DHM system environment in which embodiments are implemented. Table 3 also provides a brief explanation of how these parameters can be defined in a DHM system implementing an embodiment.

TABLE 3

MOST Parameters for General Moves, Motion characteristics, And the Availability of motion characteristics in a DHM System

MOST parameters	Motion Characteristic	Availability in a 3D environment.	The available 3D information/ Necessity of User inputs.	Explanation
Action distance (A)	A1-A16	Available	Automatic determination based on the coordinates of the 3D-designed models.	To calculate the traveled distances in a task, the starting and ending points of action can be defined in the 3D environment. The distance formula can be applied to calculate the distance traveled based on the coordination system of a specific reference point (Refer to "Action Distances" section for more detail).
Body Motion (B)	Sit/Stand Bend and Arise 50% occurrence Bend and Arise Bend and sit/stand and bend	Available	Automatic determination based on designed Postures.	A posture-tracking system determines the joint angles of a mannequin in different postures, and a decision system analyzes the angles based on defined thresholds and boundaries to label each posture with corresponding body motion parameters (Refer to Body Motions (Posture Definitions) section for more detail).
	Sit or stand with adjustments Through door Climb on/Off	Not directly recognizable from 3D models.	User input.	The adjustment concept is too obscure to describe in 3D, and the motions of climbing on/off and through doors are too complex to be modeled in a DHM system. In DHM systems, these actions can be assigned a time value and added to the directory of actions.
Gaining Control (G)	Light object Heavy Object Bulky Object	Available	Automatic determination based on objects and tools' geometry, weight, and dimension available in 3D.	DHM system includes the geometry and 3D information about the objects and tools, allowing embodiments to determine the object's shape and whether it is light, heavy, or bulky.
	Light object Simo. Light object non-Simo.	Available	Necessary user input.	A DHM system simulation panel allows embodiments to determine whether an object is carried by one or both hands simultaneously and non-simultaneously.
	Blind accessibility Obscured accessibility	Available	Automatic determination based on 3D-designed layouts.	Based on the 3D-designed layout, Blind or obscured accessibility can also be specified in a simulated task.
	Disengage Interlocked Collect	Not directly recognizable from 3D models.	User input.	A DHM cannot define these variables because these types of postures and movements require a high degree of precision and detail in the underlying algorithms and data, as well as accurate modeling of the complex interactions between body parts and external objects; actions can be assigned a time value and added to the directory of actions.
Placement (P)	Lay aside/Loose fit Loose fit Blind/Obstructed Double placement Blind/Obstructed positioning	Available	Automatic determination based on the geometry and the layout of the placement points available in 3D.	DHM system includes the geometry and 3D information of the placement points (The endpoint of an action) and the 3D layouts and specific actions the user selects when designing a task, making it possible to determine these variables.
	Place with adjustments/light pressure positioning with care/precision/heavy pressure/Intermediate moves	Not directly recognizable from 3D models.	Additional user input.	DHM systems cannot model variables containing the application of force to placements and placement accuracy and precision because they are abstract variables that require additional information beyond 3D geometric data and need to be added as new action verbs in the directory of actions.

[0081] While certain motion characteristics can be recognized in embodiments, e.g., in a DHM system implementing an embodiment, others can only be partially identified, and some may remain entirely inaccessible. Hereinbelow, functionality to address these gaps and undefined motion characteristics within a 3D environment are described.

Actions

[0082] Defining the Action that best describes the simulated task is an important step in MOST analysis.

[0083] By defining the actions, embodiments can categorize the motions based on the MOST motion categories and identify the corresponding MOST sequence model for the action. Once the sequence model is defined, an embodiment defines the corresponding parameters for time analysis (identified in Table 1).

[0084] However, obtaining the proper action from DHM simulation data can pose challenges. First, there are often differences in the action verbs used in the DHM system directory of actions and the actions used in the MOST language. These differences can make it difficult to select the correct action verb. Moreover, there are often actions that are included in one system, but lacking in others. To address these challenges, embodiments utilize two solutions, creating a common language between the PMTS and DHM system and expanding the DHM system's vocabulary.

Creating a Common Language Between MOST Data Cards and DHM System Action Verbs

[0085] To estimate times, e.g., in a DHM system implementing an embodiment, using MOST, an embodiment implements a common language for the work sequences described in the MOST and the DHM system. Utilizing a common language ensures consistency of information and easy integration into time estimation decision-making systems. Without a common language, verbs with the same meanings can be interpreted differently in DHM systems, making accurate time estimation challenging. An example embodiment implements a common language by translating the varied terms used by designers and engineers (e.g., associated with a DHM system) into a format that can be used in MOST data cards.

[0086] To create a common language, an embodiment unifies synonymous verbs, establishes clear definitions for each action, and implements modified data cards that describe the actions in a task or activity. The unified language is used practically to simulate actions using DHMs and record the time it takes to complete each action.

[0087] As an example, the verb "Place" may have synonyms such as "Put" or "Position". Moreover, different variations of the verb, like "Placement with light pressure" and "Placement with heavy pressure" could be interpreted as "Insert" and "Press" in a DHM system. To overcome these challenges and ensure accurate time estimation, an embodiment unifies the language between DHM systems (used to implement embodiments) and time systems (e.g., PMTS).

Expanding the Action Verbs Directory

[0088] Many actions existing in MOST data cards are missing from the DHM systems' directories of actions. For instance, consider the verb "Assembly". In MOST, applying forces with the verb "Assembly" is treated as an independent action with distinct time estimations. However, in many DHM systems, this action is typically represented as a single "Assemble" action. To rectify this, an embodiment introduces two new assembly actions, namely "Assembly with pressure" and "Assembly without pressure," to augment a DHM system's directory of action verbs. In another example, different levels of accuracy can be added to "Placement", such as "Placement with precision", "Placement with adjustment", or "Placement with care". Thus, an embodiment adds new attributes to existing actions in a DHM system directory of action verbs to cover more MOST action verbs. Thus, in an embodiment, a DHM system directory of action verbs is expanded to account for the unique characteristics of MOST parameters.

[0089] As part of this step, a variety of action verbs that typically cannot be modeled or do not exist in DHM systems and are utilized for MOST analysis (because they are either abstract or excessively complicated to be modeled in a 3D environment, such as thinking or grasping interlocked objects) are added to the directory of actions.

[0090] A DHM system may contain several action verbs that are not found on MOST data cards. As an example, consider the action "Grinding", which is not included in MOST data cards but can be interpreted as "Get and place a grinder" (General Move) and a series of "movements with resistance" (Controlled Move). These verbs are also translated in an embodiment and assigned time values according to MOST rules.

Body Motions (Posture Definitions)

[0091] Another challenge in estimating the time required for simulated human work is to precisely define the postures involved in the 3D models. The existing definitions for Body motions in MOST data cards were originally developed for observational body assessment, and the existing definitions lack explicit guidelines for posture determination. Time analysts often use rough observations to estimate body motions. This can lead to inaccurate time estimates, especially for complex tasks that involve multiple body motions. For example, there is uncertainty regarding the specific body angles that definitively indicate whether a human is in a standing or bending position.

[0092] An objective of an embodiment is to establish consistent boundaries and thresholds for different body motions mentioned in Table 2, which will explicitly specify the joint angles for different motions. This allows embodiments to accurately assign the appropriate body motion index value to simulated postures in 3D.

[0093] Simulated tasks in DHM systems are typically represented in static postures. This means that an embodiment can rely on two 3D models: one model that describes the mannequin in a neutral posture and another model that describes the mannequin in a critical posture of performing an action.

[0094] One way to define body motions in static postures is by comparing the joint angles and positions of the mannequin in the two models: one at the beginning (neutral posture) and the other at the end of the simulated action. These two models are often displayed in DHM systems. A tracking system can then use this information to determine the most likely body motion that corresponds to the observed joint angles and positions.

[0095] To develop a posture tracking system, an embodiment implements a process that analyzes joint angles and positions and compares the joint angles and positions to a database of known body motions (indicated in MOST data cards, such as “Sit”, “Stand”, or “Bend”). The tracking process, according to an embodiment considers the boundaries for each motion and defines the differences in joint angles and positions between the two postures to identify the proper body motion index value.

[0096] As an example, to define the sitting posture, such a process considers the following technical parameters: Trunk position, Left leg angle, and Right leg angle. Each parameter has a mean value and allowable variance, as indicated in Table 4.

TABLE 4

Technical Parameters For Defining Sitting Postures

Parameter	Mean value(degrees)	Allowable variance(degrees)
Trunk position	Upright	±20 degrees
Left leg angle	90 degrees	±20 degrees
Right leg angle	110 degrees	±20 degrees

[0097] To achieve a sitting posture, according to Table 4, the trunk should be upright, with a slight forward tilt of approximately 20 degrees. The mean value for the left leg relative angle should be set at 90 degrees, with an allowable variance of 20 degrees, while the right leg should be positioned slightly forward, with an angle of approximately 110 degrees between the thigh and the shin.

[0098] If the technical parameters for the trunk, left leg, and right leg are all within their defined ranges, then the posture can be labeled as “sitting”.

[0099] The following pseudocode shows a simple process for detecting the sitting posture: Function sitting_posture_detection(Trunk_position, Left_leg_angle, Right_leg_angle):

```
If (Trunk__position >= 20 degrees forward tilt) AND
(Left__leg__angle >= 70 degrees AND Left__leg__angle <= 110 degrees) AND
(Right__leg__angle >= 90 degrees AND Right__leg__angle <= 130 degrees):
   Return "Sitting posture detected"
Else
   Return "Not in sitting posture"
```

[0100] This process takes as input the technical parameters for the positions of the trunk, left leg, and right leg, which may be determined from input data. If these parameters fall within the defined ranges, the function returns “Sitting posture detected”; otherwise, it returns “Not in sitting posture”.

[0101] This process can be extended to detect other postures by identifying their unique technical parameters and allowable ranges. The general approach of this process follows the approach of Ma et al. (2010), with modifications to accommodate various joint angle thresholds that represent different body postures.

Action Distances

[0102] Action distance, which refers to the distance covered by a worker during specific tasks, is an important aspect of time estimation. Traditional methods involve manual recording by MOST users. However, with the use of simulation tools, embodiments can precisely calculate and visualize movements during work processes. In embodiments, the 3D models, e.g., DHM, include detailed coordinates of various body parts throughout the designed workstations.

[0103] To calculate the traveled distances in a task, an embodiment begins with the starting and ending points of the action, which are defined in a 3D environment. The Euclidean distance formula is then applied to calculate the distance traveled, based on the coordinate system of a specific reference point. For example, if we consider the center of gravity of the moving hand, object, and tools as the reference point at starting and ending points represented as (X1, Y1, Z1) and (X2, Y2, Z2) coordinates respectively, the Euclidean distance formula can be calculated as follows:

$$\text{Distance} = \sqrt{((X2 - X1)^2 + (Y2 - Y1)^2 + (Z2 - Z1)^2} \tag{1}$$

[0104] This calculated distance can then be used in the PMTS as part of the time determination.

Accuracies

[0105] Part of the accuracies required for time analyses can be automatically derived from the 3D designed models and user inputs, including a part of gain control parameter, which can be determined by having the object’s dimensions and weight, and also a part of placement parameter, that can be determined by possessing the 3D information of the placement points (The place where an action ends), as detailed in Table 3. However, similar to actions, deriving all the accuracies directly from simulation input data poses challenges, making the accurate assessment of accuracies difficult. Therefore, according to an embodiment, part of accuracies is incorporated as manual inputs during the modeling process in a DHM system implementing an embodiment.

[0106] To illustrate, a DHM system cannot attain Gain control accuracies such as Disengage, Interlocked, and Collect due to their complex nature, which requires precise algorithms, detailed data, and accurate modeling of complex interactions between body parts and external objects. However, in an embodiment, these actions are assigned time values and included in the action directory of the DHM system, thereby contributing to the expansion of DHM vocabulary, as described hereinabove in relation to the Actions description.

[0107] Similarly, a DHM system cannot typically model variables related to force application, placement accuracy, and precision, such as Place with precision/care/adjustments/light pressure/heavy pressure, as these are abstract variables that require supplementary information beyond 3D geometric data that is received as input data. Consequently, according to an embodiment, such variables are introduced as new action verbs in the action directory and the user can select them during the modeling process.

Controlled and Tool Use Moves

[0108] Existing DHM systems, such as those that may be utilized to implement embodiments, cannot currently provide the details needed to define the parameters associated with controlled and tool-use moves. Therefore, in an embodiment, users provide this information in an extension panel when creating 3D models. This extension panel can include the following: (1) If the controlled move involves interaction with a machine, the user can specify the processing time; (2) The user can specify the number of steps, stages, crank revolutions, and alignment points in controlled moves, as needed; (3) The user can specify the number of finger spins, screwdriver turns, wrench strokes, hammer taps/strikes, and wrench or ratchet cranks in Fasten or Loosen actions; (4) In cases of Cut actions, the user can define the number of scissors cuts or knife slices; (5) The user can specify the area of the surface to be cleaned in Surface treatment actions, whether it is an air nozzle clean, brush clean, or cloth wipe; (6) The user can select the measuring tool and define the distance to be measured for Measurement actions; (7) The user can specify the number of digits or words written or marked in Record actions; and (8) The user can specify the number of digits or words to be read or inspected in Think actions.

[0109] Data cards, according to an embodiment, of these two motion categories, controlled and tool-use moves, are shown in Tables 5 and 6A-B. respectively.

TABLE 5

Controlled Move Data Card
BasicMOST ® System Controlled Move A B G M X I A

	M Move Controlled		X Process Time			I	
Index ×10	Push/Pull/Turn	Crank	Seconds	Minutes	Hours	Alignment	Index ×10
1	≤12 in. (30 cm) Button Switch Knob		.5 Sec.	.01 Min.	.0001 Hr.	1 Point	1
3	>12 in. (30 cm) Resistance Seat or Unseat High Control 2 Stages ≤24 in. (60 cm) Total	1 Rev.	1.5 Sec.	.02 Min.	.0004 Hr.	2 Points ≤4 in. (10 cm)	3
6	2 Stages >24 in. (60 cm) Total 1-2 Steps	2-3 Rev.	2.5 Sec.	.04 Min.	.0007 Hr.	2 Points >4 in. (10 cm)	6
10	3-4 Stages 3-5 Steps	4-6 Rev.	4.5 Sec.	.07 Min.	.0012 Hr.		10
16	6-9 Steps	7-11 Rev.	7.0 Sec.	.11 Min.	.0019 Hr.	Precision	16

TABLE 6A

Tool Use Data Card - Fasten or Loosen
BasicMOST ® System Tool Use A B G A B P * A B P A

F Fasten or L Loosen

	Finger Action Spins	Wrist Action				Arm Action					Power Tool Screw	
	Fingers,	Turns Hand, Screwdriver,		Cranks	Taps	Turns			Cranks		Diam.	
Index ×10	Screw-driver	Ratchet, T-Wrench	Strokes Wrench	Wrench, Ratchet	Hand, Hammer	Ratchet	T-Wrench, 2-Hands	Strokes Wrench	Wrench, Ratchet	Strikes Hammer	Power Wrench	Index ×10
1	1	—	—	—	1	—	—	—	—	—	—	1
3	2	1	1	1	3	1	—	1	—	1	¼ in. (6 mm)	3
6	3	3	2	3	6	2	1	—	1	3	1 in (25 mm)	6
10	8	5	3	5	10	4	—	2	2	5		10
16	16	9	5	8	16	6	3	3	3	8		16
24	25	13	8	11	23	9	6	4	5	12		24
32	35	17	10	15	30	12	8	6	6	16		32
42	47	23	13	20	39	15	11	8	8	21		42
54	61	29	17	25	50	20	15	10	11	27		54

TABLE 6B

Tool Use Data Card - Cut, Surface Treat, Measure, Record, Think
BasicMOST ® System Tool Use A B G A B P * A B P A

	C Cut				S Surface Treat			M Measure
					Air-Clean	Brush-Clean	Wipe	
Index ×10	Cutoff Pliers Wire	Secure	Cut Scissors Cuts	Slice Knife Slices	Nozzle sq. ft. (0.1 m^2)	Brush sq. ft. (0.1 m^2)	Cloth sq. ft. (0.1 m^2)	Measure Measuring Tool
1		Grip	1	—	—	—	—	
3	Soft		2	1	—	—	½	
6	Medium	Twist Form Loop	4	—	1 Spot Cavity	1	—	
10	Hard		7	3	—	—	1	Profile Gauge
16		Secure Cotter Pin	11	4	3	2	2	Fixed Scale Caliper ≤12 in. (30 cm)
24			15	6	4	3	—	Feeler Gauge
32			20	9	7	5	5	Steel Tape ≤6 ft. (2 m) Depth Micrometer
42			27	11	10	7	7	OD-Micrometer ≤4 in. (10 cm)
54			33					ID-Micrometer ≤4 in. (10 cm)

	R Record			T Think			
				Inspect	Read Eyes		
	Write Pencil/Pen		Mark Marker	Eyes/ Fingers	Digits, Single	Text of	
Index ×10	Digits	Words	Digits	Points	Words	Words	Index ×10
1	1	—	Check Mark	1	1	3	1
3	2	—	1 Scribe Line	3	3 Gauge	8	3
6	4	1	2	5 Feel for Heat	6 Scale Value Date or Time	15	6
10	6	—	3	9 Feel for Defect	12 Vernier Scale	24	10
16	9 Signature or Date	2	5	14	Table Value	38	16
24	13	3	7	19		54	24
32	18	4	5	26		72	32
42	23	10	13	34		94	42
54	29	7	16	42		119	54

Example of MOST Estimation Within A DHM System According to Embodiment

[0110] Estimating time within a DHM system according to an embodiment encompasses the analysis of user inputs and 3D data. The techniques presented hereinabove involve gathering temporal data from user inputs and 3D data. This data contributes to shaping the decision-making system for time estimation in an embodiment. Such an embodiment analyzes the information and estimates the time required for the designed motion by following a decision tree.

[0111] This decision tree initially categorizes the actions defined by the user, facilitating the determination of the motion sequence model and parameters (i.e., codes). By analyzing the user inputs and the two 3D models associated with the motion (the model of the DHM at an initial posture in a neutral position and the model of the DHM in critical postures, i.e., performing actions), the embodiment calculates action distances, defines body motion, and establishes index values for accuracies (Gain control and Placement). In an embodiment, these values are determined based on the selected actions, characteristics of the tools and objects (such as their weights/dimensions), and the layout of the workspace. When the action involves controlled movements or tool use, the system prompts the user for additional complementary information through an extension panel. Once all the necessary parameters have been established, the MOST code is generated for the simulated task, and the corresponding task time is calculated accordingly. Table 7 provides an example of the time analysis process for the designed action illustrated in FIG. **2** (Getting the specified bolt from the designated container).

TABLE 7

Determining MOST Code For Task Designed In FIG. 2

MOST Building block elements	Processing	Output
Motion category	The “GET” motion falls under the “General move” category, determined based on the classification within the directory of action verbs.	The MOST sequence model for a general move is “ABGABPA,” encompassing the three parts of “GET” (ABG), “Put” (ABP), and “Return” (A).
Action distance(A)	The action distance is calculated according to the workspace layout. By knowing the coordinates of the mannequin in a neutral posture and the container’s coordinates defined in the DHM system panel, the action distance is determined.	In this case, the action distance is the distance between the hand at the neutral posture (the starting point) and the container within reaching distance (less than 60 cm), resulting in an index value of 1 (A1).
Body Motion(B)	This parameter can be determined by analyzing the neutral posture and the critical posture of the mannequin using the proposed posture tracking system.	In this specific scenario, no body motion occurs, as the container is located directly in front of the mannequin and the torso doesn’t tilt beyond the defined threshold (The trunk position is less than 20 degree forward tilt), resulting in an index value of 0 (B0)
Gaining control(G)	The hands performing the movements, the object’s and tool’s weight, and its dimensions are defined in the user panel. With this information, the index value for the “G” parameter can be determined.	In this case, based on the object’s dimensions and weight, the index value for the “G” parameter is 1 (indicating a light object, G1).
Placement(P)	The motion solely involves getting the object, thus, there is no placement involved.	The index values for the “Put” parameters in this code are all 0 (A0B0P0).
Return(A)	This motion exclusively includes the “Getting” action and there is no Return involved.	The index value for the “Return” parameters in this code is 0 (A0).
MOST code	After determining the different motion parameters, the MOST code is generated.	A1B0G1A0B0P0A0
MOST time	The MOST time in seconds is computed by summing the index values in the MOST code, which are then multiplied by 10 to convert them into TMUs (Time Measurement Units). Finally, the TMU total is further converted into seconds by multiplying it by 0.036, thereby determining the total time required to execute the entire task.	(1 + 0 + 1) *10*0.036 = 0.72 sec

[0112] As described herein, embodiments can automatically determine/define some parameters using input data while, in contrast, other parameters are determined/defined based on user input. FIGS. **3**-**6** are graphs **330**, **440**, **550**, and **660** illustrating the contribution of input information for the time analysis in the General move category. Using the contributions illustrated by the graphs **330**, **440**, **550**, and **660** results in about one-third of the input information for performing time estimation coming from CAD data, while the remaining information comes from user input, including standard inputs for simulating tasks in a DHM and complementary inputs that come from extensions and assumptions.

[0113] More specifically, graph **330** of FIG. **3** illustrates that action distance (A) **331** comes from 3D information **332**.

[0114] Graph **440** illustrates that gain control **441** data, which can be one of four types, light object/light object simo **442**, light object non simo **443**, disengage **444**, and interlocked **445**, is provided via user input **446**-**449**, respectively. According to an embodiment “simo” refers to actions performed simultaneously by different body members. For instance, an action where one hand gains control of a light object (G1), while the other hand obtains another light object (G1). The total time, then, is no more than that required to gain control of one light object. Graph **550** shows the data sources for body motion **551**, which includes sit **552**, stand **553**, bend and arise **554**, body motion with adjustment **555**, climb on/off **556**, and through door **557**. The data for sit **552**, stand **553**, and bend and arise **553**, is determined, e.g., automatically, from 3D information **558**, **559**, and **560**, respectively. Meanwhile, the data for body motion with adjustment **555**, climb on/off **556**, and through door **557** is determined from user input **561**, **562**, and **563**, respectively. Graph **660** shows the data sources for placement **661**, which includes lay aside/loose fit **662**, blind/obstructed **663**, adjustment **664**, light/heavy pressure **665**, double placement **666**, care/precision **667**, and intermediate moves **668**. The data for lay aside/loose fit **662**, blind/obstructed **663**, and double placement **666** is determined from 3D information **669**, **670**, and **673**, respectively. The data for adjustment **664**, light/heavy pressure **665**, care/precision **667**, and intermediate moves **668**, is determined from user input **671**, **672**, **674**, and **675**, respectively.

Case Example: Implementing Integrated Time and Ergonomic Analysis in a DHM System

[0115] Embodiments can implement a process for time estimation in a DHM system. To illustrate how time and ergonomic analysis can be performed concurrently, in an embodiment, an example is described hereinbelow. This case example showcases the seamless integration of time and ergonomic analyses in a DHM system, utilizing the EWD (Ergonomic Workplace Design) software platform.

[0116] In this illustrative example, the operation, i.e., the sequence of tasks being evaluated, comprises five successive motions that are performed for screwing a bolt in an assembly setting. This operation was defined using the input panel **790**. In turn, an embodiment, e.g., the method **100**, was carried out to determine the dynamic ergonomic risk of performing the operation.

[0117] The five motions are shown in the interfaces **770***a-e* of FIGS. **7**A-E. The operation commences with the DHM **771** grasping the specified bolt **772** from the specified storage bin **773** (illustrated in FIG. **7**A), followed by the DHM **771** placing the bolt **772** into a thread on the work desk assembly **774** and manually seating the bolt on the thread (illustrated in FIG. **7**B). Subsequently, the DHM **771** grasps air screwdriver **775** (illustrated in FIG. **7**C) and places the air screwdriver **775** onto the bolt **772** to complete the screwing operation (illustrated in FIG. **7**D). Finally, the DHM **771** returns the air screwdriver **775** to its original position, marking the end of the operation (illustrated in FIG. **7**E).

[0118] FIGS. **7**A-E illustrate the initial design of this operation. In a DHM system, ergonomic analysis aids designers in identifying ergonomic issues and making design adjustments as needed. For example, the interfaces in DHM systems can provide warnings and suggestions, e.g., **780***a-d*, that may be taken to improve ergonomics. Each designed motion in this operation contains its temporal motion characteristics. Therefore, any modifications to the design will result in changes to the parameters index values, ultimately leading to adjustments in the MOST codes and the estimated time.

[0119] In this case, following the DHM system's recommendations (e.g., **780***a-d*) to address ergonomic issues in the design, resulted in reconfiguring the layout to relocate the storage bin **773** and screwdriver **775**. As a result, the Action distances and the corresponding body motions were altered. A risk analysis indicated no issues with the new design (illustrated in interfaces **880***a-c* in FIGS. **8**A-E), and the MOST codes were subsequently updated.

Example Results

[0120] The previous section described an example of time analysis in a DHM environment. Existing methods manually conduct the time analysis after the preliminary design is completed. Manual time estimation requires expertise, and it may take a considerable amount of time for a manufacturing engineer to acquire the necessary knowledge and proficiency to effectively perform the manual time estimation.

[0121] Designing future workstations requires numerous design modifications. With each design change, time-related motion characteristics shift, and a time analyst must thoroughly reassess the entire design to identify these new time-related factors. This process is not only intricate but also time-consuming. Embodiments solve this problem by integrating time analysis within a DHM ergonomic analysis system.

[0122] As an illustration, FIG. **7**A depicts a scenario in which the mannequin **771** is observed in a posture involving a reaching motion to grasp a bolt **772** from a storage bin **773**, denoted by the associated MOST code "A1B6G1" **781**. A concerning indicator **782** highlights a significant ergonomic risk associated with the mannequin's **771** neck posture. Consequently, an imperative need arises for design modifications aimed at mitigating this ergonomic concern. Subsequently, FIG. **8**A is presented, showcasing a revised design, with the updated MOST code "A1B0G1" **881** reflecting changes in the storage bin's **882** position. These design adaptations, notably, influence the associated time estimates.

[0123] As another example, FIG. **7**C, illustrates the mannequin's **771** action in grasping an air screwdriver **775**, designated by the MOST code "A3B0G1" **783**. To make the tool **775** accessible, the arm and trunk positions should be lifted. The ergonomic analysis identifies a moderate risk concerning shoulder posture, necessitating further design adjustments. FIG. **8**C illustrates the updated design, presenting a lowered and more accessible tool **883** placement, thus mitigating the risk level. In parallel, the A index value decreases to 1, indicative of a shortened task duration in the revised MOST code "A1B0G1" **884**.

[0124] Considering the constant changes in the design and the large number of operations that need to be analyzed, automated time estimation can reduce analysis time and give users, e.g., a design engineer, more flexibility.

[0125] DHM systems are increasingly being used to design and optimize human work processes. One of the key challenges in using DHM systems for this purpose is the estimation of the time required for workers to complete specific tasks. Embodiments provide a novel method for fully automated time analysis using DHM system data.

[0126] Traditionally, time analysis, e.g., MOST, is a manual process that requires a skilled time analyst to observe workers performing the tasks. This can be time-consuming and expensive, especially for tasks that are designed in 3D environments. In contrast, embodiments decrease the amount of manual work needed for the analysis of time and enable the creation of efficient and ergonomic human work processes without adding to the design workload.

[0127] An example embodiment first identifies the information needed for the analysis of a PMTS, e.g., MOST, in a 3D environment. The embodiment determines which information can be generated automatically by simulation tools and which data should be added manually during the 3D simulation of a DHM. By manually adding the information that cannot be determined automatically, it is then possible to derive a PMTS analysis.

[0128] Embodiments can be integrated into EWD (Ergonomic Workplace Design). The integration of an embodiment into EWD allows for the automatic estimation of time required for 3D-designed tasks while simultaneously conducting comprehensive ergonomic evaluations. This multifaceted analysis empowers users to visualize design effectiveness and, ultimately, results in substantial time and resource savings before building a physical prototype. Further, embodiments can be used to analyze existing physical environments, and, in turn, the physical environments can be modified in accordance with the results of embodiments to improve ergonomics in the physical environments.

[0129] Embodiments provide a framework for estimating time in a 3D environment of a DHM system using the MOST predetermined motion time system. Other PMTSs, such as MTM or MODAPTS, can also be used, as the main parameters of movement in different time systems are similar. As such, embodiments can utilize different time estimation methods and users can select a preferred PMTS.

[0130] Embodiments balance complexity and the number of assumptions so as to optimize the accuracy of time estimation. In the preproduction phase, designers have a better understanding of the design due to the availability of more details, which allows users to more accurately estimate time with fewer assumptions. Conversely, during the initial stages of the design process, DHM systems are typically used to select design concepts, and rough estimations are therefore deemed sufficient, as intricate details are not yet a priority for design engineers. Embodiments strike a balance between complexity and the number of assumptions to optimize time estimation accurately. Embodiments streamline time estimation by minimizing assumptions while maintaining user-friendly automation, ensuring accuracy despite complexity. Although direct observation may seem to offer superior accuracy due to fewer assumptions and immediate data access, embodiments show that DHM systems also yield sufficient accuracy. Specifically, during a preproduction phase, DHM systems focus on selecting design concepts where rough estimations suffice and intricate details are not the primary concern for design engineers. This balance allows DHM system users to provide estimations fulfilling the requirements of this phase.

[0131] Despite the value of automated time analysis in 3D environments, some challenges still exist. The most common way time systems are used in real-life situations is through observation, which provides an analyst with precise information on how actions are performed. However, in 3D environments, this information is often lacking. To address this challenge, embodiments can rely on a range of assumptions and supplementary sources to establish some of the PMTS parameters used for time estimation, this involves establishing specific thresholds for "Body Motion" parameter and determining thresholds for object and tool dimensions essential for precisely defining the "Gain control" parameter where specific thresholds are lacking and need to be defined based on analyst judgment in traditional time analysis. One of the advantages of using these thresholds in DHM systems is to increase the accuracy of DHM systems.

[0132] Unlike manual recordings, which may involve estimations and measurement errors, digital simulations provide a more reliable and precise measurement of Action distances, as they rely on the coordinate system to calculate the distances automatically. This eliminates the inherent uncertainties associated with human estimations.

[0133] Another challenge of estimating time in a 3D environment using static postures is the detection of body motions. Embodiments simplify this issue by proposing a posture-tracking system. The proposed method checks the mannequin's joint angles in CAD data and determines the appropriate index value for body motion.

[0134] For example, the MOST rule states that if the worker bends over 20 degrees from a neutral posture, the body motion is considered as "Bend". In manual estimation, the analyst might doubt whether the bend is greater or lesser than 20 degrees in different cases. By automatically defining postures, the proposed method solves this problem. This is evident when comparing FIGS. **7**A and **8**A. The DHM **771** in FIG. **7**A is noticeably bent, while the DHM **885** in FIG. **8**A is only slightly bent. As soon as an embodiment checks the 3D model, such an embodiment verifies that the bending is less than 20 degrees, so it assigns B0, while, from an analyst's point of view, this might count as B3.

[0135] Because embodiments integrate time analysis methods into digital human modeling systems, embodiments allow for faster and more accurate time estimation and significantly reduce the time and effort required to estimate the duration of operations within an environment, e.g., workstation, while minimizing the potential for human error. The automated approach implemented by embodiments also provides greater flexibility for design engineers by enabling them to quickly make design adjustments without the need to re-estimate operation times.

[0136] Moreover, embodiments present a valuable resource for analyzing movements over an extended period to enhance ergonomic risk assessments and empower DHM systems to more effectively model, design, and optimize human-centric systems and products.

[0137] By integrating time analysis, embodiments can perform a comprehensive evaluation of motions and assess the sequences of events performed by workers over time. This leads to a more accurate and realistic ergonomic risk assessment. Embodiments provide a more accurate representation of human performance and safety, enabling the capture of dynamic interactions between human workers and their environment, including tools, equipment, and other workers. Through the tracking and analysis of motion patterns over time, potential sources of ergonomic risk can be more accurately identified. This information can be used to redesign workstations and equipment, adjust the workflow, and implement other interventions to reduce ergonomic risk, leading to safer and healthier work environments.

[0138] Integrating time analysis methods into DHM systems, as in embodiments, provides more advanced and accurate digital human modeling systems. Amongst other examples, embodiments can be used in a range of industries, including manufacturing, healthcare, transportation, and more. Further, embodiments can be used to design and optimize human-centric systems and products, leading to improved worker safety, health, and performance.

[0139] By implementing embodiments, users are empowered to automatically conduct time analysis, resulting in a streamlined and accelerated design process, ultimately leading to increased workplace productivity.

[0140] By automating this process in a DHM system, user can estimate time without prior knowledge while simulating a virtual task.

Computer Support

[0141] Embodiments can be implemented in the Smart Posture Engine™ (SPE™) framework inside Dassault Systèmes application "Ergonomic Workplace Design". Moreover, embodiments may be implemented in any computer architectures known to those of skill in the art. For instance, FIG. **9** is a simplified block diagram of a computer-based system **990** that may be used to assess dynamic ergonomic risk, according to any variety of the embodiments described herein. The system **990** comprises a bus **993**. The bus **993** serves as an interconnect between the various components of the system **990**. Connected to the bus **993** is an input/output device interface **996** for connecting various input and output devices such as a keyboard, mouse, display, speakers, etc. to the system **990**. A central processing unit (CPU) **992** is connected to the bus **993** and provides for the execution of computer instructions. Memory **995** provides volatile storage for data used for carrying out computer instructions. In particular, memory **995** and storage **994** hold computer instructions and data (databases, tables, etc.) for carrying out the methods described herein, e.g., **100** of FIG. **1**. Storage **994** provides non-volatile storage for software instructions, such as an operating system (not shown). The system **990** also comprises a network interface **991** for connecting to any variety of networks known in the art, including wide area networks (WANs) and local area networks (LANs).

[0142] It should be understood that the example embodiments described herein may be implemented in many different ways. In some instances, the various methods and machines described herein may each be implemented by a physical, virtual, or hybrid general purpose computer, such as the computer system **990**, or a computer network environment such as the computer environment **1000**, described herein below in relation to FIG. **10**. The computer system **990** may be transformed into the machines that execute the methods (e.g., **100**) and techniques described herein, for example, by loading software instructions into either memory **995** or non-volatile storage **994** for execution by the CPU **992**. One of ordinary skill in the art should further understand that the system **990** and its various components may be configured to carry out any embodiments or combination of embodiments of the present invention described herein. Further, the system **990** may implement the various embodiments described herein utilizing any combination of hardware, software, and firmware modules operatively coupled, internally, or externally, to the system **990**.

[0143] FIG. **10** illustrates a computer network environment **1000** in which an embodiment of the present invention may be implemented. In the computer network environment **1000**, the server **1001** is linked through the communications network **1002** to the clients **1003***a-n*. The environment **1000** may be used to allow the clients **1003***a-n*, alone or in combination with the server **1001**, to execute any of the embodiments described herein. For non-limiting example, computer network environment **1000** provides cloud computing embodiments, software as a service (SAAS) embodiments, and the like.

[0144] Embodiments or aspects thereof may be implemented in the form of hardware, firmware, or software. If implemented in software, the software may be stored on any non-transient computer readable medium that is configured to enable a processor to load the software or subsets of instructions thereof. The processor then executes the instructions and is configured to operate or cause an apparatus to operate in a manner as described herein.

[0145] Further, firmware, software, routines, or instructions may be described herein as performing certain actions and/or functions of the data processors. However, it should be appreciated that such descriptions contained herein are merely for convenience and that such actions in fact result from computing devices, processors, controllers, or other devices executing the firmware, software, routines, instructions, etc.

[0146] It should be understood that the flow diagrams, block diagrams, and network diagrams may include more or fewer elements, be arranged differently, or be represented differently. But it further should be understood that certain implementations may dictate the block and network diagrams and the number of block and network diagrams illustrating the execution of the embodiments be implemented in a particular way.

[0147] Accordingly, further embodiments may also be implemented in a variety of computer architectures, physical, virtual, cloud computers, and/or some combination thereof, and thus, the data processors described herein are intended for purposes of illustration only and not as a limitation of the embodiments.

[0148] The teachings of all patents, published applications and references cited herein are incorporated by reference in their entirety.

[0149] While example embodiments have been particularly shown and described, it will be understood by those skilled in the art that various changes in form and details may be made therein without departing from the scope of the embodiments encompassed by the appended claims.

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What is claimed is:

1. A computer-implemented method of assessing dynamic ergonomic risk, the method comprising, by a processor:
- receiving, in memory of the processor, process planning data for an operator performing a task;
- based on the received process planning data, defining parameters for a time analysis;
- performing a time analysis of the operator performing the task using the defined parameters;
- determining a static ergonomic risk based on the received process planning data; and
- outputting an indication of dynamic ergonomic risk based on (i) results of performing the time analysis and (ii) the determined static ergonomic risk.

2. The method of claim **1** wherein the received process planning data includes a natural language statement.

3. The method of claim **2** wherein defining the parameters comprises:
- performing natural language processing on the statement to extract an indicator of a movement type;
- defining a category of movement based on the indicator of a movement type;
- based on the defined category, identifying the parameters for the time analysis; and
- setting a value of at least one parameter based on the received process planning data.

4. The method of claim **2** wherein defining the parameters comprises:
- translating an element of the natural language statement to a parameter definition.

5. The method of claim **1** wherein the received process planning data includes at least one of:
- physical characteristics of a workstation in a certain real-world environment at which the task is performed;
- physical characteristics of the operator; and
- characteristics of the task.

6. The method of claim **1** wherein receiving the process planning data comprises:
- receiving a measurement from a sensor in a certain real-world environment in which the task is performed.

7. The method of claim **1** further comprising, prior to defining the parameters:
- identifying the parameters by searching a look-up table based on an indication of the task in the received data, wherein the look-up table indicates the parameters as a function of the task.

8. The method of claim **1** wherein the parameters are one of: Maynard Operation Sequence Technique (MOST) parameters, Methods-Time Measurement (MTM) parameters, Modular Arrangement of Predetermined Time Standards (MODAPTS) parameters, and Work-Factor (WF) parameters.

9. The method of claim **1** wherein defining the parameters comprises:
- automatically defining a first subset of the parameters based on the received process planning data; and
- defining a second subset of the parameters responsive to user input.

10. The method of claim **9** wherein automatically defining the first subset of parameters comprises:
- using the received process planning data, performing a computer-based simulation of a digital human model performing the task; and
- defining at least one parameter, from the first subset of parameters, based on results of performing the computer-based simulation.

11. The method of claim **9** wherein automatically defining the first subset of parameters comprises at least one of:
- defining a posture parameter based on body position indications from the received process planning data; and
- defining a distance parameter based on an indication in the received process planning data of a start point and end point of the task.

12. The method of claim **9** wherein defining a second subset of the parameters responsive to user input comprises:
- based on the received process planning data, identifying a user prompt;
- providing the user prompt to a user; and
- receiving the user input responsive to providing the user prompt.

13. The method of claim **1** wherein the indication of the dynamic ergonomic risk includes at least one of:
- a risk type;
- a risk location;
- a risk level;
- a suggestion to lower risk; and
- time to perform the task.

14. The method of claim **13** wherein the indication of the dynamic ergonomic risk includes the suggestion, and the method further comprises:
- determining the suggestion by searching a mapping between risk types, risk locations, and suggestions, wherein the determined suggestion is mapped to a given risk type and a given risk location of the dynamic ergonomic risk.

15. The method of claim **14** further comprising:
implementing the suggestion in a certain real-world environment.

16. A system for assessing dynamic ergonomic risk, the system comprising:
a processor; and
a memory with computer code instructions stored thereon, the processor and the memory, with the computer code instructions, being configured to cause the system to:
receive, in the memory, process planning data for an operator performing a task;
based on the received process planning data, define parameters for a time analysis;
perform a time analysis of the operator performing the task using the defined parameters;
determine a static ergonomic risk based on the received process planning data; and
output an indication of dynamic ergonomic risk based on (i) results of performing the time analysis and (ii) the determined static ergonomic risk.

17. The system of claim **16** wherein the received process planning data includes a natural language statement and where, in defining the parameters, the processor and the memory, with the computer code instructions, are further configured to cause the system to:
perform natural language processing on the statement to extract an indicator of a movement type;
define a category of movement based on the indicator of a movement type;
based on the defined category, identify the parameters for the time analysis; and
set a value of at least one parameter based on the received process planning data.

18. The system of claim **16** where, in defining the parameters, the processor and memory, with the computer code instructions, are configured to cause the system to:
automatically define a first subset of the parameters based on the received process planning data; and
define a second subset of the parameters responsive to user input.

19. The system of claim **16** wherein, the processor and the memory, with the computer code instructions, are further configured to cause the system to:
identify the parameters by searching a look-up table based on an indication of the task in the received data, wherein the look-up table indicates the parameters as a function of the task.

20. A non-transitory computer program product for assessing dynamic ergonomic risk, the computer program product executed by a server in communication across a network with one or more client and comprising:
a computer readable medium, the computer readable medium comprising program instructions which, when executed by a processor, causes the processor to:
receive, in memory, process planning data for an operator performing a task;
based on the received process planning data, define parameters for a time analysis;
perform a time analysis of the operator performing the task using the defined parameters;
determine a static ergonomic risk based on the received process planning data; and
output an indication of dynamic ergonomic risk based on (i) results of performing the time analysis and (ii) the determined static ergonomic risk.

* * * * *

APPENDIX B PUBLISHED CONFERENCE PAPER

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Evaluating the Accuracy of the MOST Predetermined Motion Time System Through Lab Experiments

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ABSTRACT

Ensuring the reliability of time estimations is vital for industries, as it establishes the basis for effective planning, resource allocation, and performance assessment, ultimately improving operational efficiency and optimizing workflows. This study, designed to evaluate the accuracy of the MOST predetermined motion time system (PMTS) through comprehensive laboratory experiments, involved twenty participants performing 300 various simple motions. Our focus was on motions characterized by specific features, such as those at higher levels (shoulder height), motions involving objects with varying weights, and motions occurring within the reach distance zone (between 5 cm and 60 cm from the workers). These motion characteristics are often overlooked in MOST data cards. Task durations were initially measured using an accelerometer and then estimated using both the MOST and Fitts' Law (a widely recognized method for estimating the duration of simple motions). The results unveiled a 22% underestimation of MOST estimations by Fitts' Law. These findings underscore the need to revise MOST data cards for accuracy enhancement and to mitigate potential risks to workers. Future research endeavors should incorporate real-world scenarios and a broader array of motions to further validate and refine these outcomes, ensuring a more comprehensive understanding of the capabilities and limitations of the MOST predetermined motion time system.

Keywords: Predetermined motion time system (PMTS), Fitts' law, Most, Validation study, Laboratory experiment

INTRODUCTION

In manufacturing, accurate estimation of work times is vital for ensuring successful production by effectively managing resources such as workforce and materials. Predetermined Motion Time Systems (PMTS) play a crucial role in enhancing efficiency and resource allocation in industrial settings (Genaidy et al., 1989; Neumann et al., 2002). These systems use techniques to estimate operation time, providing a standardized framework for evaluating product costs, comparing workstations or tasks, and identifying improvement areas (Heap, 2015).

PMTSs commonly used in industries include Method Time Measurement (MTM), which is known for analyzing motions in detail, and the Maynard

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Operation Sequence Technique (MOST), which is a simplified adaptation of MTM (Genaidy et al., 1989; Zandin, 2002).

MOST utilizes data cards with standardized codes and descriptions for specific motions, enabling quantification of parameters like walking time, machine usage time, and tool usage (Zandin, 2002). Fitts' law, introduced by Paul Fitts in 1954, serves as a well-established predictive model for movement time, considering both target distance and object size, as demonstrated in various studies, ranging from earlier works such as Crossman & Goodeve (1983) to more recent research conducted by Clark et al. (2020) and Xie et al. (2023).

This study explores the application of both MOST and Fitts' law in time estimation. While MOST excels in estimating complex movements, Fitts' law is more suitable for simpler ones. For simple movements, it is anticipated that Fitts' law and MOST will provide comparable time estimates.

Given technological advancements and organizational changes, regular validation of PMTS accuracy is essential for precise time estimations (Genaidy et al., 1989; Neumann et al., 2002). Despite its importance, scholarly attention to PMTS validation is relatively low. Previous studies, such as those conducted by Kurkin & Bures (2011), Bahcivancilar (2012), and Bures and Picvodova (2015), have demonstrated variations between PMTS estimates (including MTM-1, MOST, and MTM-UAS) and empirically measured actual times. As a result of these investigations, deviations of up to 17 percent were discovered between the estimated times of PMTSs and measured actual times.

The tendency of PMTSs to predict unrealistically short completion times can lead to errors in productivity estimation and inaccuracies in risk assessments. These overly optimistic time predictions, often used to set worker productivity expectations, can lead to overexertion, and increase the risk of injury among workers (Harari et al., 2018).

This study aimed to assess the accuracy of the MOST (Maynard Operation Sequence Technique) predetermined motion time system through a laboratory experiment. The research focused on comparing established time standardization methods, including direct measurement, MOST, and Fitts' law.

METHODS

Twenty participants, aged between 27 and 59 years (mean ± SD: 43 ± 10.9 years, range: 27–52 years), volunteered for the study after confirming their ability to handle objects weighing up to 5 kg and providing informed consent. The study received ethics certificate number CER-2223-38-D.

The study consisted of three experiments designed to assess the precision of MOST data cards in diverse motion scenarios, inspired by research paradigms such as Kurkin & Bures (2011) and Bahcivancilar (2012). MOST data cards often overlook specific movement characteristics, including higher-level shoulder movements, object weight, and action distances within the worker's reaching zone. Consequently, our focus was on evaluating the alignment between MOST estimations and actual time measurements in these specific movements.

The experiments were centered on seated “Get and Place” movements, requiring participants to manipulate objects accurately over specified distances. Various objects, including markers, rubber bands, and weights, were moved across different tasks based on the experimental layout (Figure 1).

In these experiments, participants performed tasks assessing motion characteristics, such as action distances, object weight, and movement precision, in diverse scenarios. In Experiment 1, the distances between these points were individually customized for each participant based on their unique maximum reach capacity. In Experiment 2, all participants were given the same distance, irrespective of their reach capacity. In Experiment 3, the table height was adjusted according to the individual’s maximum reach capacity, and movements were replicated at higher levels. In total, participants completed various tasks across various scenarios in all experiments. These tasks included motions such as precisely placing markers in bins, grasping interlocked rubber bands, and moving various weights. This diversity aimed to assess the accuracy of MOST data cards across various scenarios and understand whether specific motion characteristics impact motion times. Figure 2 illustrates a participant carrying out a task in Experiment 1.

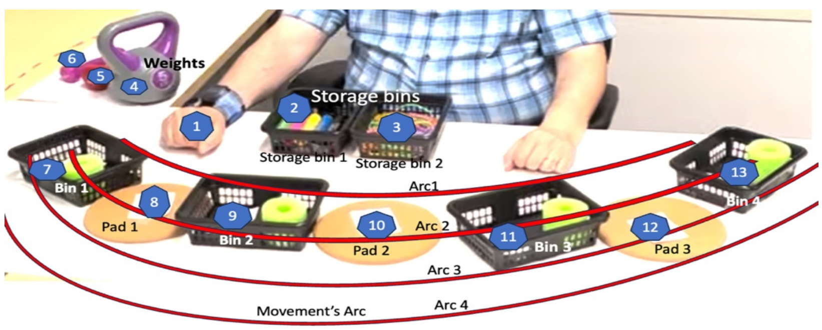

Figure 1: Experimental layout.

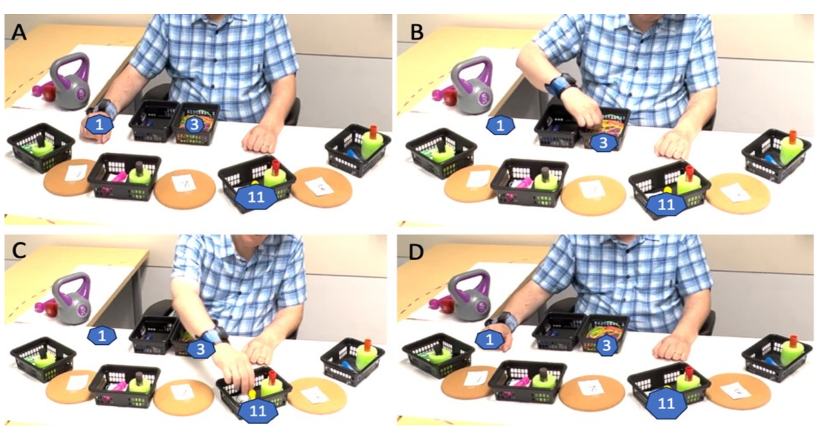

Figure 2: Participant performing a task in experiment 1.

MOST and Fitts' Law Time Estimations

Movements were selected from "MOST Work Measurement Systems" by Zandin (2002), providing detailed time estimations and reducing reliance on subjective judgments to minimize unintentional bias. The MOST time estimations, initially expressed in TMUs, were converted to seconds (1 TMU = 0.036 seconds) for consistency.

For estimating each motion time, Fitts' law was also employed, utilizing the formula MT = a + b * log2(D/W + 1) (Fitts, 1954). Coefficients a and b, set to 100 ms and 150 bits/ms, respectively, are task-specific and were determined through regression analysis. D represents distance, easily calculated based on spatial distance, and W signifies target width, measured as the effective diameter.

The dataset encompasses measured times, MOST, and Fitts' law estimations for each of the 6,000 movements from three experiments involving 20 participants (300 movements per participant).

Experimental Procedure

Participants were equipped with a wrist-mounted accelerometer that recorded motion data at 50 Hz, aligning with the axes of the forearm and trunk. The peaks and valleys in the acceleration data were identified to correspond to specific motion intervals. Through manual identification of these points, and considering the sampling rate and resolution, we determined the duration of each motion in seconds.

To complement this data, video recordings of participants' movements during the experiments were captured using an iPhone 13 Pro camera. These recordings played a crucial role in identifying and addressing outliers in the dataset.

Data Analysis

In each experiment, we replicated every motion and then computed the average value for each. Manual inspection ensured data quality by identifying and eliminating 11 outliers, which were prolonged movements caused by distractions.

Means and standard deviations were calculated for both estimation methods for N = 6000 motions. The Bland-Altman agreement test, following the methodology by Bland and Altman (1999), was also applied to assess agreement between estimated times of MOST and Fitts' Law. This involved computing the 95% Limits of Agreement (LoA) using differences between Estimated times, supplemented by ± 2 times the standard deviation of differences (SDdiff). These limits determined the upper and lower bounds of agreement, contributing to the evaluation of method accord. All statistical analyses were conducted with Microsoft Excel.

RESULTS

Due to space constraints, the results section will primarily focus on highlighting the disparity between MOST and Fitts' Law. A comparison between

Fitts' Law and MOST estimations was conducted to evaluate MOST's performance in estimating task times. The results revealed that the mean time estimated by MOST (2.33 ± 0.32 seconds) was lower than that estimated by Fitts' Law (3.09 ± 0.59 seconds), indicating a discrepancy in estimation methods.

Despite variations in tasks, the MOST time for different tasks remains consistent because MOST data cards do not account for variations in moving object weight, motion height levels, or distance covered during motions, particularly within workers' reach zones. Consequently, the time values for these motions remain consistent when estimated according to MOST rules.

The Bland-Altman method demonstrated the level of agreement between MOST and Fitts' Law, with a mean difference of −0.76 seconds (95% LoA: −1.99 to 0.47 seconds) and a standard deviation of differences at 0.63 seconds, indicating substantial variation and low agreement between the methods. Figure 3 displays the Bland-Altman plot illustrating the agreement between MOST and Fitts' Law, with the solid line representing the mean bias and dashed lines indicating the limits of agreement.

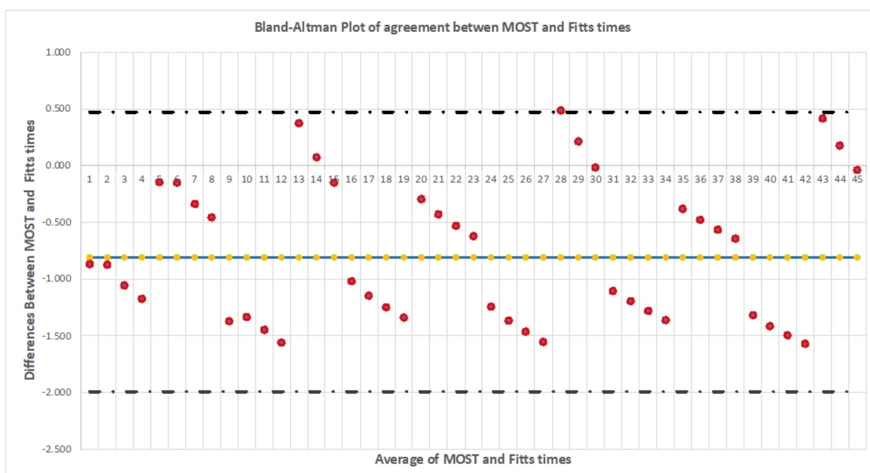

Figure 3: Bland-Altman plot, the differences between the MOST and Fitts' law in 45 tasks performed.

DISCUSSION

Considerable variability in time estimation was observed when comparing MOST and Fitts' Law, with MOST consistently underestimating Fitts' Law times by 22%. This discrepancy raises concerns, as Fitts' Law serves as the foundation for estimating basic movement times.

One of the key factors contributing to this discrepancy is our intentional focus on selecting specific types of motions that exhibit unique characteristics. These include elevated-level motions (at shoulder level), motions involving varying object weights, and motions with different reach distance zones (typically occurring between 5 cm to 60 cm from the workers). While Fitts' Law accounts for some of these aspects, such as motions with different reach distance zones, none of them are considered by the MOST system in its data cards, which could explain part of the observed difference. It underscores the significant impact of these unaccounted motion characteristics on the precision of time estimations made by MOST, suggesting the need for a more comprehensive investigation into its predictive capabilities, especially in the presence of these neglected factors.

CONCLUSION

This research assessed the accuracy of MOST data cards in estimating basic movements, revealing a notable disparity with the estimations provided by Fitts' Law, indicating a consistent underestimation of the Fitts' time for motions investigated in this study. While PMTS, including MOST, are widely employed for rough estimates during the planning phase, understanding the reasons behind these discrepancies is crucial. This study underscores the potential for enhancing the accuracy and efficiency of MOST by addressing gaps and unexplored aspects within this time system. Such improvements would contribute to better decision-making and organizational productivity for industries utilizing the MOST time system.

Future research can draw inspiration from the findings of this study, particularly focusing on the detailed analyses of factors influencing movement times across various scenarios; these analyses should aim to determine the significance of these factors, which explain the variation in MOST estimations and actual measurements. By identifying and incorporating these missing factors into MOST data cards, future research endeavors could significantly enhance MOST accuracy.

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APPENDIX C MOST DATA CARDS

Tables C.1, C.2, and C.3 present reference data cards that detail MOST controlled and tool-use motion categories.

TABLE C.1 Controlled Move Data Card (adapted from Zandin, 2002)

BasicMOST System			Controlled Move			ABGMXIA	
Index x10	**M Move Controlled**		**X Process Time**			**I Alignment**	**Index x10**
	Push/Pull/Turn	Crank	Seconds	Minutes	Hours		
1	≤ 12 in. (30 cm) Button, Switch, Knob		.5 Sec.	.01 Min.	.0001 Hr.	1 Point	**1**
3	>12 in. (30 cm) Resistance, Seat or Unseat, High Control, 2 Stages ≤ 24 in. (60 cm) Total	1 Rev.	1.5 Sec.	.02 Min.	.0004 Hr.	2 Points ≤ 4 in. (10 cm)	**3**
6	2 Stages >24 in. (60 cm) Total 1-2 Steps	2-3 Rev.	2.5 Sec.	.04 Min.	.0007 Hr.	2 Points >4 in. (10 cm)	**6**
10	3-4 Stages, 3-5 Steps	4-6 Rev.	4.5 Sec.	.07 Min.	.0012 Hr.		**10**
16	6-9 Steps	7-11 Rev.	7.0 Sec.	.11 Min.	.0019 Hr.	Precision	**16**

Table C.2 Tool Use Data Card – Fasten or Loosen (adapted from Zandin, 2002)

BasicMOST System							**Tool Use**		**ABGABP * ABPA**			
Index x 10	**F Fasten**					**or**	**L Loosen**					**Index x 10**
	Finger Action	Wrist Action				Arm Action					Power Tool	
	Spins	Turns	Strokes	Cranks	Taps	Turns		Strokes	Cranks	Strikes	Screw Diam.	
	Fingers, Screwdriver	Hand, Screwdriver, Ratchet, T-Wrench	Wrench	Wrench, Ratchet	Hand, Hammer	Ratchet	T-Wrench, 2-Hands	Wrench	Wrench, Ratchet	Hammer	Power Wrench	
1	1	-	-	-	1	-	-	-	-	-	-	**1**
3	2	1	1	1	3	1	-	1	-	1	1/4 in. (6 mm)	**3**
6	3	3	2	3	6	2	1	-	1	3	1 in. (25 mm)	**6**
10	8	5	3	5	10	4	-	2	2	5		**10**
16	16	9	5	8	16	6	3	3	3	8		**16**
24	25	13	8	11	23	9	6	4	5	12		**24**
32	35	17	10	15	30	12	8	6	6	16		**32**
42	47	23	13	20	39	15	11	8	8	21		**42**
54	61	29	17	25	50	20	15	10	11	27		**54**

Table C.3 Tool Use Data Card – Cut, Surface Treat, Measure, Record, and Think (adapted from Zandin, 2002)

BasicMOST System								Tool Use				ABGABP * ABPA			
	C **Cut**				**S** **Surface Treat**			**M** **Measure**	**R** **Record**			**T** **Think**			
	Cutoff	Secure	Cut	Slice	Air-Clean	Brush-Clean	Wipe	Measure	Write		Mark	Inspect	Read		
Index x 10	Pliers	Pliers	Scissors	Knife	Nozzle	Brush	Cloth	Measuring Tool	Pencil/Pen		Marker	Eyes/Fingers	Eyes		**Index x 10**
	Wire		Cuts	Slices	sq. ft. ($0.1\ m^2$)	sq. ft. ($0.1\ m^2$)	sq. ft. ($0.1\ m^2$)		Digits	Words	Digits	Points	Digits, Single Words	Text of Words	
1		Grip	1	-	-	-	**-**		1	-	Check Mark	1	1	3	**1**
3	Soft		2	1	-	-	**I/2**		2	-	1 Scribe Line	3	3 Gauge	8	**3**
6	Medium	Twist Form Loop	4	-	1 Spot Cavity	1	**-**		4	1	2	5 Feel for Heat	6 Scale Value Date or Time	15	**6**
10	Hard		7	3	-	-	**1**	Profile Gauge	6	-	3	9 Feel for Defect	12 Vernier scale	24	**10**
16		Secure Cotter Pin	11	4	3	2	2	Fixed Scale Caliper ≤ 12 in. (30 cm)	9 Signature or Date	2	5	14	38 Table Value		**16**
24			15	6	4	3	-	Feeler Gauge	13	3	7	19		54	**24**
32			20	9	7	5	5	Steel Tape ≤ 6 ft. (2 m) Depth Micrometer	18	4	10	26		72	**32**
42			27	11	10	7	7	OD-Micrometer ≤ 4 in. (10 cm)	23	5	13	34		94	**42**
54			33					ID-Micrometer ≤ 4 in. (10 cm)	29	7	16	42		119	**54**

APPENDIX D DEFINITIONS AND TERMINOLOGY

This section aims to provide useful definitions and terminology used in this proposal.

Work measurement

Work measurement is an effort to determine the estimated time for an average skilled and well-trained operator to perform a predefined task at a normal pace under adequate supervision [1].

Time Standard

A time standard is a total allowed time, including manual time, process time, and allowances based on the fixed and documented work circumstances and a specified work method that it should take to perform a task [1].

Normal Time

Normal time is the time required by a skilled worker, working at an average pace with supervision to complete a predefined task and without interruptions [1].

Allowances

Allowances are the time added to the normal time to consist of personal time, rest time, and minor inevitable delays [1].

Sub-operation

A sub-operation is a part of an operation that could be separated and consistently measured. Sub-operations are often referred to as building blocks or portions of work. These building blocks describe standard data which could be the same in different operations [1].

Sequence model

A sequence model is a multi-character description of a single activity. Several predefined sequence models describe different types of actions [1].

Predetermined motion time systems (PMTS)

Predetermined motion time systems (PMTSs) are Work Measurement systems that provide a time estimate to humans' motion. Classifications are assigned based on the kind of movement and the conditions under which it is made [11].

Musculoskeletal Disorders (MSDs)

Musculoskeletal Disorders or MSDs affect the human body's movement and musculoskeletal systems (i.e., muscles, tendons, ligaments, nerves, discs, and blood vessels). MSDs are also known as repetitive motion injuries [121].

Fatigue

Fatigue is a decline in mental and physical performance due to long working hours or poorly designed shift patterns. It is generally considered to be the result of extended effort, sleep impairment, and disruption of the body clock. It is also related to workload ; thus, laborers are more easily exhausted if their work is machine-paced, complex, or repetitive [122].

Manual materials handling (MMH)

Manual handling is defined as moving or handling things by lifting, lowering, pushing/pulling heavy materials, carrying, holding, or restraining. Manual handling is the most frequent cause of work-related fatigue, low back pain, and injuries [123].

Anthropometry

Anthropometry is the science of studying human body dimensions. It is used to design ergonomic patterns, assembly systems, and workspaces. The goal of anthropometry is to minimize possible design conflicts and enhance human performance [121].

Neutral posture

An ergonomically correct posture with elbows side-to-side and wrists straight. The more a joint deviates from a neutral posture, the greater the MSD risks [121].

Risk factors

Risk factors are several factors that can increase a worker's chances of suffering a work-related musculoskeletal disorder, including force, posture, repetition, and vibration [121].

Digital Human Modeling (DHM)

Digital Human Modeling (DHM) refers to the process of obtaining and analyzing biomechanical and anthropometric data of the human body of a simulated human in conjunction with its interaction with a virtual environment [124].

Definitions related to Statistical analysis

Correlation coefficient

A correlation coefficient is a numerical model of the relationship between two variables. The variables can be either two columns in a given set of observations, generally referred to as a sample, or two independent random variables with a known distribution.Correlation values range from -1.0 to 1.0. If the correlation measurement is greater than 1.0, or less than -1.0, there is an error. A positive correlation is marked by a correlation of 1.0 and a negative correlation by -1.0. Correlations of 0.0 indicate that there is no linear relationship between two variables [125].

Cronbach's Alpha coefficient

The Cronbach's alpha indicates how closely related a set of items is as a whole. The Cronbach's alpha is often used to assess scale reliability. It does not necessarily imply that a high value for alpha indicates one-dimensionality. Additional analyses can be performed if you wish to demonstrate that the scale in question is unidimensional in addition to measuring internal consistency. The exploratory factor analysis is one method for measuring dimensionality. A Cronbach's alpha is actually a coefficient of consistency (or reliability), not a statistical test [126].

Normal distribution

The normal distribution, also known as the Gaussian distribution, is a symmetric probability distribution about the mean. It demonstrates that data near the mean are more common in occurrence than data far from it. Thus, graphs of normal distribution will resemble bell curves [127].

Confidence interval

A confidence interval (CI) is an estimate based on observed data. An unknown parameter can then be expressed as a range of values (i.e., a population mean). Each interval is associated with a confidence level. When using a higher confidence level for estimation in a given sample, the confidence interval is wider [128].

Bias

The bias in a statistic is a systematic outcome due to a factor that was not considered while it was being derived [129].

Random and Systematic errors

Measurement errors may be systematic or random. A systematic error is a bias error that occurs continuously with one direction. The main concern of reliability is random errors, which are due to chance and unpredictable [130].

Paired T-test

A paired t-test is a statistical method that is commonly used in reliability studies. However, it provides information on only the systematic differences between means of two data sets, not on individual differences. Such a test should not be used in isolation but in conjunction with other methods, e.g., Bland and Altman agreement tests [131].

The Hypothesis Test

In statistics, hypothesis testing is a way to determine whether or not the results of a survey or experiment are meaningful. The idea is to figure out the odds that your results happened by chance in order to determine whether they are valid. You won't be able to repeat your experiment if the results happened by chance, and therefore the experiment is of little value [132].

Bland-Altman agreement test

Bland-Altman agreement test is a statistical method for assessing the agreement between two methods. The first step is to plot the difference between the two results against the mean value from the two methods. The standard deviation and mean of the differences between the measures are calculated in step 2. In step 3, the 95% limits of agreement are calculated (as the differences plus or minus two standard deviations), as well as the 95% confidence intervals. The advantage of this method is that scatterplots can be used to visualize data in a fairly fast manner [130].

P-value

A statistic p-value measures the probability of obtaining results no less extreme than those observed in a statistical hypothesis test, assuming that the null hypothesis is true. When used as an alternative to rejection points, the p-value identifies which level of significance would result in the null hypothesis being rejected. Smaller p-values indicate stronger support for the alternative hypothesis [133].

Significance level

The significance level, or alpha, is a measure of the strength of the evidence required before the null hypothesis can be rejected. It is determined before the experiment starts.

The significance level represents the probability of rejecting the null hypothesis when it is true. A significance level of 0.05, for example, indicates a 5% chance of concluding that a difference exists even if none actually exists. A smaller significance level will require stronger evidence for rejecting the null hypothesis [134].

Null Hypothesis

Null hypotheses are hypotheses proposed as a method of statistical analysis to propose that certain characteristics of a population (or method of generating data) are not different from one another [134].

ICC tests

Traditional correlation coefficients have some limitations. The intra-class correlation coefficient (ICC) aims to overcome those limitations. In general, it represents a single estimate of variance derived from the division of variance into within and between subjects (known as analysis of variance). It, therefore, accurately reflects both the degree of consistency as well as the degree of agreement among ratings. As a dimensionless statistic, the ICC can be used to compare the repeatability of measures based on different units [130].

Pearson correlation coefficient

The Pearson correlation coefficient is a statistical tool to measure the degree to which two variables are positively correlated. The Pearson correlation coefficient - 1 indicates a positively correlated variable, while the Pearson correlation coefficient - 1 indicates a negatively correlated variable [135].

Coefficient of determination

The coefficient of determination, also known as the multiple correlation coefficient, is well established in classical regression analysis. It is defined as the proportion of variance that can be explained by a regression model of independent variables and a dependent variable. It measures how the difference between one variable and another variable can explain the outcome of an event. Thus, it represents how strongly two variables are correlated [136].