systems

MDPI

Article

A Multi-Criteria Decision-Support Framework for Dynamic Workforce Allocation in an Internal Software-Development Service Function Embedded Within a Large Manufacturing Organization

Nuno M. S. Correia [1], Francisco J. G. Silva [1,2,*], Isabel M. Pinto [1,3], Isabel Figueiredo [1,3], Alexandra Gavina [1,3], Ana J. Viamonte [1,3], Marlene Brito [1] and Rita C. M. Sales-Contini [1,4]

[1] CIDEM, ISEP, School of Engineering, Porto Technical University, Rua Dr. António Bernardino de Almeida, 431, 4249-015 Porto, Portugal; 1070599@isep.ipp.pt (N.M.S.C.); irm@isep.ipp.pt (I.M.P.); ipf@isep.ipp.pt (I.F.); alg@isep.ipp.pt (A.G.); ajv@isep.ipp.pt (A.J.V.); mab@isep.ipp.pt (M.B.); ritarcmsc@ita.br (R.C.M.S.-C.)
[2] LAETA, INEGI, Associate Laboratory of Energy, Transports and Aeronautics, Rua Dr. Roberto Frias, 400, 4200-465 Porto, Portugal
[3] LEMA, ISEP, School of Engineering, Porto Technical University, Rua Dr. António Bernardino de Almeida, 431, 4249-015 Porto, Portugal
[4] Technological College of São José dos Campos, Centro Paula Souza, Av. Cesare Mansueto Giulio Lattes 1350, Distrito Eugênio de Melo, São José dos Campos 12247-014, SP, Brazil
* Correspondence: fgs@isep.ipp.pt

Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- A systems-oriented decision architecture integrates interacting task, workforce, and organizational dimensions into adaptive and transparent resource allocation.

What are the main findings and/or the implications of the main findings?

- The framework reduced allocation time by 84.3%, workload imbalance by 92.9%, and manual intervention by 98.0%, demonstrating substantial operational gains.

Abstract

Dynamic workforce allocation in project-oriented service environments requires simultaneous consideration of heterogeneous and continuously changing information on employee competencies, availability, workload, expertise, and project requirements. However, allocation decisions frequently remain dependent on fragmented information and managerial judgement, limiting consistency, transparency, and responsiveness. This study develops and empirically evaluates a lightweight multi-criteria decision-support framework for dynamic workforce allocation using an Action Design Research methodology. The framework structures allocation through task characterization, candidate eligibility filtering, and employee ranking based on an Allocation Suitability Score integrating competency matching, availability, normalized workload, and expertise. The weighting configuration was calibrated through four iterative rounds involving ten organizational experts and subsequently examined through sensitivity analysis, demonstrating 100% stability of the top-ranked candidate across 16 weight perturbations and a mean Spearman rank correlation of 0.994. Industrial evaluation was conducted within a project-oriented internal software-development function comprising 102 employees and an organizational portfolio of 284 projects. Quantitative validation used seven purposively selected paired

Check for updates

Academic Editor: Zhen Zhang

Received: 28 July 2026
Revised: 30 August 2026
Accepted: 20 September 2026
Published: 26 September 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

allocation cases evaluated under equivalent conventional and framework-assisted conditions. The framework was associated with an 84.3% reduction in mean allocation time, a 92.9% reduction in workload imbalance, a 12.6% relative increase in resource utilization, a 25.3% increase in allocation consistency, and a 98.0% reduction in manual intervention requirements. These quantitative findings were complemented by favorable managerial assessments of transparency, workforce visibility, responsiveness, and usability. The results provide case-specific empirical evidence that transparent, computationally lightweight multi-criteria decision support can substantially improve workforce-allocation processes while preserving managerial interpretability and implementation flexibility. The proposed framework therefore provides a reproducible foundation for dynamic workforce allocation in project-oriented, knowledge-intensive service environments, while broader generalizability requires longitudinal and cross-organizational validation.

Keywords: dynamic workforce allocation; multi-criteria decision support; competency-aware allocation; action design research; project-oriented service environments

1. Introduction

Organizations increasingly operate in dynamic, resource-constrained environments in which operational efficiency, responsiveness, and service quality depend critically on how human resources are deployed across competing activities [1]. As project complexity increases and workforce specialization becomes progressively more pronounced, assigning appropriately qualified personnel to tasks under evolving operational conditions can no longer be regarded as a purely administrative function. Rather, workforce allocation constitutes a strategic decision problem with direct implications for organizational performance, project outcomes, and sustained competitiveness [2].

The strategic relevance of resource allocation has consequently motivated extensive research across project management, operations management, optimization, and decision-support systems [3–6]. Existing contributions address different dimensions of the problem, including optimization-based resource allocation [7], performance-oriented allocation models [8], expertise-aware assignment mechanisms [9], discrete resource-allocation formulations [10], and digitally enabled management approaches designed to cope with increasingly complex industrial environments [11]. Collectively, this body of research demonstrates that allocation quality depends not only on resource availability, but also on the capacity to reconcile heterogeneous decision criteria within increasingly dynamic organizational settings.

Nevertheless, translating these advances into effective workforce-allocation practices remains challenging. Real organizational environments are characterized by continuously evolving workloads, shifting project priorities, employee absences, heterogeneous competency profiles, and recurrent arrivals of new tasks and projects. Allocation decisions must therefore reconcile several interdependent dimensions simultaneously, including technical suitability, current workload, effective availability, task requirements, and operational priorities. This complexity is particularly relevant in project-oriented and knowledge-intensive service environments, where organizational value creation depends strongly on the timely deployment of specialized human capabilities.

Human resources further differ from conventional organizational resources because their contribution cannot be adequately represented by availability or capacity alone. Knowledge, experience, expertise, and adaptability substantially influence the suitability of an employee for a particular assignment. As highlighted by Ballesteros-Pérez et al. [9],

heterogeneous competency profiles combined with finite resource availability impose intrinsic constraints on allocation decisions. Poorly structured allocation may consequently lead to workload concentration, ineffective use of specialized expertise, project delays, and deteriorating operational performance. Conversely, informed allocation can improve workforce utilization, decision transparency, knowledge deployment, and project execution.

Existing research provides sophisticated approaches for addressing different aspects of this decision problem, but two broad orientations remain identifiable. The first emphasizes mathematical rigor through optimization-based formulations capable of representing complex allocation constraints and interactions [7,9]. The second places greater emphasis on operational applicability and the practical deployment of allocation mechanisms within real organizational environments [12,13]. Although both perspectives have generated important advances, a persistent implementation challenge lies at their intersection: analytically sophisticated methods may be difficult to embed in routine managerial practice, whereas highly pragmatic approaches may lack the structured multi-criteria reasoning required to support transparent and reproducible allocation decisions.

This implementation gap becomes particularly relevant in organizations or organizational units for which sophisticated enterprise-level resource-management infrastructures are economically disproportionate, operationally excessive, or insufficiently adaptable to local decision requirements. Under such conditions, workforce allocation frequently remains supported by spreadsheets, fragmented information repositories, and experience-based managerial judgement. Although such practices can sustain routine operations, their effectiveness deteriorates as allocation complexity increases, particularly when several decision dimensions must be considered concurrently. Limited information integration can then reduce transparency, consistency, traceability, and scalability of the allocation process.

A relevant research gap therefore persists between theoretically rigorous resource-allocation models and lightweight, practically deployable decision-support mechanisms capable of integrating heterogeneous workforce and task information within a unified allocation process. In particular, there remains a need for transparent approaches that can jointly accommodate competency matching, workload balancing, employee availability, task characteristics, project priorities, and reassignment requirements without imposing excessive computational or implementation complexity. Addressing this gap requires a balance between analytical structure and operational simplicity, enabling managerial decisions to remain interpretable while reducing dependence on fragmented information and individual experience.

From this perspective, dynamic workforce allocation extends beyond conventional scheduling. It constitutes a human-centric, multi-criteria decision-support problem in which task requirements and workforce conditions interact dynamically. Effective allocation therefore requires a structured distinction between the characteristics that define and prioritize the task, the constraints that determine candidate eligibility, and the employee-level attributes used to rank suitable candidates. Such a perspective enables competency, availability, workload, expertise, project priority, task complexity, and continuity requirements to contribute to the decision process according to their respective operational roles rather than being indiscriminately aggregated into a single decision layer.

Accordingly, this study addresses the following research question: "How can dynamic workforce allocation be systematically supported through a practical and transparent decision-support framework capable of integrating employee competencies, workload, availability, expertise, project requirements, and reassignment constraints while remaining suitable for implementation in project-oriented organizational environments?"

To address this research question, the study adopts an Action Design Research (ADR) approach to develop, implement, and empirically evaluate a structured decision-support

framework for dynamic workforce allocation. The proposed approach organizes allocation into three interconnected decision layers—task characterization, candidate eligibility filtering, and employee ranking—and operationalizes the latter through a multi-criteria Allocation Suitability Score integrating competency matching, availability, normalized workload, and expertise. The resulting artefact was implemented through a lightweight software solution developed in Microsoft Excel® and Visual Basic for Applications (VBA) and evaluated within a real organizational environment. This research design enables the proposed decision logic to be examined under authentic operational conditions while preserving transparency, managerial interpretability, and implementation feasibility. The main contributions of this study are fourfold:

- Development of a structured decision-support framework for dynamic task allocation in an internal software-development service function embedded within a large manufacturing organization.
- Integration of workforce competencies, workload balancing, employee availability, project priorities, task characteristics, and reassignment logic into a unified allocation methodology.
- Demonstration of how lightweight and accessible technologies can support complex allocation decisions without requiring sophisticated enterprise systems.
- Validation of the proposed framework through an industrial case study, providing practical insights into its applicability and organizational benefits.

The remainder of this paper is organized as follows. Section 2 presents the literature review covering project management, resource allocation, and supporting decision methodologies. Section 3 describes the research methodology and framework development process. Section 4 presents the proposed solution and validation results. Section 5 discusses the main findings and implications. Finally, Section 6 summarizes the conclusions, limitations, and future research opportunities.

Scientific Contributions

This study advances the workforce-allocation and decision-support literature through four complementary contributions.

First, it develops an integrated multi-criteria framework for dynamic workforce allocation in which task characterization, candidate eligibility, and employee ranking are treated as distinct but interconnected decision layers. Rather than reducing allocation to competency matching alone, the proposed framework systematically combines competency, availability, workload, and expertise within an interpretable Allocation Suitability Score, while preserving project priority, task complexity/urgency, and continuity as task-level decision rules and constraints.

Second, the study operationalizes Action Design Research as a mechanism for translating workforce-allocation requirements into a deployable decision-support artefact. The iterative interaction between organizational diagnosis, artefact development, expert calibration, implementation, and empirical evaluation establishes a traceable methodological pathway from the identification of the allocation problem to the assessment of the resulting decision-support intervention under authentic organizational conditions.

Third, the study provides complementary quantitative and qualitative empirical evidence from industrial implementation. The evaluation combines paired operational performance measures, variability estimates, managerial assessment, and robustness analysis of the weighting configuration, thereby extending the contribution beyond conceptual model development. This empirical structure enables the operational effects associated with framework-assisted allocation to be examined while retaining explicit boundaries regarding the case-specific nature of the evidence.

Fourth, the proposed framework establishes a modular and configurable decision architecture that separates organizational decision logic from the specific technological implementation. This architecture provides a methodological basis for subsequent integration with mathematical optimization, enterprise information systems, advanced analytics, and intelligent workforce-management technologies without compromising the transparency and interpretability required for managerial decision support.

Taken together, these contributions position the scientific value of the study beyond the digitalization or aggregation of existing workforce information. The central contribution lies in a reproducible and empirically evaluated methodology for dynamic workforce allocation that formalizes how heterogeneous task requirements, eligibility constraints, and employee-level attributes are transformed into transparent and operationally actionable allocation recommendations.

The novelty of the proposed approach therefore resides not in the individual use of competency information, workforce scheduling, multi-criteria scoring, or decision-support technologies, which are established research domains, but in their structured orchestration within a unified and operationally validated decision architecture. Specifically, the framework connects task-level characterization and prioritization, explicit candidate-eligibility logic, multi-criteria employee ranking, expert-calibrated decision weights, sensitivity-based robustness assessment, and dynamic reassignment within a single transparent allocation process. Figure 1 synthesizes this scientific positioning by distinguishing the established methodological foundations from their integration and operationalization in the proposed framework, thereby clarifying the transition from fragmented allocation mechanisms toward an interpretable, empirically evaluated, and implementation-oriented workforce decision-support methodology.

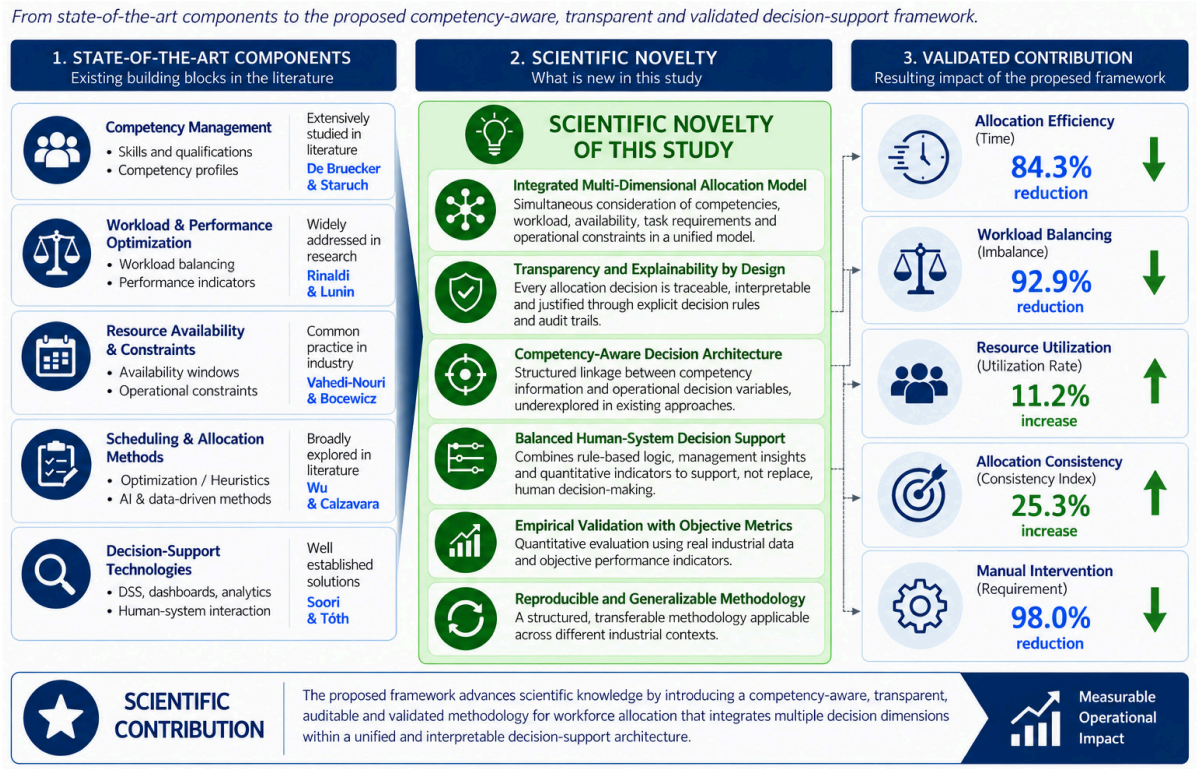


Figure 1. Scientific novelty framework illustrating the transformation of established workforce allocation concepts into a transparent, competency-aware, and quantitatively validated decision-support methodology [14–23]. Created by the authors, with GPT used to improve the visual quality.

The proposed framework is theoretically grounded in three complementary perspectives that address distinct dimensions of the research problem. First, Action Design Research (ADR) provides the overarching methodological paradigm through which the decision-support artefact is iteratively designed, implemented, evaluated, and refined in interaction with the organizational environment. Second, competency-based workforce management provides the human-resource perspective required to establish systematic correspondence between task requirements and heterogeneous employee capabilities. Third, multi-criteria decision-support theory provides the analytical foundation for structuring allocation decisions in which several potentially competing operational dimensions must be considered simultaneously under resource and organizational constraints. The integration of these perspectives establishes a coherent theoretical basis linking artefact development, workforce suitability assessment, and structured multi-criteria decision-making within a single empirical research design.

Within this theoretical structure, Figure 1 positions the proposed contribution at the intersection between established knowledge and its methodological operationalization for dynamic workforce allocation. The contribution does not derive from the isolated use of competency management, multi-criteria scoring, or decision-support technologies, but from the explicit structuring of the allocation problem into interconnected decision layers encompassing task characterization, candidate eligibility, employee suitability assessment, and dynamic reassignment. This architecture enables heterogeneous organizational information to be transformed into transparent and traceable allocation recommendations while preserving managerial interpretability and permitting empirical assessment of the associated operational effects. By establishing an explicit linkage between theoretical foundations, decision logic, artefact implementation, and case-specific empirical evidence, the framework provides a scientifically reproducible basis for investigating dynamic workforce allocation and delineates the methodological positioning of the study within the broader domain of intelligent and human-centric workforce decision support.

2. Literature Review

2.1. Resource Allocation as a Strategic Project Management Function

Project management has undergone a substantial conceptual transition from a predominantly planning- and scheduling-oriented discipline towards an increasingly adaptive management paradigm capable of responding to organizational complexity and operational uncertainty. Early methodological developments were strongly shaped by deterministic and probabilistic scheduling techniques, particularly the Critical Path Method (CPM) and the Program Evaluation and Review Technique (PERT), which established systematic mechanisms for activity sequencing, project-duration control, and resource-dependency management [24,25]. Although these approaches remain fundamental to project planning, the increasing interdependence of activities, resources, and organizational constraints has progressively broadened the project-management problem beyond schedule optimization towards uncertainty management, resource adaptability, and dynamic organizational coordination.

The progressive adoption of project-oriented organizational structures further reinforced this transition by demonstrating that project performance depends not only on planning accuracy but also on the capacity to coordinate heterogeneous resources throughout project execution. Kerzner [26] conceptualized project management as an integrated management system in which people, processes, technologies, and organizational objectives must be coordinated rather than treated as independent dimensions. More recent perspectives further reinforce this evolution: Hansen et al. [27] examined the tensions and paradoxes associated with agile-hybrid project portfolio management, while Kozarkiewicz

and Swałdek [28] addressed project-management capability from the perspective of intentionality and organizational maturity. Together, these contributions support a broader understanding of project management as an adaptive organizational capability rather than a narrowly defined scheduling function [29].

Within this expanded perspective, resource allocation has emerged as a central component of project-management performance, particularly in multi-project environments where limited resources must be dynamically distributed across competing requirements. Mao et al. [7] addressed decentralized resource-constrained multi-project scheduling through evolving multi-agent heuristics, illustrating the increasing methodological complexity associated with coordinating resources across simultaneous projects. Sözüer and Spang [30] further emphasized the importance of resource planning within project-management processes, whereas Lima et al. [31] highlighted resource flexibility as an increasingly relevant capability for managing uncertainty and changing scheduling conditions. Collectively, these studies demonstrate that effective resource coordination becomes progressively more important as project environments become dynamic, interdependent, and resource constrained.

Human resources introduce an additional level of complexity because their organizational contribution cannot be adequately represented through capacity or availability alone. In contrast to conventional physical resources, employees embody heterogeneous combinations of knowledge, experience, competencies, creativity, and problem-solving capabilities, making their suitability inherently dependent on the characteristics of the task and its organizational context. Müller and Turner [32] demonstrated the relevance of leadership competency profiles to project success, while Lopes et al. [33] reinforced the strategic importance of human capabilities within project-oriented organizations. Workforce allocation must therefore account for qualitative differences among employees, requiring decision mechanisms capable of considering competencies and expertise together with availability and other operational constraints.

The emergence of agile and adaptive project-management paradigms has further increased the relevance of dynamic resource-allocation capabilities. Rasnacis and Berzisa [34] examined mechanisms for adapting and implementing agile project-management methodologies, demonstrating the importance of organizational adaptability when project conditions evolve. Špundak [35] similarly examined the integration of agile and traditional project-management approaches, highlighting the need for methodological flexibility rather than rigid adherence to a single management paradigm. Consistent with this perspective, Collyer et al. [36] showed that dynamic environments require planning approaches capable of accommodating uncertainty and change more effectively than conventional deterministic practices. From a workforce-allocation perspective, these developments imply that assignment decisions cannot be treated as static events but must remain responsive to evolving resource states, task requirements, and project priorities.

Digital transformation provides an important technological enabler for this transition. Mourtzis et al. [2] and Mourtzis et al. [11] highlighted the potential of digitally supported approaches to enhance workforce-related information availability and strengthen resource-allocation decision processes. The increasing availability and integration of operational data therefore create opportunities to move workforce allocation away from fragmented, experience-dominated decision processes towards more structured, information-driven, and traceable decision-support mechanisms.

Nevertheless, the transition from adaptive project-management principles and digitally available workforce information to systematic allocation decisions remains incomplete. Managers operating in dynamic project environments must reconcile heterogeneous and potentially competing dimensions, including employee competencies, workload, availabil-

ity, project priority, task complexity, and continuity requirements, while retaining sufficient flexibility to respond to changing organizational conditions. The challenge is therefore not merely to schedule available resources, but to determine how heterogeneous workforce and task information should be structured and operationalized to support transparent, consistent, and dynamically adaptable allocation decisions. Accordingly, workforce allocation is more appropriately conceptualized as a strategic, human-centric decision problem embedded within project management rather than as an isolated scheduling activity. This perspective establishes the conceptual transition to the subsequent analysis of workforce optimization and decision-support mechanisms for dynamic allocation.

2.2. Human Resource Allocation and Workforce Optimization

Effective human-resource allocation constitutes a particularly complex decision problem within project and operations management because workforce resources cannot be adequately characterized solely in terms of capacity or nominal availability. Unlike physical, material, or financial resources, employees exhibit heterogeneous competency profiles, different levels of experience and expertise, variable availability, and task-dependent performance capabilities. Consequently, workforce allocation requires the simultaneous consideration of quantitative resource constraints and qualitative differences in individual suitability, substantially increasing the dimensionality of the decision problem.

Human-resource allocation can therefore be conceptualized as the systematic assignment of individuals to tasks, projects, or organizational functions while reconciling organizational objectives, task requirements, and workforce constraints. Ballesteros-Pérez et al. [9] addressed human-resource allocation across multiple projects by explicitly considering members' expertise, group heterogeneity, and social cohesion, demonstrating that allocation quality cannot be reduced to the identification of nominally available personnel. Rather, employee suitability emerges from the correspondence between individual capabilities and the specific requirements and contextual conditions associated with an assignment.

Several analytical methodologies have been proposed to structure resource-allocation decisions involving multiple and potentially competing objectives. Eilat et al. [37] developed a Data Envelopment Analysis (DEA)-based methodology for constructing and evaluating balanced portfolios of R&D projects while accounting for interactions among projects, illustrating the capacity of efficiency-oriented methods to support complex resource-related decisions. Karsu and Morton [38] subsequently incorporated balance considerations into resource-allocation decisions through a bi-criteria modelling approach, demonstrating that allocation cannot necessarily be represented through a single efficiency objective when competing organizational concerns must be reconciled. These contributions highlight the need to accommodate trade-offs explicitly rather than assuming that resource-allocation performance can be captured through a single decision criterion.

In project-oriented environments, the allocation problem is further influenced by the temporal and organizational characteristics of project work. Zwikael and Unger-Aviram [39] investigated the effect of project duration on team-development effectiveness, demonstrating that human-resource management within project groups is conditioned by the temporal structure of the project environment. From a complementary workforce-planning perspective, Yu et al. [40] employed centralized Data Envelopment Analysis for human-resource rightsizing, illustrating how analytical approaches can support the alignment of workforce capacity with organizational requirements. Together, these studies reinforce the importance of treating human resources as heterogeneous organizational assets whose effective deployment depends on both project conditions and workforce configuration.

The complexity increases further when personnel suitability must be reconciled with explicit project constraints and contextual factors. Barreto et al. [41] formulated software-project staffing as a constraint-satisfaction and optimization problem, demonstrating how personnel assignment can be systematically linked to project requirements within a formal decision structure. Wu et al. [42] extended the resource-allocation perspective by incorporating environmental factors into a DEA-based formulation, illustrating that allocation efficiency may depend on contextual variables beyond the resources directly represented in the decision model. These contributions collectively demonstrate that resource allocation is intrinsically context-dependent and that effective decision models must accommodate heterogeneous constraints and relevant organizational conditions rather than treating resources as homogeneous and interchangeable units.

Digitalization provides additional opportunities for structuring such information-intensive allocation processes. Mourtzis et al. [2] proposed an adaptive framework explicitly considering workforce skill, illustrating how digitally supported systems can incorporate employee-related information into operational decision processes. More generally, increasing access to integrated competency, availability, workload, and project information creates the technological conditions required to transition from fragmented and predominantly experience-driven allocation practices towards more systematic, data-supported, and traceable decision mechanisms.

Nevertheless, greater data availability and analytical sophistication do not automatically translate into practically deployable workforce-allocation solutions. A persistent challenge concerns the balance between methodological rigor and operational applicability. Advanced optimization formulations can represent complex combinations of objectives and constraints, but their deployment may require extensive data structures, specialized modelling expertise, computational resources, and organizational capabilities. Conversely, highly simplified allocation procedures may be readily implementable but insufficiently sensitive to the multidimensional nature of employee suitability. The relevant methodological challenge therefore lies in developing allocation mechanisms that preserve sufficient analytical structure to support consistent and transparent decisions while avoiding implementation complexity disproportionate to the operational problem.

Taken together, the literature positions workforce allocation as a multidimensional and context-dependent decision problem rather than a conventional scheduling exercise. Effective allocation requires the coordinated consideration of employee capabilities, resource constraints, organizational objectives, contextual conditions, and changing operational requirements. However, the reviewed contributions also reveal a persistent tension between analytically sophisticated allocation models and mechanisms sufficiently transparent and lightweight for routine managerial deployment. This unresolved interface provides the rationale for decision-support approaches capable of integrating heterogeneous allocation dimensions within an interpretable and operationally deployable framework, which constitutes the focus of the following section.

2.3. Decision-Support Systems for Dynamic Task Allocation

The increasing complexity of workforce-allocation decisions has intensified the need for Decision-Support Systems (DSS) capable of structuring heterogeneous information and assisting managers in evaluating alternative resource-assignment decisions. As organizational environments become more dynamic and workforce constraints increasingly interdependent, allocation based predominantly on managerial experience becomes progressively difficult to sustain in a consistent and traceable manner. The underlying challenge arises not merely from the volume of available information, but from the need to reconcile hetero-

geneous employee attributes, task requirements, resource constraints, and organizational priorities within a coherent decision process.

Within this context, DSS provide a conceptual and technological mechanism for transforming distributed workforce and project information into structured decision inputs and actionable allocation recommendations. In project-oriented environments, such systems can support the integration of competency information, availability conditions, workload states, task characteristics, and organizational requirements while preserving managerial oversight. Their principal value therefore extends beyond computational automation: appropriately designed DSS can formalize decision logic, improve information visibility, enhance consistency across comparable allocation situations, and provide greater traceability regarding how allocation recommendations are generated.

Early contributions to software-project resource allocation already illustrated the importance of systematically linking workforce characteristics with project requirements. Otero et al. [12] proposed a systematic approach for resource allocation in software projects in which resource suitability is evaluated in relation to project needs. Their work provides an important foundation for structured personnel assignment by demonstrating that workforce allocation can be formalized rather than relying exclusively on intuitive managerial judgement. At the same time, the allocation problem addressed remains comparatively focused relative to contemporary dynamic workforce environments, in which suitability must be considered together with continuously evolving availability, workload, prioritization, and reassignment conditions.

Kang et al. [13] further formalized human-resource allocation in software projects through a constraint-based approach capable of representing multiple assignment requirements within a systematic decision structure. This contribution demonstrates the analytical value of explicitly modelling the constraints governing feasible personnel assignments. It also illustrates a broader methodological trade-off: increasing representational richness enables more detailed treatment of allocation requirements, but may simultaneously increase modelling and implementation demands when decision environments involve numerous interacting constraints or require frequent operational reconfiguration.

Complementary contributions have addressed resource allocation from an optimization and efficiency perspective. Fang [8] developed a centralized resource-allocation approach based on efficiency analysis and step-by-step improvement paths, providing a formal mechanism for improving allocation decisions under centralized management conditions. Rudek and Heppner [10] investigated discrete resource-allocation problems under degressively proportional constraints and proposed efficient algorithms for solving the resulting allocation formulations. Together, these studies demonstrate the analytical sophistication achievable through formal resource-allocation models, while also illustrating that mathematical tractability and optimization performance constitute only part of the requirements associated with workforce decision support in operational organizational settings.

Digitalization has further expanded the possibilities for operationalizing workforce-allocation mechanisms. Mourtzis et al. [2] introduced an adaptive framework that explicitly incorporates workforce skills into digitally supported operational decision-making, while Mourtzis et al. [11] developed an intelligent workforce-allocation model that considers operator skills. These contributions illustrate the progressive convergence between workforce information, digital technologies, and structured allocation logic, creating opportunities for more responsive and information-rich personnel assignment than is possible through fragmented manual procedures.

Despite these methodological and technological advances, the literature reveals persistent fragmentation in the treatment of the workforce-allocation problem. Existing

approaches frequently emphasize particular dimensions—such as competency or skill matching, constraint satisfaction, resource efficiency, or algorithmic allocation—whereas operational workforce decisions may require several dimensions to be considered concurrently. Competency, availability, current workload, expertise, task priority, complexity, and continuity do not necessarily perform equivalent roles in the decision process: some characterize the task, others constrain candidate eligibility, and others differentiate among feasible employees. An integrated DSS must therefore do more than aggregate multiple variables; it must establish a transparent decision architecture defining how each information category contributes to the allocation process.

A second unresolved issue concerns the relationship between analytical sophistication and organizational deployability. Highly formalized optimization approaches provide powerful mechanisms for representing objectives and constraints, but operational adoption also depends on data availability, configurability, interpretability, computational requirements, and compatibility with existing managerial processes. Conversely, lightweight decision tools may offer greater accessibility but risk oversimplifying the allocation problem when their underlying decision logic is insufficiently structured. The relevant methodological challenge is therefore not to maximize algorithmic sophistication per se, but to achieve an appropriate balance between analytical rigor, transparency, adaptability, and implementation feasibility.

These observations motivate the development of integrated decision-support architectures capable of connecting workforce information, task characteristics, eligibility constraints, employee-ranking criteria, and reassignment logic within a coherent operational process. Such architectures should preserve sufficient formal structure to generate reproducible recommendations while remaining interpretable to managers and configurable according to organizational priorities. This requirement establishes the conceptual basis for the research gap addressed in the following section and motivates the dynamic workforce-allocation framework developed in this study.

Viewed collectively, the reviewed literature demonstrates substantial methodological diversity but also reveals that different approaches address different portions of the broader allocation problem. Competency- and skill-oriented methods emphasize employee–task correspondence; constraint-based formulations formalize assignment feasibility; efficiency and optimization models provide rigorous mechanisms for resource distribution; and digitally enabled approaches improve the integration and operational availability of workforce information. What remains less comprehensively addressed is the structured orchestration of these complementary requirements within a transparent and practically deployable decision process capable of supporting dynamic organizational conditions.

To make this positioning explicit, Figure 2 comparatively examines representative workforce-allocation approaches according to the principal decision dimensions and implementation characteristics relevant to the present study. Rather than interpreting the absence of individual features as a limitation of methods developed for different research objectives, the comparison identifies how existing contributions collectively inform the proposed framework and where methodological integration remains incomplete. The analysis thereby establishes the basis for positioning the proposed approach as a multilayer decision-support architecture combining task characterization, candidate eligibility, multi-criteria employee ranking, and dynamic reassignment within an operationally deployable structure.

The comparative synthesis presented in Figure 2 indicates that the workforce-allocation literature has generated substantial methodological advances across competency-based assignment, constraint modelling, resource optimization, workload management, and digitally enabled decision support. However, these capabilities are predominantly addressed

through approaches developed for distinct allocation objectives, leaving comparatively limited methodological integration across the multiple decision layers required in dynamic organizational settings. In particular, the simultaneous treatment of task characterization and prioritization, candidate eligibility, competency matching, employee availability, workload balancing, expertise, and reassignment requirements within a transparent and operationally deployable decision architecture remains insufficiently consolidated. The resulting research opportunity therefore lies not in introducing these allocation dimensions individually, but in structuring their complementary roles within a unified decision process capable of preserving analytical consistency, managerial interpretability, and practical implementation feasibility. This synthesis establishes the conceptual basis for the research gap examined in the following section and motivates the development of the dynamic workforce-allocation decision-support framework proposed in this study.

COMPARATIVE ANALYSIS OF WORKFORCE-ALLOCATION APPROACHES AND RESEARCH GAPS

ANALYTICAL DIMENSION	TRAD RULES (2009)	COMP MATCH (2011)	PURE OPT. (2015)	AI & ML & HYBRID (2020+)	THIS WORK	RESEARCH GAP ADDRESSED
Competency Matching	✗	✓	◐	✗	✓	Integrates soft, explicit and contextual competencies
Workload Balancing	✗	✓	◐	✓	✓	Combined skill + real-time demand evaluation
Availability Assessment	✗	◐	✗	✗	✓	Considers micro-availability and dynamic constraints
Project Priority	✗	◐	✗	✗	✓	Aligned to strategic organizational priorities
Task Complexity	✗	✗	✗	✗	✓	Maps task classification and complexity to skill requirements
Dynamic Reassignment	✗	✗	✗	✗	✓	Real-time reallocation capability under disruptions
Decision-Support Environment	◐	◐	✗	✗	✓	Operational DSS with explainable multi-criteria logic
Practical Deployment	◐	◐	✗	✗	✓	Validated in real organizations with users
Real-World Validation	✓	✓	◐	◐	✓	Validated with industry stakeholders and metrics

✓ Fully addressed ◐ Partially addressed ✗ Not addressed

TRAD RULES: Traditional Rule-Based Methods | COMP MATCH: Competency Matching Methods | PURE OPT.: Pure Optimization Methods
AI & ML & HYBRID (2020+): AI, Machine Learning and Hybrid Methods (2020 and beyond) | THIS WORK: Proposed Framework

Figure 2. Comparison of representative workforce-allocation approaches identified in the literature, the capabilities incorporated into the proposed framework, and the specific research gaps addressed by this study. Created by the authors, with GPT used to improve the visual quality.

2.4. Critical Comparison of AI-Based Workforce Allocation and Scheduling Methods

Recent research on workforce allocation and scheduling reflects a progressive transition from static and predominantly rule-based formulations towards more adaptive, data-informed, and multi-dimensional decision architectures [43–45]. Contemporary approaches increasingly seek to accommodate dynamic resource conditions, heterogeneous workforce capabilities, temporal constraints, and multiple operational requirements within the allocation process. Nevertheless, the resulting methodological families differ substantially in their mathematical foundations, information requirements, computational demands, adaptability, interpretability, and capacity to represent human- and organization-related constraints.

Classical mathematical optimization remains particularly appropriate when decision variables, objective functions, and operational constraints can be explicitly formalized. Linear, integer, and mixed-integer formulations provide rigorous mechanisms for representing assignment feasibility and resource interactions and, depending on problem structure and scale, can provide optimal or bounded solutions. Their practical complexity, however, increases rapidly as workforce-allocation problems incorporate heterogeneous

skills, temporal availability, task precedence, synchronization requirements, individual restrictions, and multiple competing objectives. Recent formulations therefore increasingly combine deterministic structure with mechanisms capable of accommodating uncertainty and dynamic workforce conditions [43–45].

Evolutionary algorithms provide an alternative when the allocation space is discrete, nonlinear, combinatorial, or difficult to solve efficiently through exact optimization. Ye et al. [46], for example, employed an improved genetic algorithm within a two-stage task-allocation problem, illustrating the flexibility of evolutionary search for complex assignment structures. Recent applications further demonstrate the applicability of genetic and related evolutionary mechanisms to operational scheduling problems: Sukmana et al. [47] integrated genetic algorithms with dispatching rules and technician-resource management, whereas Farahmand-Mehr and Mousavi [48] proposed an immune genetic local-search algorithm for resource-constrained multi-project scheduling under time-dependent resource reliability. These approaches offer considerable search flexibility, although their performance remains dependent on algorithm design, parameterization, stopping criteria, and the stochastic characteristics of the search process.

Multi-objective optimization is particularly relevant to workforce scheduling because operational allocation rarely involves a single performance criterion. Workforce utilization, skill compatibility, workload distribution, cost, service requirements, temporal performance, and schedule stability may represent concurrent or competing objectives. Multi-objective approaches provide a formal mechanism for exploring such trade-offs, including through Pareto-based representations in which alternative non-dominated solutions can be evaluated without reducing all objectives to a single aggregate criterion. Their practical use nevertheless requires an additional preference structure or managerial decision mechanism to select among competing solutions, reinforcing the continuing importance of interpretable decision support even when sophisticated optimization is employed [49].

Machine-learning approaches introduce a different capability by exploiting historical or operational data to identify patterns relevant to allocation decisions. Wang et al. [50] investigated dynamic order allocation in a hybrid workforce environment through a machine-learning approach, illustrating the potential of data-driven methods to support allocation under changing competitive and operational conditions. Such methods can enrich allocation processes by learning relationships that may be difficult to encode explicitly. However, predictive or learned relationships do not intrinsically guarantee feasible assignments or compliance with organizational constraints. Machine-learning outputs therefore become particularly valuable when embedded within a broader decision architecture capable of enforcing feasibility and operational decision rules.

Reinforcement learning provides a further methodological alternative by learning scheduling or allocation policies through repeated interaction with a decision environment. This characteristic is particularly attractive when system states evolve dynamically and decisions must adapt to disturbances, changing resource conditions, or newly arriving tasks. Chen et al. [51] combined digital-twin capabilities with reinforcement learning for adaptive job scheduling and resource allocation in industrialized construction processes, demonstrating the potential of state-responsive learning architectures for dynamic operational decision-making. Nevertheless, reinforcement-learning deployment introduces additional considerations related to training requirements, constraint enforcement, robustness, generalization beyond the training environment, reproducibility, and managerial explainability.

Fuzzy decision mechanisms are particularly relevant when allocation criteria contain qualitative, uncertain, or linguistically expressed information that cannot be represented naturally through crisp numerical thresholds. Qiu et al. [52] developed an adaptive fuzzy response-threshold method with task-age awareness for distributed task allocation, illustrat-

ing how fuzzy mechanisms can support adaptive decisions under evolving task conditions. Such approaches provide a natural mechanism for representing graded decision states and expert knowledge. Their effectiveness, however, depends on the definition of membership structures, thresholds, and rule bases, which may introduce model-design subjectivity and limit direct transferability between application contexts.

Hybrid approaches seek to exploit complementary methodological strengths rather than assuming the existence of a universally dominant allocation paradigm. Moazzami et al. [53], for example, combined fuzzy logic with deep reinforcement learning for adaptive task scheduling and resource allocation, illustrating how interpretable knowledge-representation mechanisms can be integrated with adaptive learning. More generally, hybrid architecture can combine optimization, learning, fuzzy reasoning, heuristics, or explicit organizational rules according to the structure of the decision problem. Their principal scientific challenge lies in ensuring that increased methodological capability does not produce disproportionate computational complexity or reduce the transparency required for operational adoption.

Within this methodological landscape, the framework proposed in the present study deliberately occupies an intermediate position between formal optimization and fully autonomous data-driven scheduling. It does not seek to compute a globally optimal workforce configuration, nor does it learn an allocation policy from large historical datasets. Instead, it formalizes organizational decision logic through explicit task characterization, candidate-eligibility rules, and multi-criteria employee ranking based on competency, availability, workload, and expertise. This design prioritizes interpretability, traceability, configurability, and managerial oversight while retaining sufficient analytical structure to support reproducible allocation decisions under dynamic operational conditions.

Importantly, this positioning should not be interpreted as evidence of methodological superiority over optimization, evolutionary, machine-learning, reinforcement-learning, or fuzzy approaches. Rather, these methodological families address different combinations of optimization capability, adaptability, data dependence, computational complexity, and interpretability. The proposed framework addresses a different design requirement: providing lightweight and transparent decision-making support for organizational environments in which explicit workforce information and managerial decision rules are available, but fully autonomous or computationally intensive allocation mechanisms may not be necessary or desirable.

To critically position this design choice within the current methodological landscape, Figure 3 compares the principal workforce-allocation and scheduling approaches according to their decision mechanism, principal strengths, limitations, adaptability, interpretability, and implementation characteristics. The comparison is intended not to establish a universal ranking among methodological families, but to clarify the trade-offs associated with alternative approaches and the specific design space occupied by the proposed framework.

The comparative synthesis presented in Figure 3 indicates that the principal methodological families considered in workforce allocation and scheduling embody different trade-offs among optimization capability, adaptability, computational requirements, interpretability, and implementation feasibility. Advanced approaches based on reinforcement learning and hybrid AI architectures provide substantial capabilities for adaptive decision-making in dynamic environments but may simultaneously introduce greater data and computational requirements and more complex mechanisms for ensuring decision transparency and organizational interpretability. The proposed framework addresses a complementary methodological requirement by prioritizing explicit workforce information, transparent decision logic, competency-aware assessment, traceability, and managerial oversight within a lightweight operational architecture. Its positioning should therefore not

be interpreted as methodological superiority over optimization- or AI-based approaches, but as a deliberate design choice for organizational contexts in which interpretability, configurability, and practical deployability constitute central requirements. Accordingly, the framework occupies an intermediate methodological space between highly formalized optimization and fully autonomous data-driven scheduling, seeking to preserve sufficient analytical structure for systematic workforce allocation while maintaining the transparency and managerial control required for operational implementation.

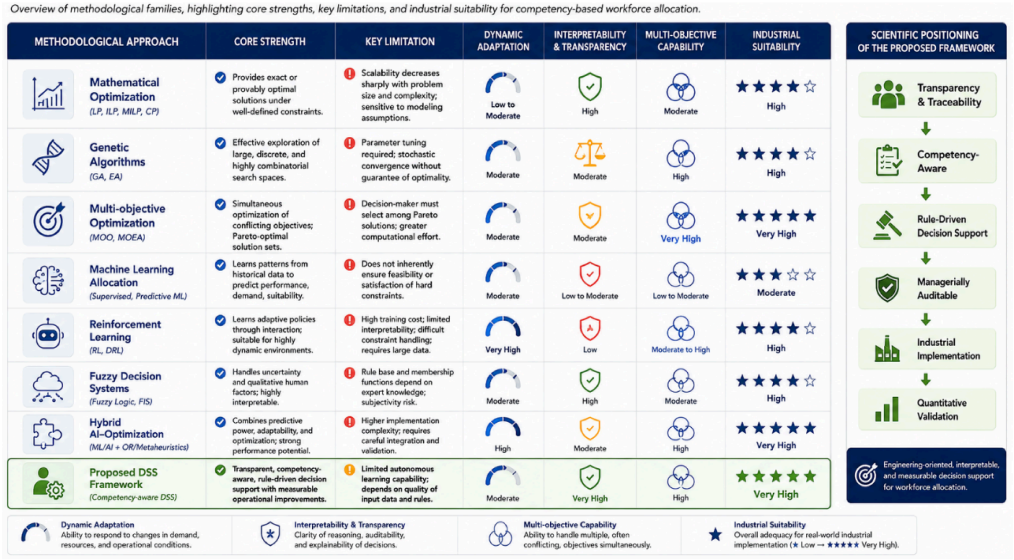


Figure 3. Critical comparison of workforce allocation and scheduling approaches, highlighting the main characteristics of mathematical optimization, evolutionary algorithms, machine learning, reinforcement learning, fuzzy decision systems, hybrid AI–optimization methods, and the proposed competency-aware decision-support framework. Created by the authors, with GPT used to improve the visual quality.

2.5. Research Gap and Framework Requirement

The literature reviewed in the preceding sections reveals substantial methodological progress across project management, workforce allocation, resource optimization, and decision-support research. Existing contributions provide established mechanisms for competency- and skill-based assignment, constraint representation, resource-efficiency assessment, workforce scheduling, evolutionary optimization, data-driven prediction, adaptive learning, and digitally supported allocation. Collectively, these developments demonstrate that workforce-allocation problems can be addressed through increasingly sophisticated analytical and computational approaches. However, they also reveal that methodological sophistication alone does not resolve the broader organizational problem of transforming heterogeneous workforce and task information into transparent, reproducible, and operationally deployable allocation decisions.

The first research gap concerns the fragmentation of allocation dimensions across existing methodological approaches. Different models have been developed to address competency matching, scheduling efficiency, constraint satisfaction, workload distribution, resource utilization, or adaptive allocation, but these dimensions frequently perform fundamentally different roles within the decision process. In operational settings, project priority and task complexity characterize the assignment problem; competency requirements and availability may determine candidate feasibility; workload and expertise differentiate among eligible employees; and continuity requirements may constrain reassignment decisions. The unresolved methodological requirement is therefore not simply to incorporate a

larger number of variables, but to structure their respective functions within a coherent multi-layer allocation architecture.

A second gap concerns the interface between analytical sophistication and organizational deployability. Formal optimization and AI-based methods provide powerful mechanisms for searching complex allocation spaces and adapting to dynamic conditions, but their operational adoption may require substantial data availability, modelling expertise, computational resources, or technological infrastructure. At the opposite extreme, lightweight managerial tools can be readily deployed but may rely excessively on fragmented information, implicit decision rules, and individual judgement. A relevant methodological opportunity consequently exists between these extremes: decision support that retains sufficient formal structure to improve consistency and reproducibility while preserving transparency, configurability, managerial oversight, and compatibility with routine organizational processes.

A third gap concerns the operational integration of dynamic workforce information. Workforce-allocation decisions are rarely static: employee availability changes, workloads evolve, priorities are revised, new assignments emerge, and continuity requirements may necessitate reassignment. Effective decision support must therefore accommodate changing organizational states without requiring the complete reformulation of the underlying allocation logic. This requirement extends beyond conventional static matching or scheduling by demanding an architecture capable of distinguishing task characterization, candidate eligibility, employee ranking, and reassignment as interconnected components of a dynamic decision process.

A further methodological gap concerns the empirical development and evaluation of workforce-allocation artefacts within authentic organizational environments. The reviewed literature contains numerous analytical allocation models, whereas comparatively less attention is devoted to research designs in which organizational requirements, artefact construction, expert calibration, implementation, and empirical evaluation are iteratively connected. An Action Design Research perspective is particularly relevant in this context because it enables the decision-support artefact to evolve through interaction with the organizational problem while simultaneously generating methodological knowledge regarding its design and application. The research opportunity therefore extends beyond proposing an allocation algorithm towards establishing a traceable pathway between organizational requirements, decision architecture, artefact implementation, and empirical evaluation.

These gaps define the principal requirements of the framework developed in this study. The proposed dynamic workforce-allocation decision-support framework is designed to integrate heterogeneous workforce and task information while explicitly separating three interconnected decision layers: task characterization, candidate eligibility, and employee ranking. Within this architecture, task priority, complexity/urgency, and continuity requirements inform the assignment context; eligibility rules determine the feasible candidate set; and competency, availability, normalized workload, and expertise support transparent multi-criteria ranking through the Allocation Suitability Score. Dynamic reassignment mechanisms complement this structure by enabling the decision process to respond to evolving operational conditions without altering its underlying logic.

Accordingly, this research is guided by the following research question:

RQ: *How can a practical, transparent, and dynamically adaptable decision-support framework systematically support workforce-allocation decisions by integrating task requirements, candidate eligibility, employee competencies, availability, workload, expertise, and reassignment constraints in project-oriented organizations?*

Addressing this question enables the study to investigate workforce allocation simultaneously as a methodological and organizational decision-support problem. Rather than seeking universal optimization or autonomous replacement of managerial judgement, the research examines whether heterogeneous allocation criteria can be operationalized within a reproducible, interpretable, and deployable decision architecture and empirically evaluated under authentic organizational conditions. In this sense, the intended contribution lies in bridging the methodological space between analytically structured allocation models and lightweight organizational decision support while explicitly preserving managerial traceability and implementation feasibility.

3. Methodology

3.1. Research Proposition

Building on the research question formulated in Section 2.5, four research propositions were defined to translate the overarching research objective into empirically observable dimensions of artefact performance. Consistent with the Action Design Research methodology, these propositions specify the expected operational effects associated with the implementation of the proposed decision-support framework and provide a structured basis for its subsequent empirical evaluation. They are not formulated as statistical hypotheses intended for confirmatory inferential testing; rather, they constitute theoretically and operationally grounded expectations against which the behaviour of the artefact can be examined under the conditions of the industrial case study. Accordingly, the propositions establish an explicit linkage between framework design, operational implementation, and the quantitative performance indicators subsequently used in the evaluation:

P1. *Framework-assisted workforce allocation is associated with lower task allocation time than the conventional allocation procedure.*

P2. *Framework-assisted workforce allocation is associated with lower workload imbalance across the available workforce than the conventional allocation procedure.*

P3. *Framework-assisted workforce allocation is associated with higher resource utilization and greater allocation consistency than the conventional allocation procedure.*

P4. *Framework-assisted workforce allocation is associated with a lower requirement for manual managerial intervention than the conventional allocation procedure.*

3.2. Research Strategy

This study adopted the Action Design Research (ADR) methodology, which is particularly suitable for research aiming to simultaneously generate scientific knowledge and solve real-world organizational problems through the development of practical artefacts. Unlike purely observational research approaches, ADR combines problem diagnosis, artefact design, implementation, evaluation, and continuous learning within an iterative process, thereby facilitating the interaction between theory and practice [54].

The selection of ADR was motivated by the nature of the research problem. Workforce allocation in project-oriented and knowledge-intensive service environments is characterized by a strong practical component, requiring the development of an operational solution capable of supporting real managerial decisions while simultaneously contributing to the body of knowledge on resource allocation and decision-support systems. Furthermore, ADR is widely employed in Information Systems research due to its ability to support the design, implementation, and refinement of artefacts in close collaboration with end users [55].

The adopted research process follows four interconnected stages: (i) Problem Formulation, (ii) Building, Intervention and Evaluation, (iii) Reflection and Learning, and (iv) Formalization of Learning. These stages collectively establish a continuous improvement cycle comparable to the Plan–Do–Check–Act (PDCA) philosophy frequently employed in organizational improvement initiatives [46]. The overall ADR workflow adopted in this study is presented in Figures 4 and 5 describes the main tasks to be performed in each step of the methodology, as well as the corresponding expected output.

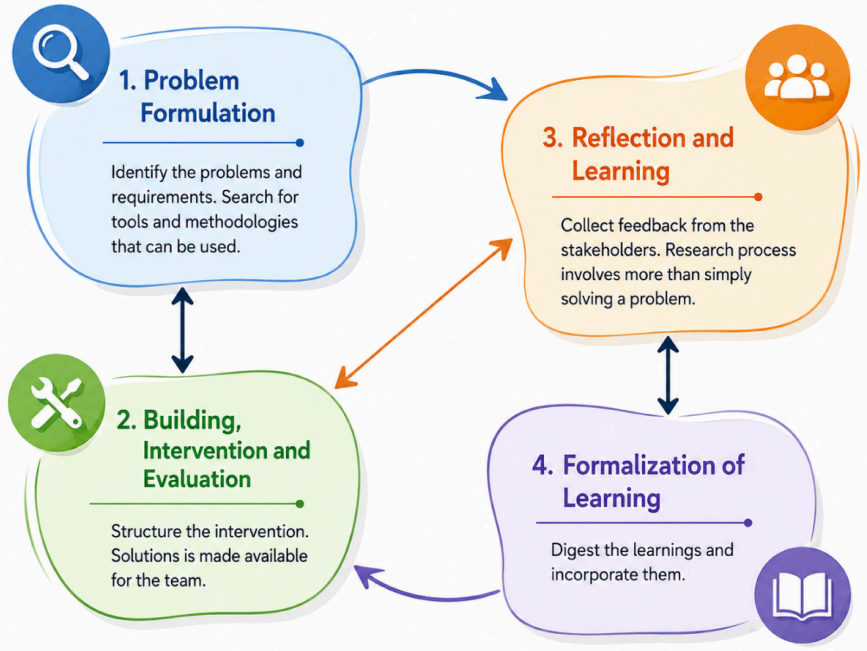


Figure 4. Action design research cycle with arrows showing the interrelations between different methodology steps. Created by the authors, with GPT used to improve the visual quality.

ADR Stage	Primary Objective	Key Activities	Knowledge / Output Generated
1 Porblem Formulation	Identify workforce-allocation challenges and define framework requirements.	• Organizational diagnosis and process mapping • Stakeholder engagement and interviews • Brainstorming and requirement elicitation • Root-cause identification (Fishbone analysis)	Clear definition of the allocation problem, operational constraints, and decision-support requirements.
2 Building, Intervention and Evaluation	Develop and iteratively refine the proposed solution.	• Design of the allocation framework • Allocation algorithm development • Software implementation and integration • Testing, validation and iterative refinement	Dynamic Task Allocation Decision-Support Framework and operational allocation algorithm.
3 Reflection and Learning	Evaluate performance and capture organizational learning.	• Analysis of allocation scenarios and outcomes • Stakeholder feedback collection • Assessment of effectiveness and usability • Identification of strengths and limitations	Identification of strengths, limitations, and opportunities for improvement.
4 Knowledge Formalization	Transform practical findings into transferable scientific knowledge.	• Consolidation of lessons learned • Abstraction of design principles • Formulation of generalized guidelines • Documentation and knowledge dissemination	Validated decision-support framework and scientific contribution to workforce-allocation research.

Figure 5. Summary of the objectives of each ADR stage and their role in the development and validation of the proposed allocation framework. Created by the authors, with GPT used to improve the visual quality.

3.3. Problem Formulation and Organizational Diagnosis

The first stage focused on understanding the resource-allocation challenges affecting the case-study organization and identifying the requirements that would guide the development of the proposed framework. Particular attention was devoted to understanding how allocation decisions were being performed, which variables influenced these decisions,

and which operational limitations affected workforce management [56]. The diagnostic stage employed established quality and root-cause analysis tools, including Fishbone diagrams and structured brainstorming techniques, which are widely recognized as effective mechanisms for organizational problem identification and continuous-improvement initiatives [57,58].

To support this diagnosis, several complementary analysis techniques were employed, including brainstorming sessions with managers, process analysis, workflow mapping, and cause–effect analysis [59–61]. These techniques facilitated the identification of critical issues associated with workforce allocation and resource management, while simultaneously capturing the expectations and requirements of the main stakeholders involved in the process.

The diagnostic phase revealed that allocation decisions were largely dependent on managerial experience and fragmented information sources. As a consequence, limited visibility existed regarding employee workload, availability, competencies, project priorities, and task ownership. This situation frequently resulted in subjective allocation decisions, estimation difficulties, workload imbalances, and reduced transparency throughout project execution.

To systematically identify the root causes affecting organizational performance, an Ishikawa (Fishbone) diagram was developed, as presented in Figure 6. The analysis revealed that the identified challenges could be grouped into six major categories: External Environment, Corporate Structure, Project Management Approach, Team and Staff, Management Team, and Business Constraints.

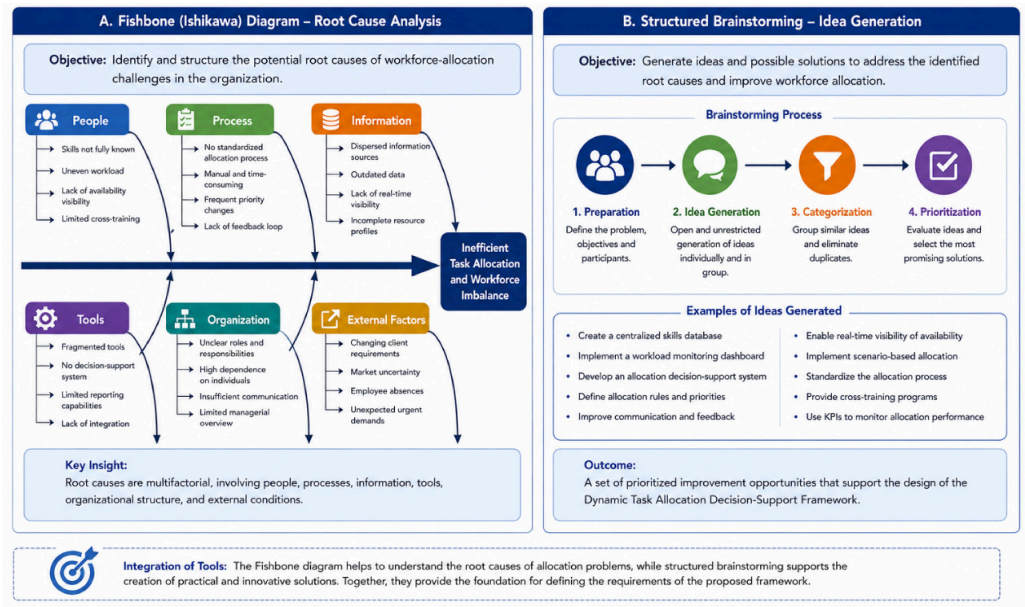


Figure 6. Diagnostic tools used in the problem-formulation stage: Fishbone diagram and structured brainstorming. Created by the authors, with GPT used to improve the visual quality.

The main findings extracted from the diagnostic phase are summarized in Figure 7. Although obtained from a specific case-study organization, the identified issues are representative of challenges commonly encountered in service-oriented organizations operating under dynamic and resource-constrained environments.

The outcomes of this diagnostic stage established the functional requirements that guided the subsequent development of the proposed Decision-Support Framework for Dynamic Task Allocation.

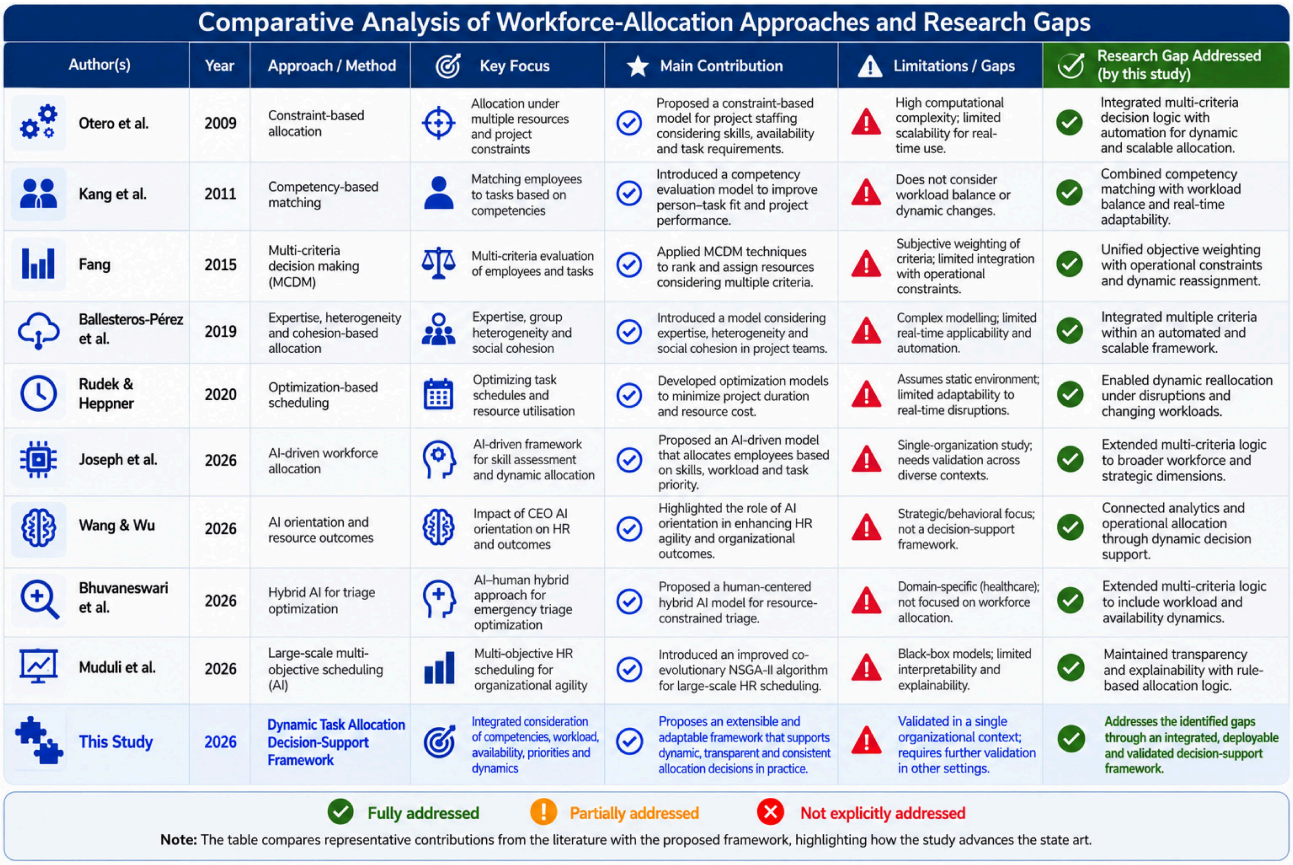


Figure 7. Summary of the main task allocation approaches identified in the literature [1,3,5,6,8–10,12,13]. Created by the authors, with GPT used to improve the visual quality.

3.4. Framework Development

The organizational diagnosis conducted during the problem-formulation stage of the Action Design Research process revealed that workforce-allocation decisions depended on multiple interdependent sources of information that were not systematically integrated within the existing decision process. Although managers possessed substantial contextual knowledge regarding employee capabilities, workforce conditions, and project requirements, allocation decisions relied predominantly on managerial experience and fragmented information sources. This configuration limited the consistency and traceability of the decision process, reduced visibility over workforce utilization and workload distribution, and constrained the systematic assessment of resource suitability under changing operational conditions.

In response to these requirements, a decision-support framework for dynamic workforce allocation was developed to formalize the allocation process without replacing managerial judgement. The framework was conceived as a transparent and configurable decision architecture through which heterogeneous task- and employee-related information could be transformed into structured allocation recommendations. Its purpose was therefore not to automate managerial decision-making autonomously, but to provide an explicit, reproducible, and traceable mechanism for identifying feasible candidates, differentiating their relative suitability, and supporting reassignment when operational conditions change.

The framework was designed according to three interrelated principles. First, allocation feasibility should be established before candidate ranking by determining whether employees satisfy the requirements and constraints associated with the assignment. Second, employee suitability should be assessed through an explicit multi-criteria structure

integrating competency matching, effective availability, normalized workload, and expertise, thereby distinguishing among feasible candidates while simultaneously discouraging workload concentration and ineffective use of workforce capacity. Third, dynamic responsiveness should be preserved by incorporating task-level characteristics, including project priority, complexity/urgency, and continuity requirements, together with mechanisms capable of accommodating changes in availability, workload, and assignment conditions. These principles establish a layered decision logic in which task characterization, candidate eligibility, employee ranking, and dynamic reassignment perform distinct but complementary functions within the overall workforce-allocation process.

Based on the findings extracted from the literature review and the organizational diagnosis, six primary information dimensions incorporated into the overall decision-support framework: (a) Employee competencies; (b) Employee expertise level; (c) Current workload; (d) Resource availability; (e) Project priority; (f) Task complexity and urgency. These information dimensions operate at different stages of the allocation process and should not be interpreted as equivalent weighted components of the employee-ranking function.

Figure 8 presents the conceptual architecture of the proposed Dynamic Task Allocation Framework.

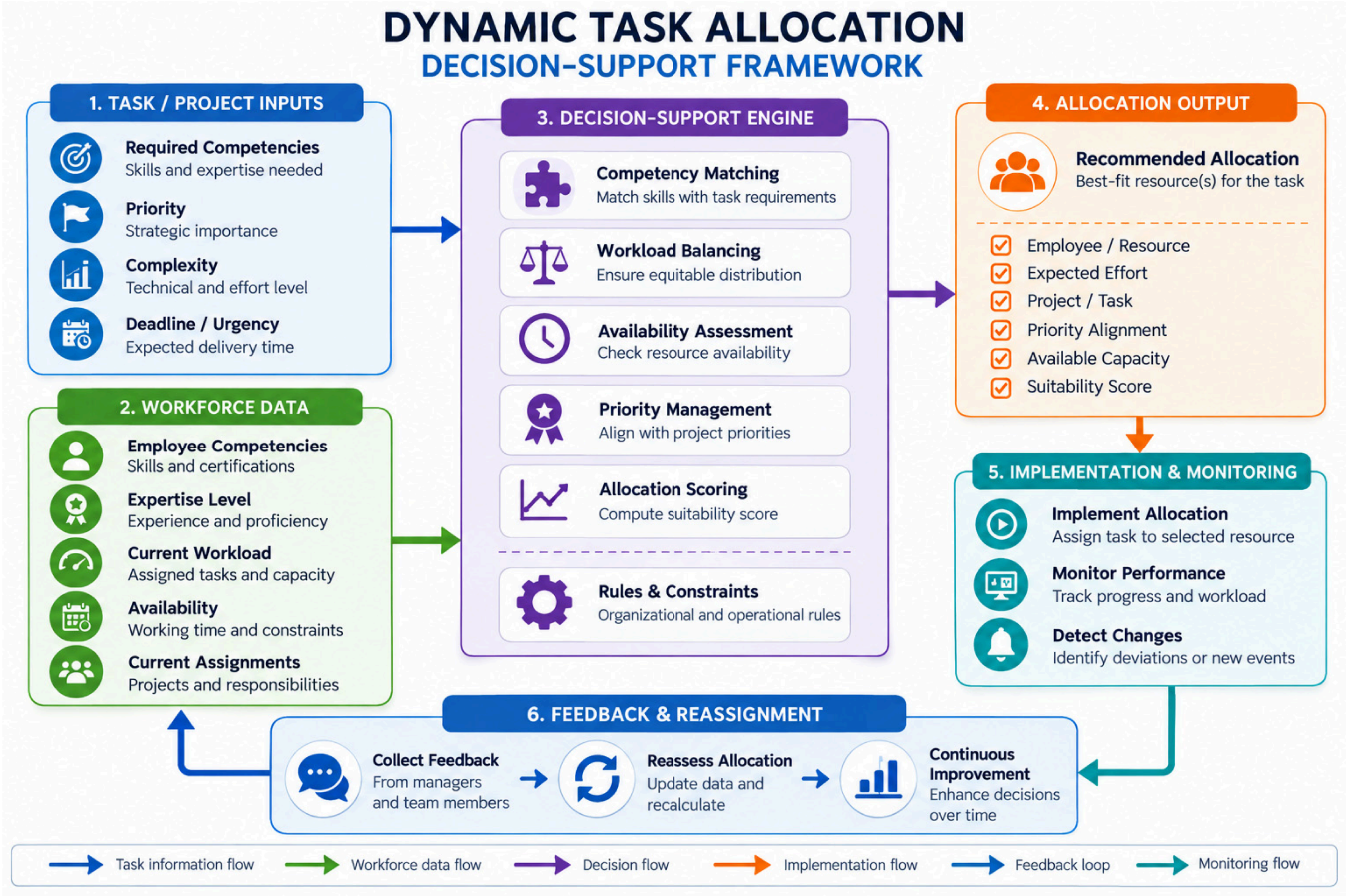


Figure 8. Conceptual architecture of the proposed Dynamic Task Allocation Decision-Support Framework, integrating competencies, workload, availability, task requirements, and organizational constraints to generate adaptive workforce-allocation recommendations. Created by the authors, with GPT used to improve the visual quality.

The operational logic of the framework begins with the systematic characterization of each incoming task or project requirement. Task-level information defines the decision context through required competencies, priority, complexity/urgency, expected delivery

conditions, and, where applicable, continuity requirements. In parallel, workforce information characterizes the current state of the candidate resource pool through employee competency profiles, expertise, effective availability, normalized workload, and existing assignments. Maintaining this distinction between task-level requirements and employee-level attributes is essential because these information categories perform different functions within the subsequent allocation process.

The interaction between task and workforce information is operationalized through a sequential decision structure rather than through the unrestricted aggregation of all available variables. Task requirements and organizational constraints first determine candidate eligibility, thereby excluding employees who do not satisfy the conditions required for a feasible assignment. The remaining candidates are subsequently differentiated through the Allocation Suitability Score, which integrates competency matching, effective availability, normalized workload, and expertise according to the calibrated weighting configuration. The resulting ranking therefore supports the identification of the most suitable candidate among feasible alternatives while preserving explicit visibility over the criteria underlying the recommendation.

A defining characteristic of the framework is its capacity to accommodate changes in the operational state without modifying the underlying decision logic. Variations in employee availability, workload distribution, project priorities, task requirements, or assignment continuity can trigger reassessment of candidate feasibility and relative suitability. Dynamic allocation is therefore implemented through repeated evaluation of an explicit and stable decision architecture rather than through an autonomous adaptive-learning mechanism. This distinction is particularly relevant in project-oriented, knowledge-intensive service environments, where workforce conditions and assignment requirements may evolve substantially during project execution.

From a methodological perspective, the framework integrates allocation dimensions that perform complementary roles within a layered decision architecture: task characteristics establish the assignment context, eligibility conditions delimit the feasible candidate set, multi-criteria scoring differentiates candidate suitability, and reassignment mechanisms accommodate subsequent changes in operational conditions. From an implementation perspective, this architecture remains computationally lightweight and technologically accessible because its decision logic does not depend on large historical datasets, specialized optimization solvers, or computationally intensive AI models. The resulting artefact therefore preserves managerial interpretability and traceability while providing sufficient formalization to support reproducible workforce-allocation decisions.

This decision architecture subsequently provided the conceptual and functional basis for the allocation algorithm and software artefact developed during the following stages of the Action Design Research process. Importantly, the technological simplicity of the implementation should not be interpreted as restricting the framework to organizations of a particular size. Rather, its modular and configurable structure enables the underlying decision logic to be adapted to organizational environments with different levels of digital maturity, resource availability, and decision-support infrastructure. This characteristic may be particularly relevant to small and medium-sized enterprises, for which project-management practices frequently need to be aligned with the specific needs, capabilities, and organizational context of the firm rather than directly transferred from approaches developed for substantially different organizational settings, as emphasized by Turner and Ledwith [62].

3.5. Allocation Algorithm Development

To enhance the transparency, reproducibility, and consistency of the proposed allocation process, a quantitative evaluation model was developed to support employee-selection decisions. Although the framework was designed with a strong emphasis on practical applicability and ease of deployment, it was considered important to formalize the key decision variables influencing task allocation. Consequently, an Allocation Suitability Score (AS) model was established to integrate competency matching, employee availability, workload conditions, and expertise levels into a unified evaluation mechanism.

The first component of the model evaluates the degree of alignment between employee capabilities and task requirements. A competency matrix was established to represent employee proficiency levels across the skills considered relevant to the organization:

$$S = \left[s_{ij}\right]_{n \times m} \tag{1}$$

where n represents the number of employees, m the number of relevant skills, and s_{ij} the proficiency level of employee i in skill j. Based on the competency matrix, a competency matching score (C_i) is calculated through a weighted aggregation process:

$$C_i = \sum_{j=1}^{m} w_j s_{ij} \tag{2}$$

where C_i is the competency matching score of employees i, w_j is the relative importance assigned to skill j, and s_{ij} corresponds to the proficiency level of employee i in that skill. This score quantifies the degree of alignment between employee competencies and task requirements. Consequently, employees who possess stronger competency profiles in critical skills obtain higher matching scores.

Employee availability was also incorporated into the model to ensure that allocation recommendations only consider resources capable of supporting the task within the required timeframe. The availability score (A_i) can be expressed as:

$$A_i = \frac{H_i^{avail}}{H_i^{total}} \tag{3}$$

where H_i^{avail} represents the available working capacity of employee i during the allocation period, and H_i^{total} represents the total working capacity of the same employee over that period.

To prevent over-allocation and promote a balanced distribution of work, workload conditions were incorporated into the allocation model. The workload utilization ratio (W_i) is defined as:

$$W_i = \frac{\sum_{k=1}^{p} h_{ik}}{H_i} \tag{4}$$

where W_i represents the workload utilization ratio of employee i, h_{ik} corresponds to the hours allocated to task k, p is the total number of active tasks assigned to the employee, and H_i represents the total available working capacity of employee i. The workload ratio is subject to

$$0 \leq W_i \leq 1 \tag{5}$$

Lower workload values indicate greater availability to accommodate additional activities, whereas higher values suggest a potential risk of overallocation. This mechanism contributes to a more balanced distribution of work across the team and supports sustainable resource utilization.

The expertise level score (E_i) was included to distinguish employees with different levels of maturity, experience, or proven capability within a given technical domain. It can be normalized as:

$$E_i = \frac{Exp_i}{Exp_{max}} \tag{6}$$

where Exp_i represents the expertise level assigned to employee i, and Exp_{max} represents the maximum expertise level considered in the organization.

The conceptual structure of the proposed suitability model is presented in Figure 9. The model transforms multiple workforce-allocation dimensions into a single weighted score, enabling the systematic ranking of candidate employees and supporting more consistent and objective allocation decisions.

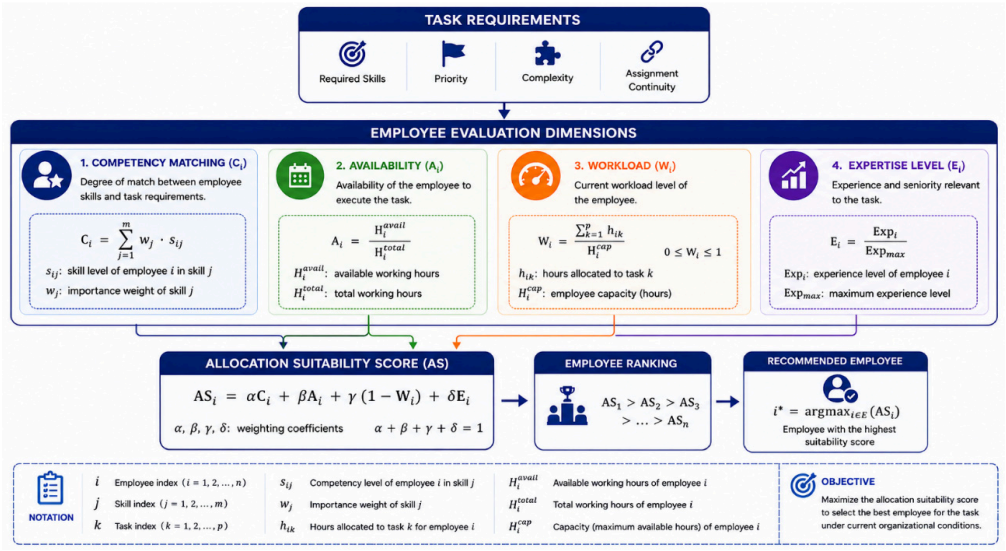


Figure 9. Allocation Suitability Score (AS) model integrated into the proposed Dynamic Task Allocation Decision-Support Framework. Created by the authors, with GPT used to improve the visual quality.

As illustrated in Figure 9, the allocation process begins with the characterization of task requirements, including required competencies, priority level, complexity, and assignment continuity considerations. Candidate employees are subsequently evaluated across four complementary dimensions: competency matching, availability, workload, and expertise. These dimensions are aggregated into an Allocation Suitability Score, which serves as the primary decision criterion for employee ranking.

To avoid ambiguity between task-level decision attributes and employee-level ranking criteria, the implemented allocation logic distinguishes three sequential decision layers. First, each task is characterized according to required competencies, complexity, urgency, priority, and continuity requirements. Second, eligibility rules exclude employees who do not satisfy mandatory competency or availability requirements. Third, the remaining eligible candidates are ranked using the Allocation Suitability Score (ASS), which exclusively integrates four employee-level dimensions: competency matching, availability, normalized workload, and expertise. Project priority, task complexity/urgency, and continuity are therefore not additional weighted components of the Allocation Suitability Score. The adoption of a weighted scoring approach provides a balanced compromise between model simplicity and decision-support capability. Unlike highly complex optimization-based allocation models, the proposed approach maintains computational efficiency and practical deployability

while still incorporating the most relevant factors affecting workforce-allocation decisions in project-oriented environments. The Allocation Suitability Score (AS_i) is calculated as:

$$AS_i = \alpha C_i + \beta A_i + \gamma(1 - W_i) + \delta E_i \quad (7)$$

where AS_i is the Allocation Suitability Score of employee i, C_i is the competency matching score, A_i is the availability score, W_i is the workload utilization ratio, E_i is the expertise level score, and α, β, γ, and δ are weighting coefficients associated with each allocation dimension. Accordingly, project priority operates as a task-sequencing rule when competing allocation requirements coexist; task complexity and urgency define task requirements and influence eligibility and processing precedence; and continuity is applied as a reassignment preference when ongoing activities require replacement of an unavailable employee. These attributes influence the allocation workflow but do not modify the mathematical structure of the Allocation Suitability Score. The weighting coefficients are subject to:

$$\alpha + \beta + \gamma + \delta = 1 \quad (8)$$

The weighting coefficients (α, β, γ, and δ) are configurable organizational parameters that determine the relative influence of each decision dimension within the allocation model and may be adapted according to organizational priorities. The Allocation Suitability Score represents the overall suitability of employee i for the task under evaluation. Higher scores indicate a better alignment between employee characteristics and task requirements. The weighting coefficients allow organizations to adjust the relative importance of each allocation dimension according to their operational priorities and workforce-management policies.

Finally, the employee selected for the assignment corresponds to the candidate presenting the highest suitability score:

$$i = argmax(AS_i) \quad (9)$$

where i represents the employee with the highest allocation suitability score among all eligible candidates.

This formulation provides a structured and transparent decision-support mechanism capable of integrating technical competencies, resource availability, workload balancing, and expertise considerations into a single allocation criterion, thereby supporting more objective, scalable, and reproducible workforce-allocation decisions.

3.5.1. Implemented Weight Calibration Strategy

The weighting coefficients used throughout the industrial validation were $\alpha = 0.30$ for competency matching, $\beta = 0.30$ for employee availability, $\gamma = 0.25$ for normalized workload, and $\delta = 0.15$ for expertise, satisfying the normalization condition $\alpha + \beta + \gamma + \delta = 1$. These coefficients were calibrated during four iterative Action Design Research (ADR) rounds involving ten organizational experts, six Project Managers and four Senior Operational Staff, selected for their direct involvement in workforce-allocation decisions and their operational knowledge of competency requirements, resource availability, workload distribution, and task-assignment constraints.

During each calibration round, the expert panel assessed the operational coherence of the candidate rankings generated by the Allocation Suitability Score (ASS). The relative weights were adjusted when the resulting rankings were considered inconsistent with task requirements or established allocation practice. The allocation cases used during calibration were kept independent from those subsequently employed for quantitative performance evaluation. After the fourth iteration, the configuration (α, β, γ, δ) = (0.30,

0.30, 0.25, 0.15) was frozen and applied without further adjustment during the performance-evaluation stage.

The resulting coefficients should not be interpreted as universal constants or mathematically optimal values. Rather, they represent expert-calibrated organizational parameters reflecting the relative importance assigned to the four employee-level decision dimensions in the investigated setting. Figure 10 summarizes their practical interpretation, source, and operational rationale.

Coefficient	Decision Dimension (ASS Component)	Implemented Weight	Interpretation	Notes
α (alpha)	Competency Matching (C: Competency)	0.30	Alignment between employee competencies and the task requirements.	– Measures the fit between employee capabilities and task requirements.
β (beta)	Availability (A: Availability)	0.30	Availability of the employee during the required assignment period.	– Higher availability increases the allocation suitability.
γ (gamma)	Workload (W . Normalized Workload)	0.25	Penalization of candidates with higher current workload. (The normalized workload is inversely represented so that higher values are more favorable.)	– Workload is a cost-type criterion and is therefore inversely transformed.
δ (delta)	Expertise (E: Expertise)	0.15	Relevant experience and expertise of the employee contributing to task execution.	– Reflects the employee's prior experience and domain knowledge relevant to the task.

Note: The Allocation Suitability Score (ASS) is computed as:

$$ASS_i = \alpha C_i + \beta A_i + \gamma W_i + \delta E_i, \quad \text{with } \alpha + \beta + \gamma + \delta = 1.$$

Project priority, task complexity/urgency, and continuity are handled outside the ASS as task-level sequencing, eligibility requirements, and reassignment decision rules, respectively.

Figure 10. Interpretation of the weighting coefficients adopted in the proposed workforce allocation model. Created by the authors, with GPT used to improve the visual quality.

The adopted configuration gives equal priority to competency, matching and employee availability, followed by workload balancing and expertise. This reflects the operational requirement to identify personnel who are technically suitable and effectively available while avoiding excessive workload concentration and retaining expertise as an additional differentiating criterion. Because the coefficients are configurable, the same decision structure can be recalibrated to reflect different organizational priorities without modifying the underlying ASS formulation.

3.5.2. Weight Sensitivity Analysis

To assess the robustness of the Allocation Suitability Score (ASS) to uncertainty in the expert-calibrated weighting coefficients, a one-at-a-time (OAT) sensitivity analysis was performed around the nominal configuration. Each coefficient was independently perturbed by −20%, −10%, +10%, and +20% relative to its nominal value. Whenever one coefficient was modified, the resulting difference was proportionally redistributed among the three remaining coefficients, thereby preserving the normalization condition. This procedure generated 16 perturbed weighting configurations in addition to the nominal configuration.

The analysis was conducted using a representative five-candidate allocation case, with each candidate characterized by the same four normalized dimensions incorporated

into the implemented ASS: competency matching, availability, workload, and expertise. For every perturbed configuration, the ASS was recalculated for all candidates, and the resulting ranking was compared with that obtained using the nominal weighting configuration. Robustness was evaluated using three complementary indicators: stability of the top-ranked candidate, stability of the complete candidate ranking, and Spearman's rank correlation coefficient () between the nominal and perturbed rankings.

Under the nominal weighting configuration, the resulting candidate ranking was established. Figure 11 summarizes the ranking response obtained under each coefficient perturbation and provides the corresponding Spearman rank correlation relative to the nominal configuration.

Scenario	Perturbed coefficient	Variation	Top-ranked candidate	Complete ranking (best to worst)	Spearman ρ (vs. nominal)
S0	Nominal configuration	—	**D**	D > C > B > A > E	1.00
S1	α – Competency	−20%	**D**	D > C > B > A > E	1.00
S2	α – Competency	−10%	**D**	D > C > B > A > E	1.00
S3	α – Competency	+10%	**D**	D > C > B > A > E	1.00
S4	α – Competency	+20%	**D**	D > C > B > A > E	1.00
S5	β – Availability	−20%	**D**	D > C > B > A > E	1.00
S6	β – Availability	−10%	**D**	D > C > B > A > E	1.00
S7	β – Availability	+10%	**D**	D > C > B > A > E	1.00
S8	β – Availability	+20%	**D**	**D > B > C > A > E**	0.90
S9	γ – Workload	−20%	**D**	D > C > B > A > E	1.00
S10	γ – Workload	−10%	**D**	D > C > B > A > E	1.00
S11	γ – Workload	+10%	**D**	D > C > B > A > E	1.00
S12	γ – Workload	+20%	**D**	D > C > B > A > E	1.00
S13	δ – Expertise	−20%	**D**	D > C > B > A > E	1.00
S14	δ – Expertise	−10%	**D**	D > C > B > A > E	1.00
S15	δ – Expertise	+10%	**D**	D > C > B > A > E	1.00
S16	δ – Expertise	+20%	**D**	D > C > B > A > E	1.00

Note: Nominal weights were $\alpha = 0.30$, $\beta = 0.30$, $\gamma = 0.25$, and $\delta = 0.15$. Each coefficient was independently perturbed by ±10% and ±20%, with the resulting difference proportionally redistributed among the remaining coefficients to preserve $\Sigma w = 1$.

Top-ranked candidate stability = 100%; complete-ranking stability = 93.75%; mean Spearman ρ = 0.994.

Figure 11. Sensitivity analysis of candidate-ranking robustness under one-at-a-time perturbations of the ASS weighting coefficients. Created by the authors, with GPT used to improve the visual quality.

The results demonstrate high ranking robustness, with the top-ranked candidate remaining unchanged across all perturbations and the complete ranking preserved in 93.75% of the scenarios. The mean Spearman correlation of 0.994 further confirms that moderate variations in the calibrated weights have negligible influence on the overall

allocation ranking. The sensitivity analysis demonstrated a high degree of robustness of the implemented weighting configuration. Candidate D remained the highest-ranked allocation alternative across all 16 perturbed configurations, corresponding to a top-ranked candidate stability of 100%. The complete candidate ranking remained unchanged in 15 of the 16 perturbations (93.75%). The only ranking modification occurred when the availability coefficient was increased by 20%, producing a minor inversion between candidates B and C while leaving the preferred candidate unchanged. Spearman's rank correlation was 1.00 for all other perturbations and 0.90 for this specific configuration, resulting in a mean of 0.994 across the 16 sensitivity scenarios.

These results indicate that moderate variations in the expert-calibrated coefficients do not materially affect the primary allocation recommendation. At the same time, the limited inversion observed between two closely ranked secondary candidates indicates that the model remains responsive to meaningful changes in organizational preferences rather than being insensitive to its weighting structure. The sensitivity analysis therefore supports the robustness of the adopted weighting configuration while reinforcing the interpretation of the ASS as a transparent and configurable decision-support mechanism rather than a fixed optimization model.

3.5.3. Normalization Procedures

Because the four criteria incorporated into the Allocation Suitability Score (ASS) are expressed using different operational scales, normalization is required before weighted aggregation. All employee-level criteria are therefore transformed to a common dimensionless interval [0, 1], ensuring comparability and preventing differences in measurement scale from disproportionately influencing the final suitability score.

For benefit-type criteria, namely competency matching, availability, and expertise, higher values represent greater suitability. Min–max normalization is therefore applied as:

$$x_{ij}^{norm} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{10}$$

where x_{ij} is the original value of employee i for criterion j, and x_j^{min} and x_j^{max} are the minimum and maximum values observed among the eligible candidates for that criterion.

Workload is treated as a cost-type criterion because higher current utilization reduces the desirability of assigning additional work to an employee. In the implemented DSS, workload is represented by the workload utilization ratio W_i, which is already bounded within the interval $[0, 1]$, where 0 represents no allocated workload and 1 represents full utilization. Consequently, no additional min–max normalization is applied to this criterion. To ensure directional consistency with the benefit-type criteria included in the Allocation Suitability Score, workload is transformed through its complement:

$$W_i^* = 1 - W_i \tag{11}$$

where W_i^* represents the workload suitability contribution of employee i.

Accordingly, employees with lower current workload receive higher workload suitability scores, while employees approaching full utilization receive progressively lower contributions to the Allocation Suitability Score. This is the workload transformation implemented in the industrial DSS and used throughout the calculations reported in this study.

The resulting dimensionless criterion values for competency matching, availability, workload suitability, and expertise are subsequently combined using the calibrated weighting coefficients defined in Section 3.5.1 to calculate the ASS. Project priority, task

complexity/urgency, and continuity are not included in the ASS because, as established in Section 3.5, they operate as task-level sequencing, eligibility, or reassignment rules rather than weighted employee-ranking criteria.

3.5.4. Baseline Benchmarking Scenario

To distinguish the contribution of multi-criteria decision integration from the general benefits of computerization, a controlled benchmarking scenario was developed. The proposed Allocation Suitability Score (ASS) was compared with a simple competency-first greedy heuristic representing a lightweight computerized allocation rule. Under the baseline heuristic, the available employee with the highest competency match is selected, with current workload used only as a tie-breaking criterion.

A representative task-allocation scenario involving five eligible employees was constructed using normalized values for the four criteria incorporated into the ASS: competency matching, availability, workload, and expertise. The candidate profiles were configured to reproduce a realistic allocation trade-off in which the employee with the highest technical competency simultaneously presents limited availability and high current workload. Both approaches were applied to identical candidate information, thereby isolating the effect of the decision logic from that of data digitalization. Figure 12 summarizes the resulting comparison.

Candidate	Competency score, C	Availability, A	Workload ratio, W	Expertise, E	Greedy rank (competency-first) [a]	Allocation Suitability Score, ASS [b]	Multi-criteria rank (proposed model) [c]
E1	0.95	0.60	0.85	0.90	1	0.638	5
E2	0.90	0.90	0.35	0.85	2	**0.830**	**1**
E3	0.85	0.80	0.45	0.80	3	0.753	3
E4	0.80	0.95	0.30	0.70	4	**0.805**	**2**
E5	0.75	0.70	0.55	0.65	5	0.645	4

Notes: All values are normalized in the interval [0,1]. Workload ratio, W, represents the proportion of assigned work relative to the employee's available capacity (higher values indicate higher workload).

(a) Competency-first greedy heuristic: employees are ranked by decreasing competency score; ties (if any) are broken by selecting the employee with the lowest workload ratio.

(b) Allocation Suitability Score computed as:

$$ASS = 0.30\,C + 0.30\,A + 0.25\,(1 - W) + 0.15\,E$$

where $1 - W$ is the normalized workload (cost-type criterion).

(c) Ranking under the proposed multi-criteria allocation model based on the Allocation Suitability Score (higher values indicate greater suitability).

Figure 12. Controlled baseline scenario comparing competency-first greedy allocation with the proposed multi-criteria decision model. **In bold**: best two values obtained for Allocation Suitability Score. Created by the authors, with GPT used to improve the visual quality.

As shown in Figure 12, the competency-first greedy heuristic selects E1 because this candidate presents the highest competency score (0.95). However, E1 also exhibits the highest workload ratio (0.85) and comparatively limited availability (0.60), resulting in an ASS of 0.638 and the lowest overall multi-criteria ranking. In contrast, E2 combines slightly lower competency (0.90) with substantially higher availability (0.90), lower workload (0.35), and strong expertise (0.85), yielding the highest ASS (0.830).

This controlled comparison illustrates the incremental decision value of simultaneously considering multiple workforce dimensions rather than relying predominantly on

competency. It is intended as a transparent baseline benchmark of the proposed decision logic and not as a comprehensive performance comparison with advanced optimization, evolutionary, machine-learning, or reinforcement-learning methods. Such comparative benchmarking remains outside the scope of the present study and is identified as a direction for future research.

3.6. System Implementation

3.6.1. Software Implementation

The proposed Dynamic Task Allocation Framework was implemented through a software-based Decision-Support System developed using Microsoft Excel® and Visual Basic for Applications (VBA). The selection of this technological environment was motivated by three factors: widespread availability within organizations, ease of deployment, and the possibility of rapidly integrating allocation logic, databases, reporting functionalities, and user interfaces into a single operational platform. The operational workflow adopted by the system for new task allocation is presented in Figure 13. The workflow illustrates how project requirements are transformed into allocation recommendations through the execution of the proposed decision-support framework and allocation algorithm.

The software architecture was designed to operationalize the allocation framework presented in Section 3.3 and the allocation algorithm described in Section 3.4. Rather than functioning as a standalone optimization tool, the system was conceived as a decision-support environment capable of assisting managers throughout the resource-allocation process. Accordingly, the software integrates workforce information, project requirements, allocation criteria, and reporting functionalities within a unified interface.

The implemented system is structured around three functional modules. The first module, Team Management, maintains information regarding employee competencies, availability, vacations, absences, and workforce composition. The second module, Task Management, supports the creation, modification, reassignment, and monitoring of tasks and projects. Within this module, the allocation algorithm is executed to identify the most suitable resources according to the framework criteria. The third module, Status and Reporting, provides visibility over workload distribution, employee occupation rates, project assignments, and historical allocation records, supporting managerial monitoring and decision-making.

A key characteristic of the software implementation is its ability to continuously update allocation recommendations based on changes in workforce availability, project requirements, and workload levels. This dynamic capability enables managers to rapidly assess alternative allocation scenarios and respond to unforeseen organizational events, such as employee absences, workload fluctuations, or changes in project priorities.

In addition to supporting new task allocation, the system incorporates automated reassignment functionalities that allow ongoing projects to be redistributed whenever workforce composition changes. This capability contributes to maintaining project continuity while minimizing the managerial effort required to reallocate activities manually.

Although the software was implemented using Microsoft Excel® 2024 and VBA v7.1, the proposed framework remains independent of the underlying technological platform. Consequently, the allocation logic can be integrated into alternative enterprise systems, databases, or web-based applications without altering the conceptual structure of the framework. The implementation developed in this study therefore serves as a proof-of-concept demonstrating the practical applicability and operational feasibility of the proposed Decision-Support Framework for Dynamic Task Allocation.

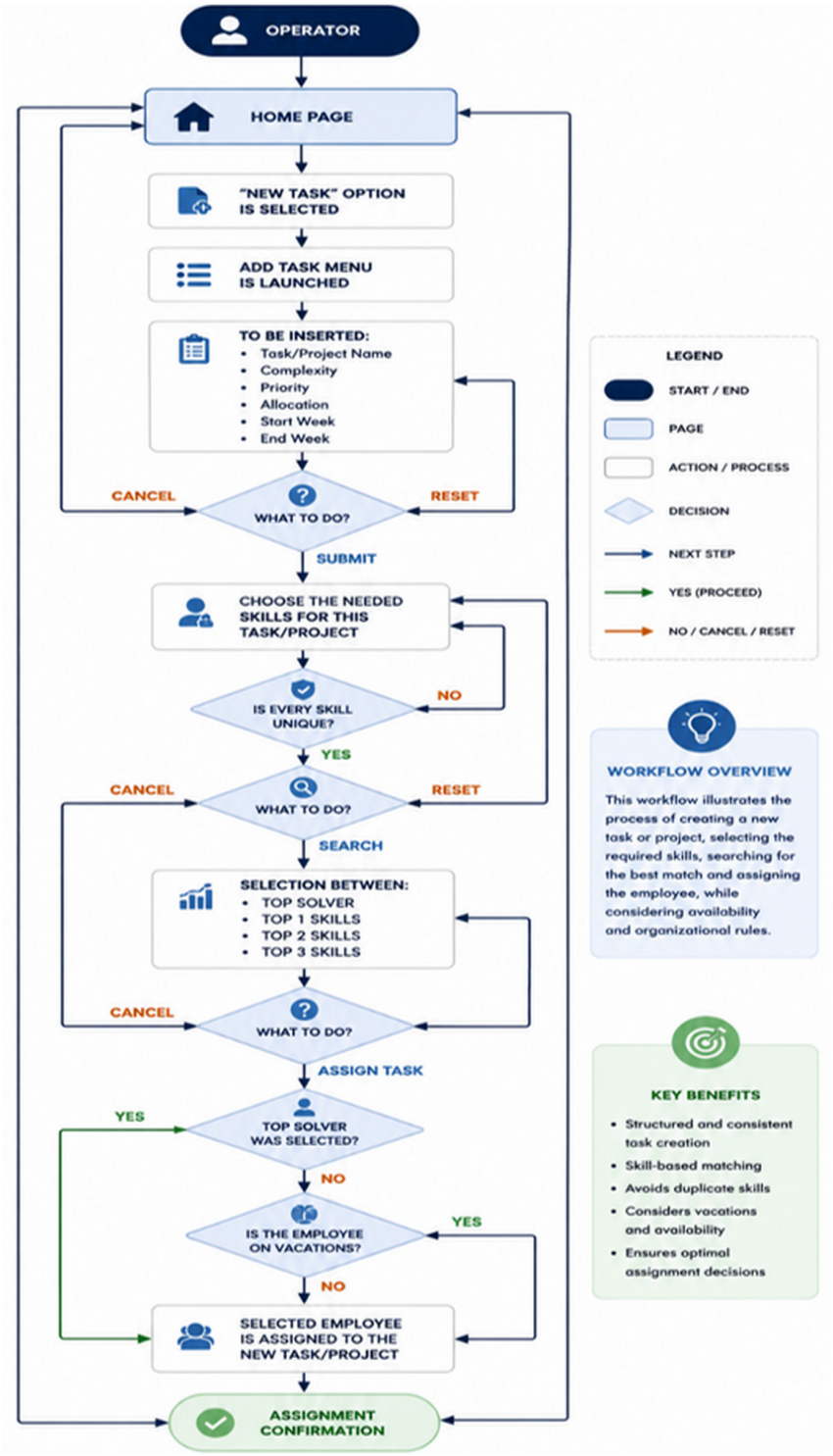


Figure 13. Operational workflow for new task allocation, illustrating the integration of task requirements, competency matching, workload assessment, and allocation recommendation generation. Created by the authors, with GPT used to improve the visual quality.

3.6.2. Enterprise Deployment Architecture

Although the prototype presented in this study was implemented using Microsoft Excel and Visual Basic for Applications (VBA) to support rapid development and iterative validation within the Action Design Research process, the proposed decision support framework is not intrinsically tied to this technological platform. Although the reference implementation was developed in Microsoft Excel/VBA to facilitate rapid industrial deployment and user

acceptance, the proposed decision logic is platform-independent. The allocation engine can be migrated to web-based, database-driven or cloud-native enterprise environments without modifications to the underlying decision framework, enabling large-scale deployment across geographically distributed organizations. Figure 14 illustrates a conceptual enterprise deployment architecture demonstrating how the proposed allocation engine can be integrated with modern organizational information systems, cloud infrastructures, and enterprise software platforms while preserving the underlying decision logic.

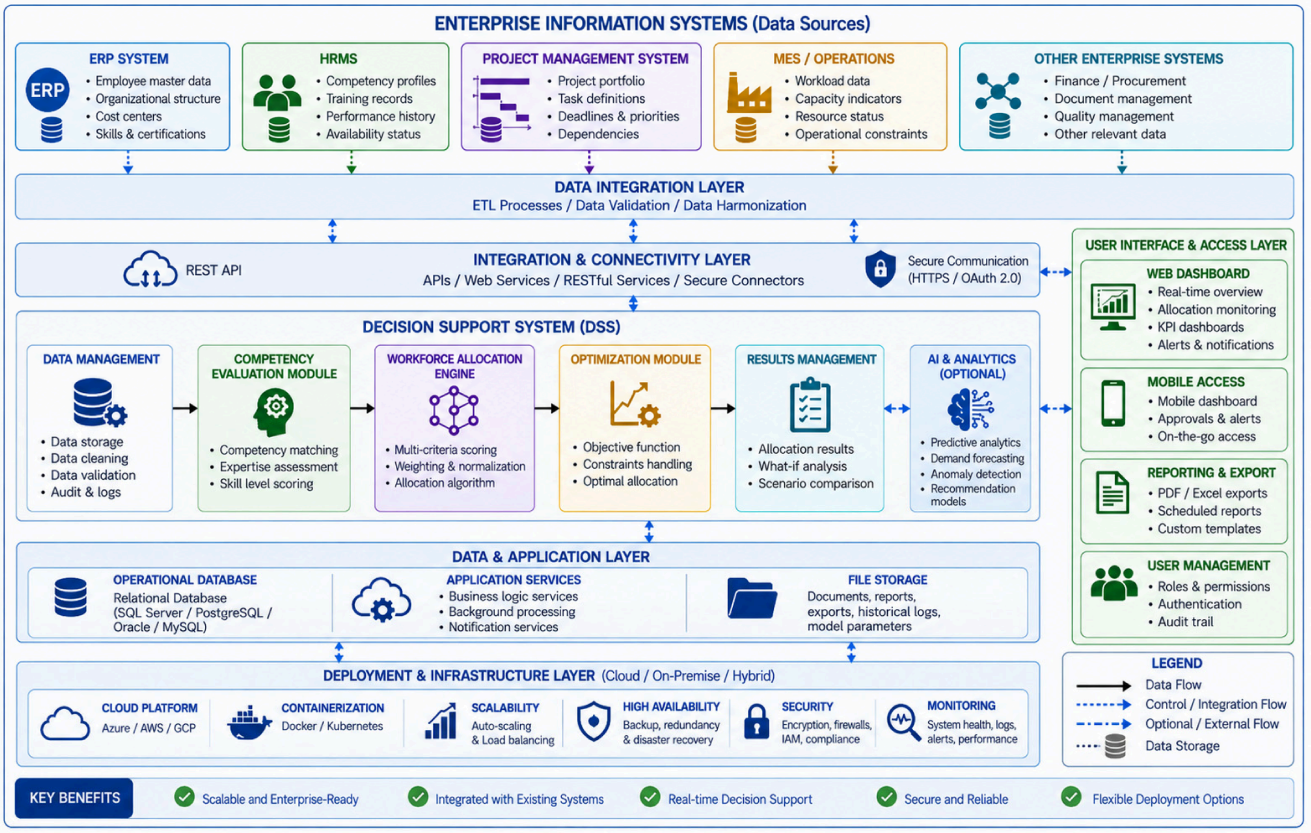


Figure 14. Enterprise deployment architecture of the proposed decision support system, illustrating its integration with enterprise information systems, cloud services, databases, APIs, and organizational decision-making processes. Created by the authors, with GPT used to improve the visual quality.

The conceptual architecture presented in Figure 14 demonstrates that the proposed workforce allocation framework can be readily extended from a proof-of-concept implementation to an enterprise-scale decision support platform. By incorporating standardized interfaces for ERP, HRMS, MES, and project management systems, together with cloud deployment, database connectivity, and API-based communication, the framework supports scalable, secure, and interoperable workforce management across complex industrial environments. This architectural flexibility reinforces the practical applicability of the proposed methodology and facilitates its future deployment within digital manufacturing and Industry 4.0 ecosystems.

3.6.3. Computational Complexity Analysis

To assess the scalability of the proposed decision support system, the computational complexity of the allocation algorithm was analysed considering the number of available employees (n) and the number of project tasks (m).

For each task, the framework first evaluates task-level eligibility and sequencing conditions and subsequently computes the Allocation Suitability Score for each eligible

employee using the four weighted ranking criteria: competency matching, availability, workload, and expertise. Because both the number of task-level rules and the number of ASS criteria remain fixed, each candidate evaluation requires constant time, O(1).

Consequently, evaluating all candidate employees for a single task requires $O(n)$ time, whereas allocating m tasks require $O(nm)$ in the worst case.

Because the number of decision criteria remains fixed, the computational complexity grows linearly with both the number of employees and the number of project tasks, making the proposed framework suitable for real-time industrial decision support applications.

The memory complexity is $O(n)$, since the algorithm only stores the evaluation scores associated with the candidate employees during each allocation cycle.

To complement the mathematical formulation, it is also important to evaluate the computational efficiency of the proposed allocation framework. Figure 15 summarizes the execution flow of the algorithm together with the computational complexity associated with each processing stage, from candidate evaluation to final task allocation. This analysis provides an estimate of the algorithm's scalability and demonstrates its suitability for supporting workforce allocation decisions in industrial environments involving multiple employees and concurrent projects.

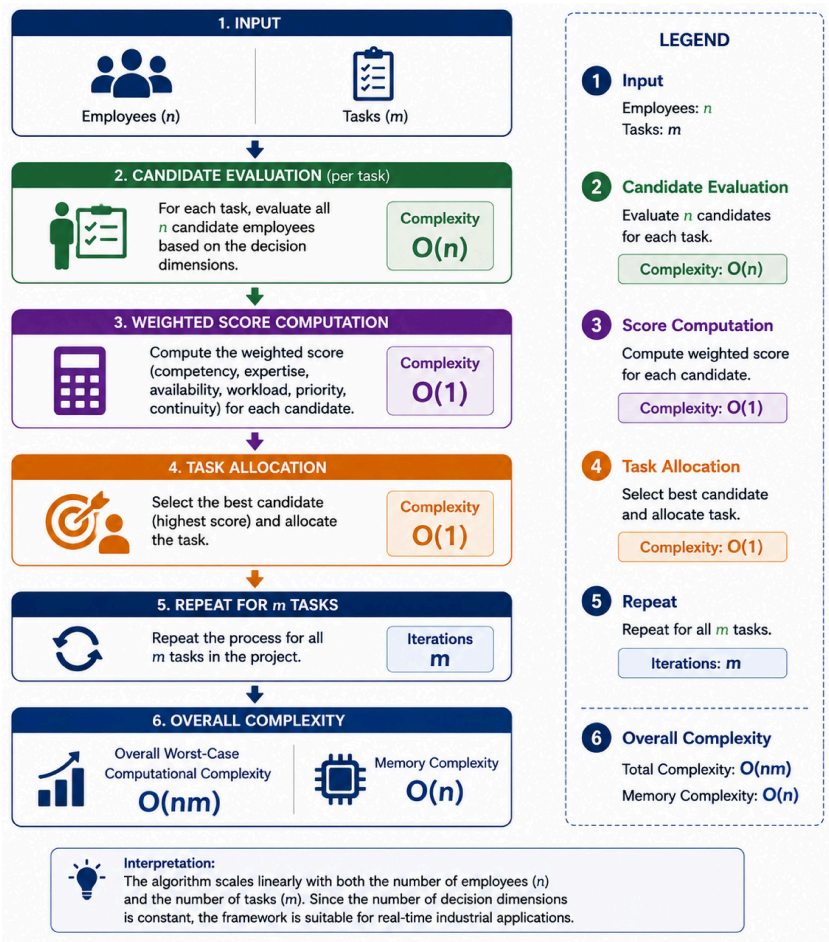


Figure 15. Computational complexity analysis of the proposed workforce allocation algorithm, illustrating the execution workflow and the computational cost associated with each processing stage. Created by the authors, with GPT used to improve the visual quality.

As illustrated in Figure 15, the computational cost of the proposed framework increases linearly with both the number of candidate employees and the number of project tasks, resulting in an overall worst-case time complexity of $O(nm)$ and a memory complexity of $O(n)$. Since the number of decision criteria remains fixed throughout the allocation process,

the algorithm maintains predictable computational performance and can be efficiently applied in large-scale industrial environments requiring timely and transparent workforce allocation decisions.

Computational efficiency demonstrated by the proposed algorithm complements the empirical performance improvements presented in Section 4, indicating that the framework combines decision quality with computational scalability, thereby supporting its practical deployment in real industrial environments.

3.7. Validation Methodology

3.7.1. Validation Strategy

The validation of the proposed Dynamic Task Allocation Framework was conducted through a real-world industrial case study following the principles of Action Design Research. Consistent with the ADR philosophy, the validation process was not performed in a controlled laboratory environment but rather within the operational context of an organization facing genuine workforce-allocation challenges. This approach enabled the assessment of both the technical functionality of the framework and its practical applicability under real decision-making conditions.

The validation focused on evaluating whether the framework could effectively support managers in allocating tasks and projects while simultaneously considering employee competencies, workload levels, availability constraints, project priorities, and continuity requirements. Particular attention was devoted to assessing the ability of the framework to transform fragmented workforce information into structured allocation recommendations capable of improving transparency and consistency throughout the allocation process.

The validation procedure consisted of four sequential stages. First, organizational data regarding employee competencies, workload levels, availability schedules, vacations, and ongoing projects were collected and structured within the decision-support system. Second, representative allocation scenarios were defined based on real organizational requirements, including new project assignments, workload fluctuations, employee absences, and task reallocation situations. Third, the allocation algorithm was executed to generate allocation recommendations according to the framework criteria. Finally, the generated recommendations were reviewed by department managers and compared with traditional allocation practices previously adopted within the organization.

Several allocation scenarios were analyzed during the validation process. These scenarios included the assignment of new projects, the evaluation of employee suitability according to required competencies, the identification of workload constraints, and the reassignment of ongoing activities following workforce availability changes. Such scenarios allowed the framework to be tested under conditions representative of everyday organizational operations. The validation was primarily qualitative in nature, focusing on the practical usefulness of the framework and its ability to support managerial decision-making. The assessment therefore emphasized dimensions such as allocation transparency, consistency of recommendations, visibility over workforce capacity, responsiveness to organizational changes, and ease of use. In addition, the ability of the framework to preserve assignment continuity while avoiding excessive workload concentration was evaluated throughout the analyzed scenarios.

The results obtained during the validation phase demonstrated that the proposed framework successfully integrated multiple allocation variables within a unified decision-support environment. The recommendations generated were consistent with managerial expectations while simultaneously providing a higher degree of visibility regarding workforce utilization and project allocation status. Furthermore, the framework proved capable of dynamically adapting to changes in employee availability and workload conditions,

supporting more informed allocation decisions than those previously achieved through manual and experience-based approaches.

Consequently, the case study provided evidence of the practical feasibility and organizational relevance of the proposed Dynamic Task Allocation Framework, establishing the basis for the results and discussion presented in the following sections.

3.7.2. Data Collection and Case Selection

The empirical study was conducted within a large multinational manufacturing organization operating in a project-intensive environment. Although the case organization belongs to the manufacturing sector, the organizational unit investigated performs a knowledge-intensive internal service function rather than direct manufacturing operations. The workforce considered in the study comprised 102 software developers responsible for designing, developing, and supporting digital applications for internal organizational use. Their activities were distributed across multiple concurrent projects requiring dynamic allocation according to technical competencies, availability, workload, expertise, and project requirements. Accordingly, the investigated setting exhibits the main characteristics of a project-oriented, knowledge-intensive service environment embedded within a large industrial organization.

The broader organizational portfolio comprised 284 projects. This portfolio characterized the operational environment from which allocation practices, recurrent constraints, competency requirements, and project-management conditions were examined; it should not be interpreted as the quantitative validation sample. To ensure comparability and operational relevance, eligible projects were required to have a duration between two working days and five working weeks and to correspond to new projects rather than revisions of existing ones.

Data collection combined documentary analysis with expert knowledge acquisition. Organizational records provided information on workforce profiles, competency requirements, project characteristics, historical allocation practices, availability, and workload conditions. These data were complemented by interviews, calibration sessions, and validation activities involving ten organizational experts—six Project Managers and four Senior Operational Staff. The Project Managers contributed direct knowledge of project requirements and workforce-allocation decisions, whereas the Senior Operational Staff provided complementary expertise regarding resource capacity, workload conditions, operational constraints, and organizational feasibility.

Figure 16 summarizes the industrial case-study environment and the principal data sources used to support the development and evaluation of the decision-support framework. It illustrates the connection between the organizational project portfolio, workforce information, competency and workload data, and the managerial expertise incorporated throughout the ADR process.

As illustrated in Figure 16, the validation protocol combines operational data with expert knowledge within a structured ADR process, thereby linking organizational diagnosis, artefact development, calibration, implementation, and evaluation. This integrated structure improves methodological traceability while clearly distinguishing the broader industrial environment from the observations subsequently used for quantitative performance assessment.

To provide a concise and reproducible overview of the empirical setting, Figure 17 summarizes the principal characteristics of the industrial case study, including the organizational context, project portfolio, workforce population, expert involvement, observation period, data sources, and project-selection criteria.

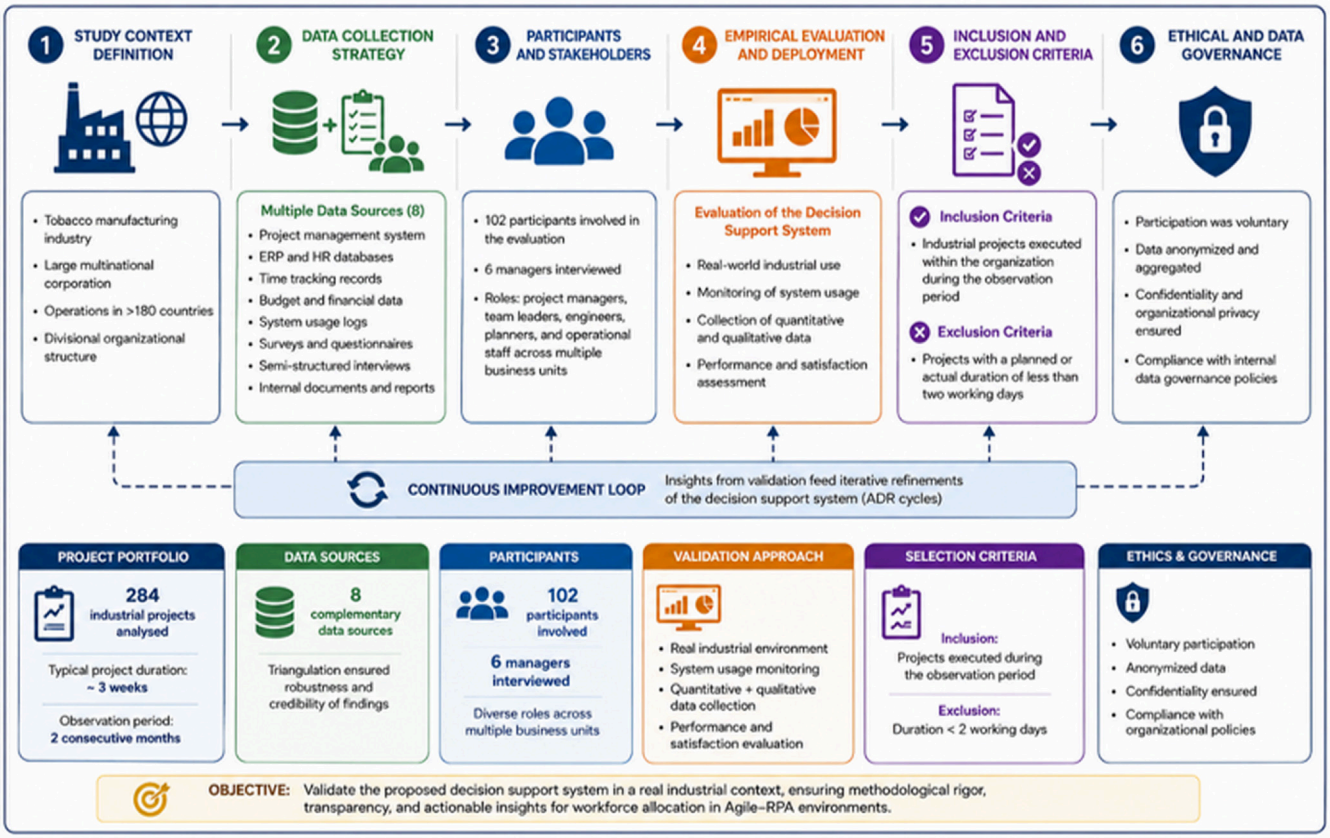


Figure 16. Industrial validation protocol adopted for the empirical evaluation of the proposed decision support system. Created by the authors, with GPT used to improve the visual quality.

Category	Description
Industrial sector	Tobacco manufacturing industry, specializing in the production and commercial distribution of cigarette products.
Organization profile	Large multinational corporation with a global manufacturing and distribution network.
Company size	Large-scale multinational enterprise with operations spanning more than 180 countries.
Number of employees	Global workforce exceeding 83,100 employees.
Organizational structure	Divisional organizational structure comprising multiple business units operating under a common corporate governance framework.
Number of projects analysed	284 industrial projects included in the empirical evaluation.
Typical project duration	Typical project duration of approximately three weeks.
Observation period	Observation period of two consecutive months.
Participants	102 participants involved in the empirical evaluation of the proposed decision support system.
Managers interviewed	Six managerial staff members interviewed as part of the empirical study.
Data sources	Eight complementary data sources used for data collection and triangulation.
Inclusion criteria	Industrial projects executed within the organization during the observation period.
Exclusion criteria	Projects with a planned or actual duration of less than two working days were excluded from the analysis.
Ethical considerations	Participation was voluntary and data were anonymized to ensure confidentiality and organizational privacy.

Figure 17. Characteristics of the industrial case study and empirical data collection protocol. Created by the authors, with GPT used to improve the visual quality.

The information summarized in Figure 17 establishes the empirical boundaries of the study and clarifies the respective roles of the organizational portfolio, workforce population, and expert panel. Operational and personnel information was processed in anonymized form, and the analysis was restricted to organizational data required for framework development and evaluation. The specific analytical sample used for the paired quantitative validation is defined separately in Section 3.7.3.

3.7.3. Validation Dataset and Experimental Design

The participating organization managed an overall portfolio of 284 concurrent projects during the industrial study. As described in Section 3.7.2, this portfolio defines the broader operational environment of the research and should not be interpreted as 284 independent experimental observations. The analytical sample used for the quantitative before–after evaluation comprised seven paired workforce-allocation cases ($n = 7$), purposively selected to capture recurrent and operationally distinct allocation situations encountered within the investigated environment.

The selected cases covered five principal types of allocation situations: new project assignment, workload redistribution, employee unavailability, changes in project priority, and reassignment of ongoing tasks. All cases satisfied the eligibility criteria established in Section 3.7.2; cases with incomplete documentation, missing competency information, exceptional operational conditions, or insufficient historical information were excluded to preserve comparability and data quality.

Each case was evaluated under two matched conditions: (i) the organization's conventional workforce-allocation procedure and (ii) the proposed DSS-supported procedure. Within each pair, the same task requirements, workforce information, competency profiles, resource-availability conditions, and workload state were retained. This paired design enabled the two allocation procedures to be compared under equivalent operational conditions rather than across unrelated cases. The resulting seven paired observations constituted the analytical sample used for the quantitative KPI evaluation reported in Section 4.5.

The broader resource population available to the allocation process comprised the 102 software developers characterized in Section 3.7.2; these employees therefore represent the workforce pool rather than independent experimental observations. For each selected allocation case, task-level priority, complexity/urgency, and continuity requirements were processed together with employee-level competency, availability, workload, and expertise information. Candidate eligibility was first determined according to task requirements and operational constraints, after which eligible employees were ranked using the four-component Allocation Suitability Score defined in Section 3.5.

To consolidate the experimental basis of the validation and clearly distinguish the organizational context from the analytical sample, Figure 18 summarizes the principal characteristics of the dataset, including the project portfolio, workforce population, paired allocation cases, data sources, decision variables, and evaluation metrics.

Figure 18 establishes the respective analytical roles of the different empirical components: the 284-project portfolio defines the broader operational context, the 102 software developers constitute the available workforce population, and the seven paired allocation cases form the quantitative analytical sample. This distinction prevents the organizational population and project portfolio from being conflated with the number of independent observations used to estimate framework-associated performance changes.

Validation Aspect	Description	Details
Organization	Industrial context in which the framework was developed and validated	Large multinational manufacturing company
Organizational Project Portfolio	Concurrent project portfolio defining the industrial validation environment	284 projects
Workforce Population	Employees represented in the organizational allocation environment	102 employees
Expert Panel	Experts involved in ADR development, calibration, and validation	6 Project Managers + 4 Senior Operational Staff
Calibration Process	Iterative expert-driven calibration of the ASS weighting configuration	4 ADR calibration iterations
Quantitative Validation Sample	Allocation cases used for the before–after performance evaluation	7 paired allocation cases
Case Selection Strategy	Procedure used to select quantitative validation cases	Purposive sampling of recurrent and operationally distinct allocation situations
Comparison Design	Conditions evaluated for each selected allocation case	Conventional allocation vs. DSS-supported allocation
Observation Period	Period during which industrial data were collected	Two months
Typical Project Duration	Typical duration of projects within the industrial environment	Three weeks
Data Sources	Organizational information sources supporting framework development and validation	ERP, HRMS, project-management system, workload records, and skills database
Allocation Variables	Decision dimensions incorporated into	Competency, availability, workload, and expertise
Contextual Decision Rules	Additional factors considered outside the ASS weighting structure	Task priority, project continuity, complexity/urgency, and operational constraints
Quantitative KPIs	Indicators used for paired performance evaluation	Allocation time, workload imbalance, resource utilization, allocation consistency, and manual intervention
Statistical Reporting	Aggregation and variability measures used for quantitative comparison	Mean ± SD, paired mean difference, and 95% CI

Figure 18. Summary of the experimental validation dataset adopted for assessing the proposed workforce allocation decision support system. Created by the authors, with GPT used to improve the visual quality.

3.7.4. Experimental Validation Design

Following the characterization of the validation dataset, an experimental design was established to systematically assess the performance of the proposed decision-support framework under real industrial operating conditions. The evaluation was structured to compare the organization's conventional workforce-allocation procedure with the allocation process supported by the proposed framework, using equivalent operational scenarios and a common set of performance indicators.

The experimental design integrated five principal components: the industrial project portfolio, the participating workforce, the managerial evaluators, the organizational data sources, and the proposed decision-support system. Workforce-allocation scenarios were constructed from actual operational requirements and included new project assignments, workload redistribution, employee unavailability, changes in project priority, and reassignment of ongoing tasks. These scenarios were selected because they represent recurrent decision situations encountered within the participating organization.

For each allocation scenario, the conventional procedure and the proposed framework were evaluated according to the same operational dimensions. Under the conventional approach, managers identified and assigned suitable employees using fragmented organizational information, previous experience, and manual verification of competencies, availability, and workload. Under the proposed approach, the same information was processed through the competency-aware allocation model, which generated ranked recommendations based on the Allocation Suitability Score.

The comparison between both allocation procedures was conducted using five quantitative performance indicators: allocation time, workload imbalance, resource utilization, allocation consistency, and the level of manual intervention required. These indicators were selected because they directly correspond to the research propositions established in Section 3.1 and capture complementary dimensions of allocation efficiency, workforce balance, operational utilization, decision reproducibility, and process automation.

In addition to the quantitative comparison, managerial feedback was collected to assess the perceived organizational effects of the framework, including workforce visibility, decision transparency, responsiveness, conflict detection, and practical usability. The combination of objective operational indicators and qualitative managerial assessment enabled the evaluation to consider both measurable performance improvements and the practical relevance of the artefact within the organizational context.

Figure 19 summarizes the experimental validation design and illustrates the sequence connecting industrial data acquisition, allocation scenario definition, execution of the conventional and framework-supported procedures, performance measurement, managerial assessment, and validation of the research propositions.

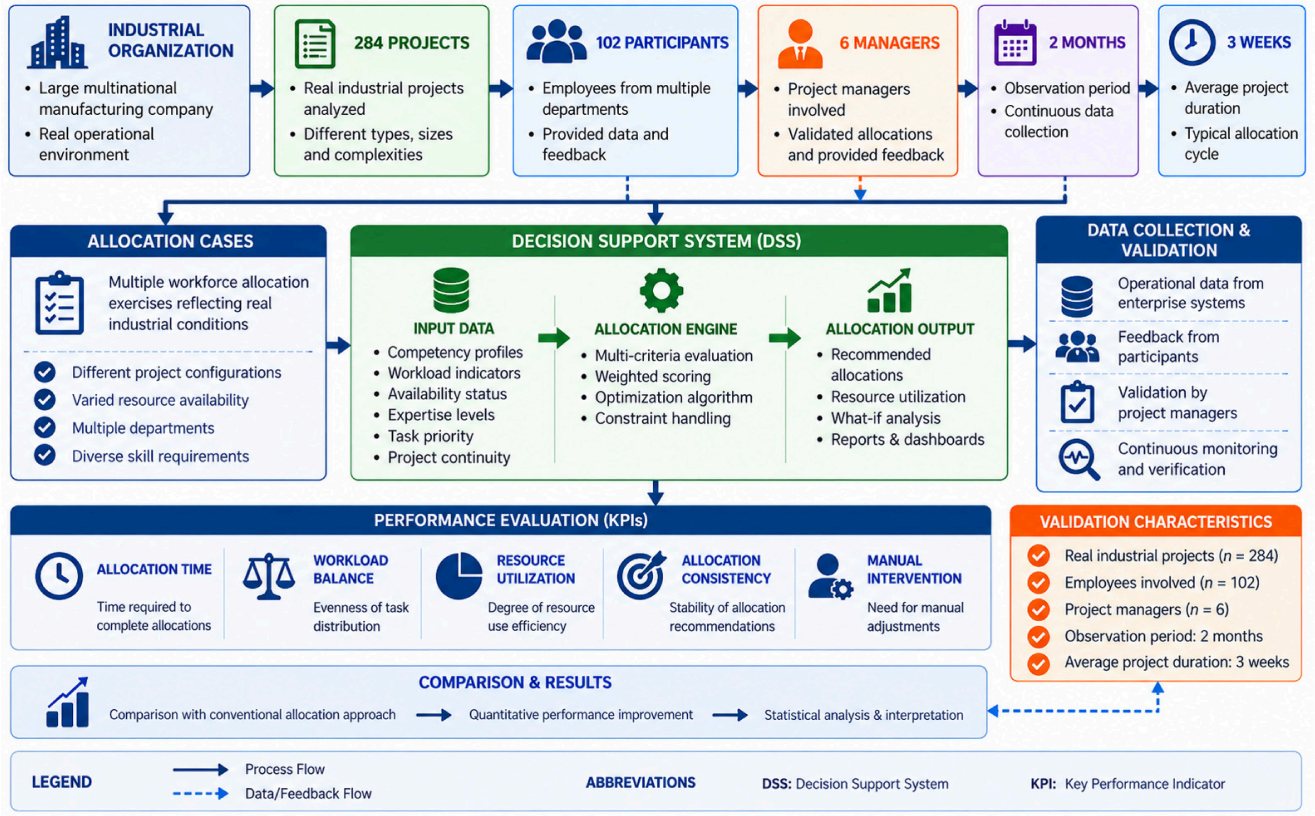


Figure 19. Experimental validation design adopted for assessing the proposed workforce allocation decision support system under real industrial operating conditions. Created by the authors, with GPT used to improve the visual quality.

As illustrated in Figure 19, the validation process establishes a direct relationship between the organizational problem, the proposed decision-support artefact, and the empirical evidence used to assess its effectiveness. By applying both allocation procedures to representative industrial scenarios and evaluating them through common quantitative and qualitative criteria, the adopted design provides a structured basis for determining whether the framework satisfies the research propositions defined at the beginning of the methodology. This experimental structure therefore strengthens the traceability, transparency, and reproducibility of industrial validation.

3.7.5. Quantitative KPI Definition and Calculation

Five quantitative Key Performance Indicators (KPIs) were used to compare the conventional workforce-allocation procedure with the proposed decision-support framework: allocation time, workload imbalance, resource utilization, allocation consistency, and manual intervention requirement. The unit of analysis was one complete workforce-allocation case, defined as the decision process required to assign an eligible employee to a specific task or project requirement. Seven paired allocation observations (n = 7) were evaluated under both conditions, with each case processed using the conventional procedure and the framework-assisted procedure under equivalent task and workforce information. These seven paired observations constitute the analytical sample used for the quantitative KPI comparison and should be distinguished from the broader organizational participants and project portfolio involved in the ADR development and industrial validation process.

Allocation time (AT) was defined as the elapsed time, expressed in seconds, between initiation of the allocation decision and identification of the final employee assignment. For each condition, the reported AT corresponds to the arithmetic mean of the seven observations:

$$AT = \frac{1}{n}\sum_{j=1}^{n} t_j \tag{12}$$

where t_j represents the allocation time measured for case j, and $n = 7$.

Workload imbalance (WI) quantified the relative dispersion of workload across the resources considered in each allocation case and was calculated using the coefficient of variation:

$$WI = \frac{s_L}{\overline{L}} \times 100 \tag{13}$$

where s_L is the standard deviation of individual resource workload and $\overline{L}$ is the corresponding mean workload. WI is expressed as a percentage, with lower values indicating a more balanced workload distribution.

Resource utilization (RU) represented the proportion of available workforce capacity effectively assigned during the evaluated allocation condition and was calculated as:

$$RU = \frac{\sum_{i=1}^{m} L_i^{assigned}}{\sum_{i=1}^{m} L_i^{available}} \times 100 \tag{14}$$

where $L_i^{assigned}$ is the assigned capacity and $L_i^{available}$ is the available capacity of employee i, with m representing the number of resources considered in the allocation case. Higher RU values indicate more effective utilization of the available workforce capacity.

Allocation consistency (AC), also referred to as the alignment index, quantified the proportion of allocation decisions that coincided with the reference allocation previously assessed as appropriate by the expert evaluators according to the established organizational decision criteria:

$$AC = \frac{N_{aligned}}{N_{evaluated}} \times 100 \tag{15}$$

where $N_{aligned}$ represents the number of allocation decisions matching the expert-approved reference allocation and $N_{evaluated}$ represents the total number of allocation decisions evaluated. Higher AC values therefore indicate greater reproducibility and alignment with the reference decision.

Manual intervention requirement (MI) represented the proportion of allocation decisions requiring direct managerial intervention to complete or correct the resulting assignment:

$$MI = \frac{N_{manual}}{N_{evaluated}} \times 100 \tag{16}$$

where N_{manual} represents the number of decisions requiring manual managerial intervention and $N_{evaluated}$ represents the total number of evaluated allocation decisions. Lower MI values indicate a greater degree of autonomous decision support.

For all five KPIs, the baseline and framework-assisted values reported in the Results correspond to arithmetic means across the seven paired observations rather than medians, totals, or single-case measurements. Variability was characterized using the sample standard deviation (SD). To further quantify the consistency and uncertainty of the observed changes, the mean paired difference between the baseline and framework-assisted conditions and its corresponding 95% confidence interval (CI) were calculated for each KPI. For percentage-based indicators, absolute changes are reported in percentage points (p.p.) and, where relevant, accompanied by the corresponding relative percentage improvement.

3.7.6. Qualitative Managerial Evaluation Protocol

In addition to the quantitative performance evaluation, a qualitative managerial assessment was conducted to capture the organizational effects of the proposed decision-support framework as perceived by the professionals directly involved in workforce-allocation activities. The assessment was conducted through an individual survey conducted by ten organizational experts comprising six Project Managers and four Senior Operational Staff.

Respondents independently evaluated the perceived organizational changes associated with framework implementation using a five-point Likert scale: 1 = No improvement, 2 = Slight improvement, 3 = Moderate improvement, 4 = Substantial improvement, and 5 = Very substantial improvement. Individual administration was adopted to minimize group influence and capture each respondent's independent perception of the framework.

For each assessed dimension, the ten individual responses were aggregated using the arithmetic mean:

$$\overline{S}_d = \frac{1}{10}\sum_{r=1}^{10} S_{dr} \quad (17)$$

where S_{dr} represents the score assigned to dimension by respondent r. The resulting mean scores were interpreted according to predefined intervals: 1.00–1.49 = No improvement; 1.50–2.49 = Slight improvement; 2.50–3.49 = Moderate improvement; 3.50–4.49 = Substantial perceived improvement; and 4.50–5.00 = Very substantial perceived improvement. This classification was used exclusively to characterize the magnitude of the perceived organizational improvement and does not imply statistical significance.

4. Results and Framework Validation

4.1. Framework Application

The proposed Dynamic Task Allocation Framework was implemented and evaluated within the organizational environment described in Section 3.2. The objective of the application phase was to assess the ability of the framework to support workforce-allocation decisions while simultaneously integrating employee competencies, workload levels, availability constraints, project priorities, and task-specific requirements.

The implementation process involved the migration of workforce information, competency profiles, project records, and availability data into the decision-support environment developed during this study. Once the relevant organizational information was structured, the framework became capable of generating allocation recommendations based on the decision criteria established during the framework-development stage.

Compared with the previous experience-based procedure, implementation of the framework introduced a centralized and structured allocation process in which competencies, availability, workload, and project requirements were evaluated through common decision criteria. This enabled managers to obtain ranked allocation recommendations, monitor workforce utilization, and identify potential allocation conflicts within a single

decision-support environment, thereby establishing the operational basis for the validation presented in the following sections.

4.2. Allocation Scenarios and Decision-Support Performance

To evaluate the operational performance of the framework, a series of representative allocation scenarios were analysed. These scenarios reproduced situations frequently encountered in project-oriented environments, including the assignment of new projects, employee absences, workload constraints, and task reassignment requirements.

As a complementary controlled benchmark, the proposed multi-criteria allocation model was compared with the competency-first greedy heuristic described in Section 3.5.3. While the greedy rule selected the candidate presenting the highest competency match, the multi-criteria model produced a different ranking by simultaneously accounting for competency, availability, workload, and expertise. In the illustrative scenario, the technically strongest candidate was not identified as the most suitable overall allocation because its competency advantage was offset by comparatively high workload and limited availability. This result demonstrates that the decision-support contribution of the proposed framework extends beyond the digitalization of workforce information, since multi-criteria integration can effectively modify the resulting allocation decision.

The first scenario involved the allocation of a new project requiring a specific combination of competencies over a predefined execution period. The framework successfully identified employees possessing the required skill set while simultaneously considering availability and workload constraints. Although certain employees demonstrated higher competency scores, the framework correctly excluded resources that were unavailable or operating near full capacity, thereby preventing unrealistic allocation recommendations.

A second scenario evaluated the framework's response to workforce availability constraints. The presence of vacation periods and temporary absences was automatically incorporated into the allocation logic, ensuring that unavailable employees were excluded from the recommendation process. This capability eliminated the need for manual verification and reduced the likelihood of allocation errors.

A third scenario focused on balancing workload. The framework continuously evaluated employee occupation rates and prevented allocation recommendations that would exceed predefined capacity thresholds. Consequently, workload distribution became more balanced across the team, reducing the risk of resource overutilization and improving visibility regarding future capacity limitations.

The reassignment functionality was also evaluated through simulated workforce changes. When a resource became unavailable during ongoing project execution, the framework automatically identified alternative candidates according to the same allocation criteria used during the original assignment process. This capability ensured continuity of operations while minimizing managerial intervention. One of the most valuable functionalities of the framework is its ability to dynamically reallocate ongoing activities when workforce availability changes. The reassignment logic implemented within the system is illustrated in Figure 20.

Collectively, these scenarios demonstrated the framework's ability to support dynamic allocation decisions under realistic organizational conditions. More importantly, the results confirmed that the integration of competencies, workload balancing, availability constraints, and project continuity requirements within a unified decision-support environment improves allocation consistency and organizational visibility.

Unlike conventional workforce allocation approaches that optimize isolated decision variables, the proposed framework simultaneously integrates competency matching, workload balancing [63–66], personnel availability, expertise level, task priority, and project

continuity within a unified decision-making architecture. This multidimensional integration enables more robust, transparent, and operationally consistent allocation decisions while supporting the dynamic requirements.

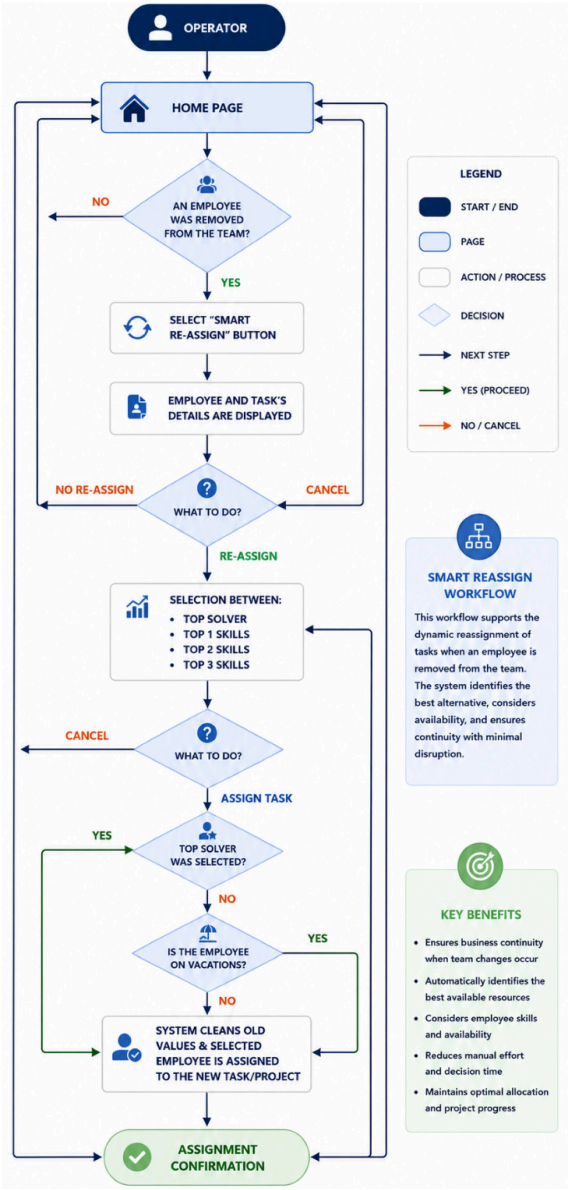


Figure 20. Dynamic task reassignment workflow used to preserve project continuity following workforce availability changes. Created by the authors, with GPT used to improve the visual quality.

4.3. Managerial Implications

Beyond its technical functionality, the proposed framework generated important managerial benefits. One of the most significant contributions was the transformation of workforce allocation from an experience-driven process into a structured decision-support activity supported by transparent and objective criteria. The framework improved managerial visibility regarding workforce capacity by consolidating information previously dispersed across multiple sources. This enhanced visibility facilitated the identification of overloaded resources, underutilized competencies, and future capacity shortages, enabling more proactive planning activities.

Another important contribution relates to organizational resilience. Because allocation recommendations are generated dynamically, managers can rapidly respond to changes in project priorities, employee availability, and workload distribution. This capability

is particularly valuable in service-oriented environments characterized by high levels of uncertainty and frequent operational changes.

From a broader perspective, the framework contributes to organizational knowledge management by formalizing allocation criteria that would otherwise remain embedded within managerial experience. This reduces dependence on individual decision-makers and promotes greater consistency across allocation decisions over time.

The reporting capabilities generated by the framework provide managers with enhanced visibility regarding workforce utilization and project allocation status. An example of the reporting output generated by the system is presented in Figure 21.

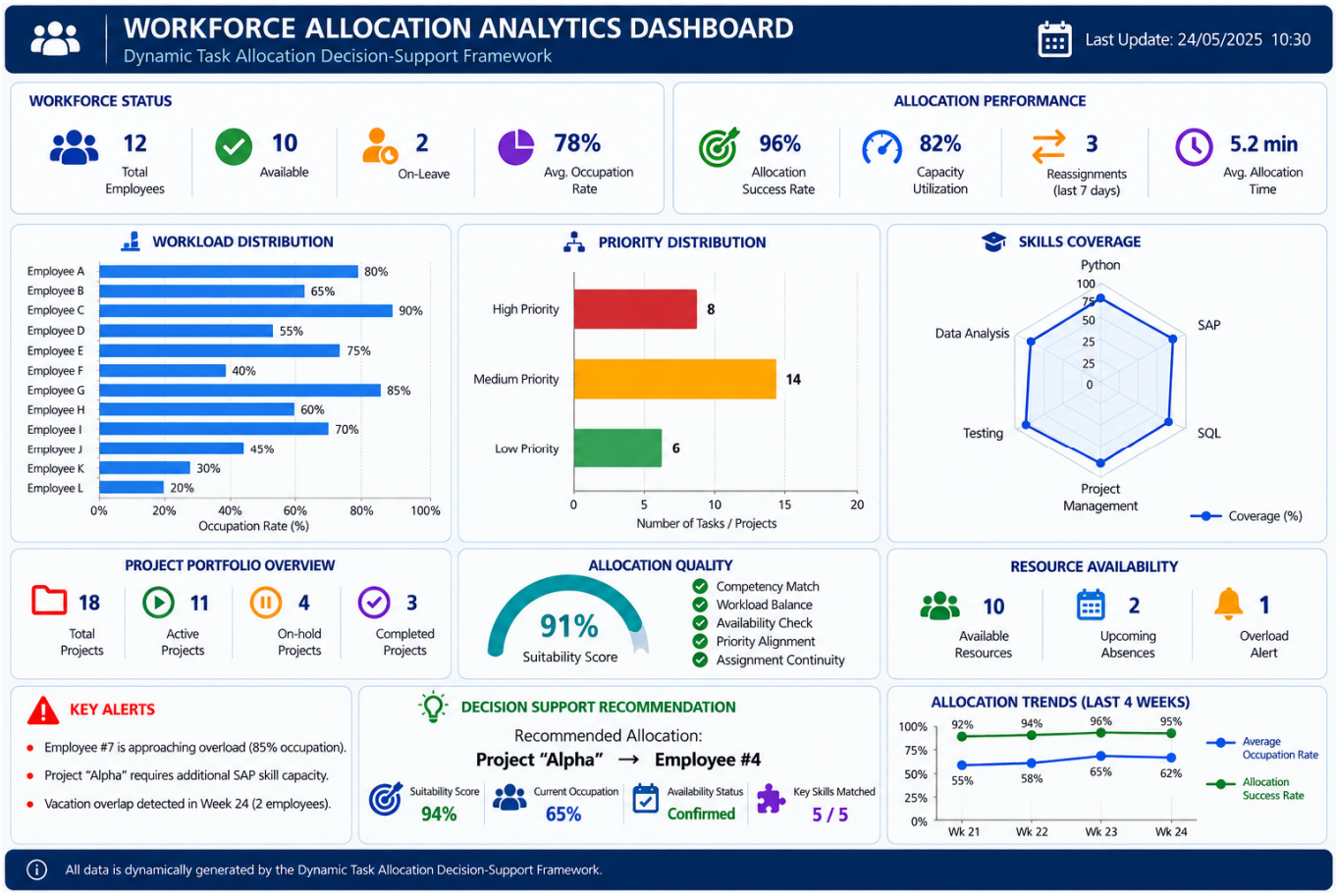


Figure 21. Workforce Allocation Analytics Dashboard generated by the proposed Decision-Support Framework, providing real-time visibility of workforce availability, workload distribution, project-priority profiles, allocation quality indicators, and managerial decision-support recommendations. Created by the authors, with GPT used to improve the visual quality.

Finally, the results suggest that lightweight decision-support frameworks can provide substantial practical value without requiring sophisticated enterprise systems or computationally intensive optimization models. Consequently, the proposed approach represents a viable alternative for organizations seeking to improve workforce-allocation practices while maintaining implementation simplicity and operational flexibility. The overall benefits generated by the implementation of the proposed framework are summarized in Figure 22. The framework enhances workforce visibility, allocation consistency, organizational agility, workload balancing, knowledge retention, and resources utilization, ultimately improving decision quality and overall organization performance.

Beyond the technical implementation of the framework, it is important to evaluate its impact on workforce-allocation practices. A comparative assessment was therefore

conducted based on stakeholder feedback collected throughout the Action Design Research validation process. The comparison highlights the main organizational improvements observed after implementation of the Dynamic Task Allocation Framework and is presented in Figure 23.

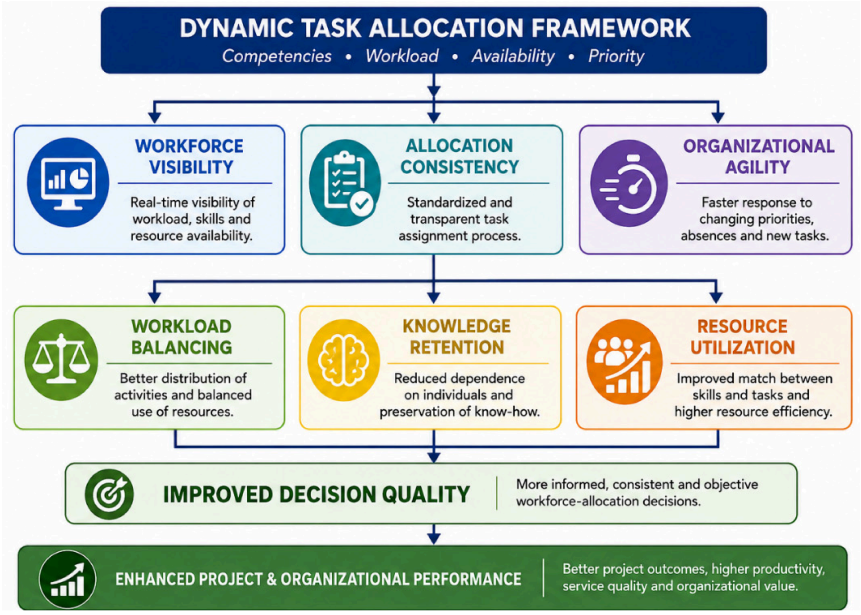


Figure 22. Organizational benefits generated by the Dynamic Task Allocation Decision-Support framework. Created by the authors, with GPT used to improve the visual quality.

Descriptive organizational transformation observed after the implementation of the decision-support framework.

ORGANIZATIONAL DIMENSION	BEFORE IMPLEMENTATION	AFTER IMPLEMENTATION	OBSERVED TRANSFORMATION (Descriptive Impact)
Workforce Visibility	Information dispersed across multiple sources and dependent on individual knowledge.	Centralized visibility through an integrated dashboard and reporting system.	**Improved situational awareness.** Managers obtain a comprehensive and real-time view of workload, skills, and resource availability, supporting better understanding of organizational capacity.
Allocation Transparency	Task assignments predominantly based on managerial experience and informal knowledge.	Structured and traceable allocation process supported by predefined criteria.	**Increased decision transparency.** Allocation decisions are documented and traceable, promoting accountability and building trust among employees and stakeholders.
Workload Monitoring	Limited visibility of employee occupation levels and ongoing commitments.	Real-time overview of workload distribution and resource utilization.	**Enhanced workload control.** Managers can identify overloads or underutilization early and rebalance workloads to ensure a more even distribution of tasks across the workforce.
Resource Availability Tracking	Availability verification performed manually and independently for each allocation decision.	Availability constraints integrated directly into the allocation process.	**Faster allocation decisions.** Reduction of manual checks and administrative effort, enabling managers to allocate resources more quickly and with greater confidence.
Assignment Consistency	Allocation outcomes dependent on individual manager judgment.	Standardized allocation logic applied across projects and tasks.	**Greater consistency and fairness.** The same rules and criteria are applied consistently, reducing subjectivity and ensuring equitable treatment of employees and projects.
Knowledge Retention	Critical allocation knowledge embedded in individual managers, leading to risk of knowledge loss.	Allocation knowledge formalized and embedded within the framework.	**Reduced dependency on individuals.** Organizational knowledge is preserved within the system, facilitating onboarding, succession, and continuity of decision practices.
Adaptability to Organizational Changes	Reactive response to absences, workload changes, and project priority shifts.	Dynamic reassignment capabilities supporting rapid adaptation.	**Improved organizational agility.** The organization can respond quickly to unforeseen events, absences, and priority changes with minimal disruption to ongoing projects.
Decision-Support Capability	Limited analytical support for allocation decisions.	Integrated recommendations and reporting enhancing managerial decisions.	**Enhanced decision quality.** Data-driven insights and clear recommendations enable managers to make more informed, consistent, and strategic allocation decisions.

Note: This table presents a descriptive comparison of organizational perceptions and practices before and after the implementation of the decision-support framework, as reported by managers and team leaders during the Action Design Research (ADR) evaluation process.

Figure 23. Comparative Assessment of Workforce-Allocation Practices Before and After Framework Implementation. Created by the authors, with GPT used to improve the visual quality.

Overall, stakeholder evaluation indicated substantial improvements in workforce visibility, allocation consistency, workload monitoring, resource availability tracking, and decision-support capability, confirming the practical value of the proposed framework for dynamic workforce-allocation environments.

To complement the qualitative validation, a set of quantitative implementation indicators was defined to objectively characterize the operational scope and decision-support capabilities of the proposed framework (Figure 24). Rather than evaluating isolated algorithmic performance metrics, these indicators quantify the complexity of the allocation process, the diversity of information simultaneously processed, and the practical deployment conditions under which the framework was validated.

Validation Indicator	Measured Value	Engineering Significance
Workforce size included in validation	12 employees	Real organizational environment
Allocation dimensions evaluated	6	Skills, workload, availability, priority, task characteristics, continuity
Operational scenarios assessed	4	New allocation, balancing, absence, reassignment
Candidate recommendations	Top-3 employees	Managerial decision support
Data sources integrated	5	Skills, workload, availability, tasks, employee database
Decision-support platform	MS Excel® + VBA	Low-cost and easily deployable
Research methodology	Action Design Research	Iterative industrial validation
Allocation strategy	Multi-criteria rule-based	Simultaneous organizational constraints
Validation environment	Industrial case study	Dynamic operational conditions
Framework objective	Dynamic workforce allocation	Continuous adaptation to changing workloads

Figure 24. Quantitative validation indicators summarizing the operational scope, implementation characteristics, and decision-support capabilities of the proposed framework. Created by the authors, with GPT used to improve the visual quality.

The quantitative indicators demonstrate that the proposed framework integrates multiple allocation dimensions within a single decision-support environment while remaining computationally lightweight and operationally practical. Although the primary objective of the study was not algorithm benchmarking, the presented indicators objectively characterize the framework's implementation complexity and provide measurable evidence of its applicability to dynamic workforce-allocation problems in project-oriented organizations. Moreover, industrial validation showed a mean reduction of 84.3% in task-allocation time and 92.9% in workload imbalance, together with a 12.6% relative increase in resource utilization, a 25.3% increase in allocation consistency, and a 98.0% reduction in manual intervention requirements.

4.4. Qualitative Managerial Assessment

To complement the qualitative assessment performed during the Action Design Research validation process, a set of key performance indicators (KPIs) was defined to evaluate the practical impact of the proposed framework on workforce-allocation activities. The selected KPIs were chosen because they directly represent the principal dimensions of workforce allocation performance, namely decision efficiency, workload distribution, resource utilization, allocation quality, and automation level.

While the quantitative KPIs provide objective evidence of the operational effects of the proposed decision-support system, they do not fully capture the organizational benefits perceived by the professionals involved in workforce allocation. Accordingly, the individual survey described in Section 3.7.6 was used to evaluate the perceived effects of the framework across the selected organizational dimensions. The aggregated results are presented in Figure 25.

Assessment Dimension	Mean Likert Score (1 = No Improvement; 5 = Very Substantial Improvement)	Interpretation (Based on Mean Likert Score)
1. Workforce Visibility Ability to identify available and suitable personnel	4.70	Very Substantial Perceived Improvement (4.50–5.00)
2. Workload Visibility Clarity of workload distribution across employees	4.60	Very Substantial Perceived Improvement (4.50–5.00)
3. Allocation Conflict Detection Identification of allocation inconsistencies and conflicts	4.50	Very Substantial Perceived Improvement (4.50–5.00)
4. Resource Availability Assessment Evaluation of resource availability status	4.40	Substantial Perceived Improvement (3.50–4.49)
5. Assignment Transparency and Consistency Clarity and consistency in assignment decisions	4.60	Very Substantial Perceived Improvement (4.50–5.00)
6. Organizational Responsiveness Ability to respond to changes and new demands	4.50	Very Substantial Perceived Improvement (4.50–5.00)
7. Decision Transparency Transparency and traceability of allocation decisions	4.60	Very Substantial Perceived Improvement (3.50–4.49)
8. Workload Balance Balance of workload among team members	4.40	Substantial Perceived Improvement (3.50–4.49)
9. Allocation Accuracy Accuracy of personnel-task matching	4.70	Very Substantial Perceived Improvement (4.50–5.00)
10. Time-to-Allocate Speed of workforce allocation process	4.60	Very Substantial Perceived Improvement (4.50–5.00)
11. Framework Usability Ease of use and usability of the framework	4.50	Very Substantial Perceived Improvement (4.50–5.00)
12. Overall Organizational Impact Overall perceived organizational impact of the framework	4.80	Very Substantial Perceived Improvement (4.50–5.00)

Figure 25. Qualitative managerial assessment of the organizational benefits perceived after implementing the proposed decision support system. Created by the authors, with GPT used to improve the visual quality.

The managerial assessment revealed consistently positive perceptions of the framework across the evaluated organizational dimensions. The aggregated scores indicate substantial to very substantial perceived improvements in workforce visibility, decision transparency, workload monitoring, conflict detection, allocation consistency, resource-availability awareness, and organizational responsiveness. These findings complement the quantitative performance results by showing that the operational benefits of the framework were also recognized by the professionals directly involved in workforce-allocation activities.

4.5. Quantitative Performance Evaluation

The operational performance of the proposed decision-support framework was evaluated using the five KPIs formally defined in Section 3.7.5: task allocation time, workload imbalance, resource utilization, allocation consistency, and manual intervention requirement. The quantitative comparison was based on the seven paired allocation cases (n = 7) defined in Section 3.7.3, with each case evaluated under equivalent baseline and framework-assisted conditions.

Figure 26 summarizes the aggregate performance obtained under both allocation procedures and the corresponding relative changes.

The aggregate results show favorable changes across all five operational indicators. Mean task allocation time decreased from 204 s to 32 s, corresponding to an 84.3% reduction, while workload imbalance decreased from 28% to 2% (−92.9%). Resource utilization increased from 87% to 98%, corresponding to an absolute increase of 11 percentage points

and a relative increase of approximately 12.6% Resource utilization increased from 87% to 98%, corresponding to an absolute increase of 11 percentage points and a relative increase of approximately 12.6%, allocation consistency increased from 79% to 99% (+25.3%), and manual intervention requirement decreased from 100% to 2% (−98.0%). These results characterize the magnitude of the observed operational changes within the evaluated cases but do not, by themselves, describe their case-to-case variability.

Performance Dimension	Key Performance Indicator (KPI)	Conventional Approach	Proposed DSS Approach	Improvement
Decision Efficiency *Measures the time required to generate an allocation*	**Allocation Time** *(per allocation cycle)*	204 s	32 s	↓ −84.3% *(Reduction)*
Workload Distribution *Measures the balance of workload across resources*	**Workload Imbalance** *(standard deviation)*	28%	2%	↓ −92.9% *(Reduction)*
Resource Efficiency *Measures the level of resource utilization*	**Resource Utilization** *(average)*	87%	98%	↑ +11.0 p.p. *(+12.6% relative)*
Allocation Quality *Measures the alignment of assignments with requirements*	**Allocation Consistency** *(alignment index)*	79%	99%	↑ +25.3% *(Increase)*
Automation Level *Measures the need for human manual intervention*	**Manual Intervention** *(frequency)*	100%	2%	↓ −98.0% *(Reduction)*

Note: *Percentage improvements are calculated relative to the conventional approach. For resource utilization, both the absolute change in percentage points (p.p.) and the corresponding relative improvement are reported.*

Figure 26. Quantitative performance comparison between conventional and framework-assisted workforce allocation across the seven paired cases. Created by the authors, with GPT used to improve the visual quality.

To examine the consistency and uncertainty of these changes, the five KPIs were further analyzed across the seven paired observations. For each indicator, the mean and standard deviation were calculated under both conditions, together with the mean paired change and its corresponding 95% confidence interval. These statistics are reported in Figure 27.

KPI	n	Baseline, mean ± SD	Framework, mean ± SD	Mean paired change	95% CI of paired change	Relative improvement
Task allocation time (s)	7	204.00 ± 4.55	32.00 ± 1.41	−172.00 s	[−176.92, −167.08] s	−84.3%
Workload imbalance (%)	7	28.00 ± 2.77	2.00 ± 0.14	−26.00 p.p.	[−28.56, −23.44] p.p.	−92.9%
Resource utilization (%)	7	87.00 ± 2.16	98.00 ± 1.53	+11.00 p.p.	[+8.86, +13.14] p.p.	+12.6%
Allocation consistency (%)	7	79.00 ± 3.79	99.00 ± 0.58	+20.00 p.p.	[+16.84, +23.16] p.p.	+25.3%
Manual intervention requirement (%)	7	100.00 ± 0.00	2.00 ± 0.08	−98.00 p.p.	[−98.08, −97.92] p.p.	−98.0%

Notes: *p.p. = percentage points. Negative values indicate a reduction (improvement) for metrics where lower is better. Positive values indicate an increase (improvement) for metrics where higher is better. The zero baseline SD for Manual intervention requirement reflects that, in the previous procedure, all seven allocation cases required manual managerial intervention.*

Figure 27. Paired descriptive analysis of the key operational performance indicators under baseline and framework-assisted allocation conditions (n = 7). Created by the authors, with GPT used to improve the visual quality.

The paired analysis indicates that the favorable aggregate changes were consistently observed across the seven evaluated cases. The 95% confidence intervals for the mean paired changes remained separated from zero for all five indicators. Particularly pronounced changes were observed for task allocation time (−172.00 s; 95% CI: −176.92 to −167.08 s), workload imbalance (−26.00 percentage points; 95% CI: −28.56 to −23.44), and manual intervention requirement (−98.00 percentage points; 95% CI: −98.08 to −97.92). Resource utilization and allocation consistency increased by 11.00 and 20.00 percentage points, respectively.

From an operational perspective, the reduction in allocation time reflects the replacement of sequential manual consultation and evaluation with a structured decision process integrating competency, availability, workload, and expertise information. Similarly, the reduction in workload imbalance is consistent with the explicit consideration of current workload during candidate ranking, while the increase in resource utilization indicates more effective use of available workforce capacity. The higher allocation-consistency values reflect greater agreement with expert-approved reference allocations, whereas the marked reduction in manual intervention indicates that most allocation decisions could be completed without subsequent managerial correction.

Taken together, these findings provide case-specific quantitative evidence of favorable operational effects associated with the proposed framework relative to the conventional allocation procedure. The results should nevertheless be interpreted within the boundaries of the seven paired cases and the investigated organizational setting, rather than as inferential evidence of general superiority over alternative workforce-allocation approaches.

5. Discussion

The results obtained throughout this study demonstrate that workforce allocation should not be viewed merely as an operational scheduling activity but rather as a strategic decision-making process that directly influences organizational performance, resource utilization, and project execution. The framework developed in this work emerged from the recognition that many organizations continue to allocate resources through fragmented information sources and experience-based judgment, despite the existence of extensive research dedicated to resource-allocation methodologies.

5.1. Theoretical Implications

The findings provide empirical support for addressing the theory–practice gap identified in the literature review. Existing research has established sophisticated optimization, competency-matching, and constraint-based approaches to resource allocation [8,10,12,13]; however, the present results demonstrate the practical value of an alternative design logic in which analytical structure, interpretability, and operational deployability are jointly considered. Rather than pursuing mathematical optimality under restrictive assumptions, the proposed framework operationalizes competency, workload, availability, project priority, and task-related criteria within a lightweight decision-support structure applied under real organizational conditions. This positioning is also consistent with the broader transition from traditional project-control perspectives toward more adaptive and flexible management approaches discussed by Söderlund [63].

5.2. Contribution to Workforce Allocation Research

From a scientific perspective, the study extends workforce-allocation research by operationalizing multiple organizational decision dimensions within a unified and empirically validated allocation methodology. Its contribution is therefore primarily integrative: competency matching, workload balancing, availability, expertise, priority, and continuity

are treated as interacting components of a single decision-support process rather than as isolated allocation criteria.

Furthermore, the adoption of Action Design Research enabled the simultaneous generation of practical and scientific knowledge. The framework was not developed as a theoretical construct detached from organizational reality but rather through iterative interaction with real users operating in a genuine workforce-allocation environment. This characteristic strengthens the practical relevance and ecological validity of the proposed approach within the investigated organizational setting. However, transferability to other organizations and sectors should be regarded as a proposition requiring further empirical validation rather than as an established outcome of the present single-organization study.

5.3. Practical Implications

From a managerial perspective, the framework transforms workforce allocation from a predominantly experience-based activity into a structured and transparent decision process. Centralized visibility of competencies, workload, availability, and project assignments enables managers to identify allocation conflicts earlier, respond more systematically to changing operational conditions, and reduce dependence on knowledge held by individual decision-makers.

Beyond individual task assignments, the same decision structure can support broader resource-planning activities by improving visibility of workforce capacity and anticipated competency requirements across concurrent projects. This extends the practical relevance of the framework from short-term allocation toward medium-term workforce planning, while retaining managerial oversight for decisions requiring contextual or strategic judgement.

The findings obtained in this study reinforce previous observations that effective resource management remains a critical determinant of project performance. Sanchez et al. [54] identified resource planning and management practices among the most influential factors affecting project cost and schedule performance. The proposed framework contributes to this perspective by providing managers with enhanced visibility regarding workforce utilization and allocation decisions, thereby supporting more effective project execution. Moreover, the findings also suggest that substantial improvements in resource-allocation performance can be achieved without requiring complex enterprise-level optimization systems. This observation is particularly relevant for small and medium-sized organizations, where implementation costs and operational simplicity are critical considerations.

To establish a direct link between the research objectives and the empirical validation of the proposed decision-support framework, the research propositions formulated in the introductory section were systematically assessed using the quantitative performance indicators obtained during the industrial validation. Figure 28 summarizes the validation outcome for each proposition together with the corresponding quantitative evidence.

The validation results provide case-specific empirical support for all four research propositions within the investigated organizational setting. Across the seven paired allocation cases, the framework-assisted procedure was associated with reductions in allocation time, workload imbalance, and manual intervention, together with improvements in resource utilization and allocation consistency. These findings demonstrate favorable operational performance relative to the conventional allocation procedure under the evaluated conditions; however, they should not be interpreted as evidence of general superiority over alternative workforce-allocation or optimization methods that were not included in the empirical comparison.

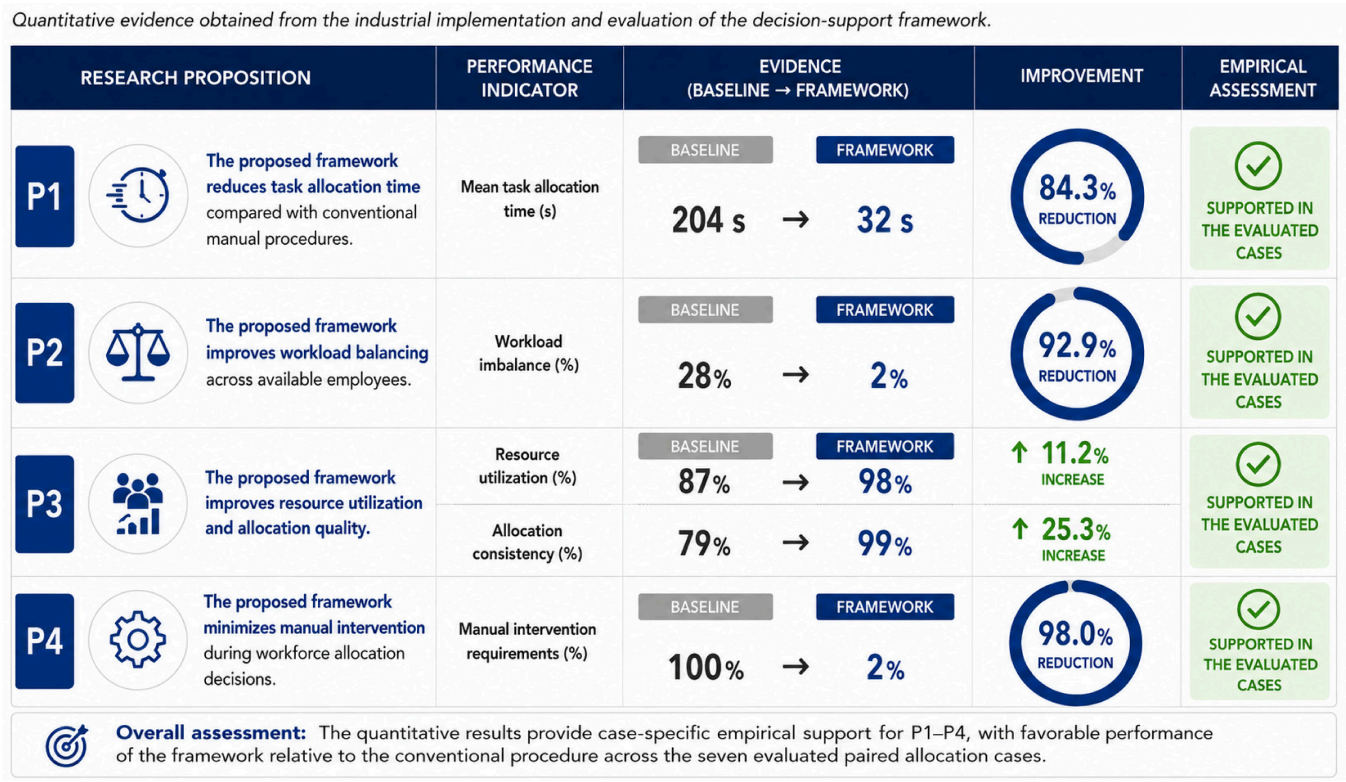


Figure 28. Case-specific empirical assessment of the research propositions based on quantitative performance indicators obtained during industrial implementation and evaluation. Created by the authors, with GPT used to improve the visual quality.

5.4. Enterprise Deployment and System Integration

The prototype presented in this work was implemented using Microsoft Excel and Visual Basic for Applications (VBA) to facilitate rapid development, iterative refinement, and validation within the Action Design Research methodology. This implementation should be regarded as proof-of-concept rather than a technological limitation of the proposed decision support framework.

The underlying allocation methodology is platform-independent and can be implemented using alternative software architectures better suited for enterprise-scale environments. For instance, the decision engine may be deployed as a standalone application, a web-based platform, or a cloud-native service capable of supporting distributed project management across multiple organizational units.

From a systems integration perspective, the proposed framework is compatible with modern enterprise information systems. Personnel information, competency profiles, workload indicators, project schedules, and availability records may be retrieved automatically from Enterprise Resource Planning (ERP), Human Resource Management Systems (HRMS), Project Management Information Systems (PMIS), or Manufacturing Execution Systems (MES) through standardized database connections or Application Programming Interfaces (APIs).

Similarly, the allocation results generated by the decision engine may be returned to enterprise platforms to support project planning, workforce scheduling, and resource management without modifying the underlying optimization logic.

Consequently, although the present implementation adopts Excel/VBA for experimental validation, the proposed framework is readily transferable to scalable enterprise software environments supporting cloud computing, distributed databases, and service-oriented architectures.

5.5. Mechanisms Underlying the Observed Improvements

The favorable performance observed for the proposed framework across the evaluated allocation cases can be interpreted through five complementary mechanisms.

- Integrated multi-criteria decision-making.
- Competency-driven allocation.

Continuous workload balancing.

- Automated evaluation of resource availability.
- Standardized decision rules reducing subjective variability.

Collectively, these mechanisms provide a plausible explanation for the favorable performance observed for the proposed decision-support framework relative to the conventional manual allocation procedure across the evaluated cases. This interpretation is specific to the investigation of organizational setting and should not be construed as evidence of general superiority over alternative workforce-allocation methods.

5.6. Limitations and Future Research Directions

Despite the encouraging results obtained during the industrial validation, several limitations should be acknowledged.

First, the empirical evaluation was conducted within a single industrial organization. Although the selected company represents a complex multinational manufacturing environment, organizational structures, competency management practices, and resource allocation procedures may differ across industrial sectors. Consequently, additional multi-company validation studies are required to further assess the external validity and transferability of the proposed framework.

Second, the industrial validation was performed on a finite number of projects and participants during a defined observation period. Although this dataset provided a realistic basis for evaluating the proposed decision support system under operational conditions, larger-scale longitudinal studies involving multiple organizations and extended deployment periods would provide additional evidence regarding the long-term robustness and organizational impact of the framework.

Third, part of the evaluation relies on managerial perceptions regarding organizational benefits. While these qualitative assessments complement the objective performance indicators reported in the quantitative validation, future research should incorporate additional objective organizational performance measures collected over extended operational periods.

Fourth, the current prototype was implemented using Microsoft Excel® and Visual Basic for Applications (VBA). This implementation was intentionally adopted to facilitate rapid industrial deployment and user acceptance during the Action Design Research process. Nevertheless, the proposed decision model is independent of the implementation platform and could be integrated into enterprise information systems, cloud-based decision support platforms, or ERP and HRMS environments to support larger-scale industrial applications.

Fifth, the present study focuses on demonstrating the practical usefulness of the proposed decision support framework rather than performing formal statistical hypothesis testing. This methodological choice is consistent with the objectives of Action Design Research, which emphasize artefact development and industrial validation. Future investigations based on larger datasets may incorporate inferential statistical analyses to further strengthen empirical generalization.

Sixth, although the framework was compared with the organization's conventional manual workforce allocation procedure, it was not benchmarked against advanced opti-

mization techniques such as mathematical programming, genetic algorithms, reinforcement learning, or other artificial intelligence-based scheduling methods. Comparative benchmarking against alternative optimization approaches represents an important direction for future research.

Although the additional baseline comparison provides further evidence regarding the value of the multi-criteria integration, the present study was not designed as a benchmarking investigation against alternative mathematical optimization, evolutionary, machine-learning, or reinforcement-learning approaches. Consequently, the findings should not be interpreted as demonstrating methodological superiority over these alternative solution paradigms.

Finally, the present evaluation reflects the short-term organizational impact observed during the industrial deployment. Future longitudinal studies should investigate user adoption, organizational learning, decision quality evolution, and sustained operational performance over extended implementation periods.

Future research may investigate the sensitivity of the allocation framework to different weighting configurations and explore adaptive weight calibration using optimization and machine learning techniques.

Overall, these limitations provide valuable opportunities for future research and should be interpreted as natural extensions of an initial industrial validation rather than as constraints affecting the practical relevance of the proposed decision support framework.

From a broader perspective, this study illustrates that practical decision-support systems do not necessarily require increasingly complex optimization or artificial intelligence techniques to generate substantial organizational value [55]. Instead, the combination of structured decision logic, organizational expertise, and transparent multicriteria reasoning may offer a more readily deployable solution for many industrial environments. This highlights an important trade-off between computational sophistication and organizational usability that deserves further investigation in future workforce allocation research.

The scope of empirical validation should also be considered when interpreting the findings. Although the investigated workforce operates as a project-oriented, knowledge-intensive internal service function, the study was conducted within a single large industrial organization over a two-month observation period, with the quantitative evaluation based on seven purposively selected paired allocation cases. Consequently, the results demonstrate the operational feasibility and effectiveness of the framework within the investigated setting but do not establish statistical generalizability across organizations, sectors, or workforce configurations. The configurable architecture of the framework nevertheless provides a basis for potential transferability to comparable software-development, engineering, IT-service, consultancy, and other project-oriented knowledge-intensive environments. Future research should therefore evaluate the framework through longitudinal, multi-organization, and cross-sector studies to determine the extent to which the observed performance improvements are reproducible under different organizational and operational conditions.

6. Conclusions

This study presented and industrially validated a competency-based Decision Support System (DSS) for workforce allocation developed following the principles of Action Design Research (ADR). The proposed framework was designed to support managerial decision-making by integrating multiple workforce allocation criteria, including employee competencies, availability, workload distribution, expertise, project priority, and assignment continuity within a structured and transparent decision-making process. Unlike conventional allocation approaches that rely predominantly on managerial experience and subjective judgement, the proposed framework formalizes the allocation process through a

consistent multi-criteria evaluation mechanism while preserving managerial oversight for exceptional decision scenarios.

The industrial validation provided case-specific empirical evidence of favorable operational effects associated with the proposed framework under the investigated organizational conditions. The quantitative evaluation showed substantial case-specific improvements in workforce-allocation performance, including considerable reductions in allocation time and workload imbalance, increased resource utilization, improved allocation consistency, and a substantial reduction in manual intervention. Together, these results indicate that the framework effectively supports more efficient and standardized workforce allocation while reducing the operational burden associated with manual decision-making.

Beyond the measurable operational improvements, the qualitative managerial assessment provided empirical support that the framework contributes to enhanced workforce visibility, improved workload transparency, more effective identification of allocation conflicts, better awareness of resource availability, greater assignment consistency, and increased organizational responsiveness. These complementary findings demonstrate that the proposed decision support system not only improves operational efficiency but also strengthens the transparency and consistency of managerial decision-making processes. Accordingly, the industrial validation suggests that the framework supports more structured, informed, and consistent workforce allocation decisions, while recognizing that broader empirical evidence is required before making generalized claims regarding decision quality improvements across different organizational contexts.

From a scientific perspective, this work contributes to the growing body of knowledge on intelligent workforce management by proposing an integrated competency-based decision support framework that combines practical applicability with methodological rigor. The study extends existing workforce allocation research by demonstrating how multiple organizational decision criteria can be systematically integrated within an ADR-based artefact and validated through deployment in an industrial environment. Furthermore, the separation between quantitative operational performance evaluation and qualitative managerial assessment provides a more comprehensive validation strategy that is consistent with the objectives of Design Science and Action Design Research.

From an industrial perspective, the proposed framework offers organizations a practical approach for supporting workforce allocation within increasingly dynamic manufacturing and project-oriented environments. Although the current implementation was developed using Microsoft Excel® and Visual Basic for Applications (VBA) to facilitate rapid deployment and industrial adoption, the underlying decision model is platform-independent and may be integrated into enterprise information systems, Human Resource Management Systems (HRMS), Enterprise Resource Planning (ERP) platforms, Manufacturing Execution Systems (MES), or cloud-based decision support environments.

Despite the encouraging results obtained during the industrial validation, several limitations should be acknowledged. The empirical evaluation was conducted within a single industrial organization over a limited observation period, and the prototype implementation was assessed using a finite number of projects and participants. Moreover, although the study includes objective operational performance indicators together with qualitative managerial assessment, it does not incorporate formal inferential statistical testing, benchmarking against advanced optimization algorithms, or long-term organizational deployment evaluation. Consequently, the present findings should be interpreted as evidence of the practical usefulness and industrial applicability of the proposed framework rather than as definitive proof of universal superiority over alternative workforce allocation approaches.

Future research should therefore focus on validating the framework across multiple organizations and industrial sectors, performing longitudinal studies to evaluate long-term organizational adoption and operational performance, benchmarking the proposed approach against optimization and artificial intelligence-based workforce allocation techniques, and integrating the framework into enterprise-scale digital platforms. Additional research may also investigate adaptive weighting strategies, explainable artificial intelligence techniques, and real-time optimization mechanisms capable of supporting autonomous workforce allocation within Industry 5.0 environments.

Overall, the results demonstrate that the proposed decision-support framework provides a practical and scientifically grounded approach to competency-based workforce allocation. By combining structured multi-criteria decision-making with industrial validation, the study establishes a basis for more transparent, consistent, and efficient allocation processes while identifying clear opportunities for future development toward adaptive and intelligent workforce decision-support systems.

Author Contributions: Conceptualization, N.M.S.C. and F.J.G.S.; methodology, F.J.G.S.; software, N.M.S.C. and I.M.P.; validation, F.J.G.S., I.M.P., I.F., A.G., M.B. and R.C.M.S.-C.; formal analysis, I.M.P., I.F., A.G., A.J.V. and M.B.; investigation, N.M.S.C.; resources, F.J.G.S.; data curation, R.C.M.S.-C., M.B., A.G., I.F. and A.J.V.; writing—original draft preparation, N.M.S.C. and F.J.G.S.; writing—review and editing, I.M.P., M.B., A.J.V., I.F. and A.G.; visualization, R.C.M.S.-C.; supervision, F.J.G.S.; project administration, F.J.G.S.; funding acquisition, F.J.G.S. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was funded by the Drivolution–Transition to the factory of the future, Project Code 02/C05-i01.02/2022, Project no 23, supported by European Structural and Investment Funds with the "Portugal2020" program scope.

Institutional Review Board Statement: Ethical review and approval were waived for this study due to Legal Regulation (EU) 2016/679. Link: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32016R0679 (accessed on 1 September 2026).

Informed Consent Statement: Patient consent was waived due to Legal Regulation (EU) 2016/679. Link: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32016R0679 (accessed on 1 September 2026).

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to time limitations.

Acknowledgments: During the preparation of this manuscript, the authors used ChatGPT v5 Plus for the purposes of improving the visual quality of figures and tables. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Muduli, A.; Choudhury, A. Digital technology adoption, workforce agility and digital technology outcomes in the context of the banking industry of India. *J. Sci. Technol. Policy Manag.* **2026**, *17*, 829–849. [CrossRef]
2. Mourtzis, D.; Xanthi, F.; Zogopoulos, V. An adaptive framework for augmented reality instructions considering workforce skill. *Procedia CIRP* **2019**, *81*, 363–368. [CrossRef]
3. Wang, X.; Wu, W. CEO AI orientation, human resources and green innovation: An attention-based view. *Kybernetes* **2026**, *55*, 584–611. [CrossRef]
4. Bhuvaneswari, E.; Prasad, K.D.V.; Ashraf, M.; Jadhav, S.; Rao, T.K.R.K.; Rani, T.S. A human-centered hybrid AI framework for optimizing emergency triage in resource-constrained settings. *Intell.-Based Med.* **2025**, *12*, 100311. [CrossRef]
5. Huang, J.; Yao, F.; Zhan, H.; Zhang, Z.; Chen, C.; Xing, L.; Song, Y. Large-scale multi-objective human resource scheduling for organizational agility: An improved co-evolutionary NSGA-II algorithm. *Expert Syst. Appl.* **2026**, *331*, 133270. [CrossRef]

6. Joseph, S.; Gowsalya, M. A stochastic-deterministic framework for seasonal workforce allocation and labor slack analysis in waste management. *Results Eng.* **2026**, *32*, 112082. [CrossRef]
7. Mao, H.; Mao, Y.; Yuan, J.; Guo, X.; Su, J. Evolving multi-agent heuristics for the decentralized resource-constrained multi-project scheduling problem with multiple modes. *Knowl.-Based Syst.* **2026**, *351*, 116891. [CrossRef]
8. Fang, L. Centralized resource allocation based on efficiency analysis for step-by-step improvement paths. *Omega* **2015**, *51*, 24–28. [CrossRef]
9. Ballesteros-Pérez, P.; Phua, F.T.T.; Mora-Melià, D. Human resource allocation to multiple projects based on members' expertise, group heterogeneity, and social cohesion. *J. Constr. Eng. Manag.* **2019**, *145*, 04018134. [CrossRef]
10. Rudek, R.; Heppner, I. Efficient algorithms for discrete resource allocation problems under degressively proportional constraints. *Expert Syst. Appl.* **2020**, *149*, 113293. [CrossRef]
11. Mourtzis, D.; Siatras, V.; Angelopoulos, J.; Panopoulos, N. An intelligent model for workforce allocation taking into consideration the operator skills. *Procedia CIRP* **2021**, *97*, 196–201. [CrossRef]
12. Otero, L.D.; Centeno, G.; Ruiz-Torres, A.J.; Otero, C.E. A systematic approach for resource allocation in software projects. *Comput. Ind. Eng.* **2009**, *56*, 1333–1339. [CrossRef]
13. Kang, D.; Jung, J.; Bae, D.-H. Constraint-based human resource allocation in software projects. *Softw. Pract. Exp.* **2011**, *41*, 551–577. [CrossRef]
14. De Bruecker, P.; Van den Bergh, J.; Beliën, J.; Demeulemeester, E. Workforce planning incorporating skills: State of the art. *Eur. J. Oper. Res.* **2015**, *243*, 1–16. [CrossRef]
15. Staruch, B.; Staruch, B. Competence-based assignment of tasks to workers in factories with demand-driven manufacturing. *Cent. Eur. J. Oper. Res.* **2021**, *29*, 553–565. [CrossRef]
16. Rinaldi, M.; Fera, M.; Bottani, E.; Grosse, E.H. Workforce scheduling incorporating worker skills and ergonomic constraints. *Comput. Ind. Eng.* **2022**, *168*, 108107. [CrossRef]
17. Lunin, A. Balancing physical workload during workforce scheduling for fair task assignment in a manual warehouse. *IFAC-PapersOnLine* **2024**, *58*, 712–717. [CrossRef]
18. Vahedi-Nouri, B.; Tavakkoli-Moghaddam, R.; Hanzálek, Z.; Dolgui, A. Workforce planning and production scheduling in a reconfigurable manufacturing system facing the COVID-19 pandemic. *J. Manuf. Syst.* **2022**, *63*, 563–574. [CrossRef] [PubMed]
19. Bocewicz, G.; Golinska-Dawson, P.; Szwarc, E.; Banaszak, Z. Preventive maintenance scheduling of a multi-skilled human resource-constrained project's portfolio. *Eng. Appl. Artif. Intell.* **2023**, *119*, 105725. [CrossRef]
20. Wu, X.; Schworm, P.; Yi, L.; Glatt, M.; Aurich, J.C. An approach to quantum annealing-based workforce assignment in manufacturing systems. *Procedia CIRP* **2023**, *120*, 1022–1027. [CrossRef]
21. Calzavara, M.; Faccio, M.; Granata, I.; Trevisani, A. Achieving productivity and operator well-being: A dynamic task allocation strategy for collaborative assembly systems in Industry 5.0. *Int. J. Adv. Manuf. Technol.* **2024**, *134*, 3201–3216. [CrossRef]
22. Soori, M.; Karimi Ghaleh Jough, F.; Dastres, R.; Arezoo, B. AI-based decision support systems in Industry 4.0: A review. *J. Econ. Technol.* **2026**, *4*, 206–225. [CrossRef]
23. Tóth, A.; Nagy, L.; Kennedy, R.; Bohuš, B.; Abonyi, J.; Ruppert, T. The human-centric Industry 5.0 collaboration architecture. *MethodsX* **2023**, *11*, 102260. [CrossRef] [PubMed]
24. Kelley, J.E.; Walker, M.R. Critical-path planning and scheduling. In Proceedings of the Eastern Joint IRE-AIEE-ACM Computer Conference, Boston, MA, USA, 1–3 December 1959. [CrossRef]
25. Malcolm, D.G.; Roseboom, J.H.; Clark, C.E.; Fazar, W. Application of a technique for research and development program evaluation. *Oper. Res.* **1959**, *7*, 646–669. [CrossRef]
26. Kerzner, H. *Project Management: A Systems Approach to Planning, Scheduling, and Controlling*, 12th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2017.
27. Hansen, L.K.; Brandt, C.J.; Kampf, C.E. Agile hybrid project portfolio management: Rethinking its paradoxes. *Int. J. Manag. Proj. Bus.* **2026**, *19*, 415–438. [CrossRef]
28. Kozarkiewicz, A.; Swałdek, T. Intentional immaturity: Rethinking project management in start-ups through an intentionality–capability lens. *Int. J. Organ. Anal.* **2026**, *in press*. [CrossRef]
29. Chao, Y.; Zhuang, C.; Guo, H.; Liu, J. A genetic programming hyper-heuristic with whale optimization algorithm for the dynamic resource-constrained multi-project scheduling problems. *Expert Syst. Appl.* **2026**, *295*, 128881. [CrossRef]
30. Sözüer, M.; Spang, K. The importance of project management in the planning process of transport infrastructure projects in Germany. *Procedia Soc. Behav. Sci.* **2014**, *119*, 601–610. [CrossRef]
31. Lima, R.; Tereso, A.; Faria, J. Project management under uncertainty: Resource flexibility visualization in the schedule. *Procedia Comput. Sci.* **2019**, *164*, 381–388. [CrossRef]
32. Müller, R.; Turner, R. Leadership competency profiles of successful project managers. *Int. J. Proj. Manag.* **2010**, *28*, 437–448. [CrossRef]

33. Lopes, R.O.A.; Sbragia, R.; Qualharini, E.L. The psychological contract and project management as a core competence of the organization. *Procedia Soc. Behav. Sci.* **2016**, *226*, 148–155. [CrossRef]
34. Rasnacis, A.; Berzisa, S. Method for adaptation and implementation of agile project management methodology. *Procedia Comput. Sci.* **2017**, *104*, 43–50. [CrossRef]
35. Špundak, M. Mixed agile/traditional project management methodology—Reality or illusion? *Procedia Soc. Behav. Sci.* **2014**, *119*, 939–948. [CrossRef]
36. Collyer, S.; Warren, C.; Hemsley, B.; Stevens, C. Aim, fire, aim—Project planning styles in dynamic environments. *Proj. Manag. J.* **2010**, *41*, 108–121. [CrossRef]
37. Eilat, H.; Golany, B.; Shtub, A. Constructing and evaluating balanced portfolios of R&D projects with interactions: A DEA-based methodology. *Eur. J. Oper. Res.* **2006**, *172*, 1018–1039. [CrossRef]
38. Karsu, Ö.; Morton, A. Incorporating balance concerns in resource allocation decisions: A bi-criteria modelling approach. *Omega* **2014**, *44*, 70–82. [CrossRef]
39. Zwikael, O.; Unger-Aviram, E. HRM in project groups: The effect of project duration on team development effectiveness. *Int. J. Proj. Manag.* **2010**, *28*, 413–421. [CrossRef]
40. Yu, M.-M.; Chern, C.-C.; Hsiao, B. Human resource rightsizing using centralized data envelopment analysis: Evidence from Taiwan's airports. *Omega* **2013**, *41*, 119–130. [CrossRef]
41. Barreto, A.; Barros, M.O.; Werner, C.M.L. Staffing a software project: A constraint satisfaction and optimization-based approach. *Comput. Oper. Res.* **2008**, *35*, 3073–3089. [CrossRef]
42. Wu, J.; An, Q.; Ali, S.; Liang, L. DEA-based resource allocation considering environmental factors. *Math. Comput. Model.* **2013**, *58*, 1128–1137. [CrossRef]
43. Porto, A.F.; Lusa, A.; Herazo, S.A.; Henao, C.A. Improving the robustness of retail workforce management with a labor flexibility strategy and consideration of demand uncertainty. *Oper. Res. Perspect.* **2025**, *15*, 100345. [CrossRef]
44. Demiray, O.; Tolga, D.; Yücel, E. An optimization framework for a dynamic multi-skill workforce scheduling and routing problem with time windows, synchronization constraints, and anticipated tasks. *Comput. Ind. Eng.* **2026**, *219*, 112203. [CrossRef]
45. Toaza, B.; Esztergár-Kiss, D. Integrating non-traditional factors into a deterministic utility function for optimizing daily activity schedules. *Expert Syst. Appl.* **2026**, *332*, 133613. [CrossRef]
46. Ye, X.; Guo, H.; Luo, Z. Two-stage task allocation for multiple construction robots using an improved genetic algorithm. *Autom. Constr.* **2024**, *165*, 105583. [CrossRef]
47. Sukmana, F.; Santosa, B.; Wibisono, A. Enhancing dispatching rules for work order scheduling using genetic algorithms and technician resource management. *Procedia Comput. Sci.* **2026**, *284*, 1017–1027. [CrossRef]
48. Farahmand-Mehr, M.; Mousavi, S.M. Resource-constrained multi-project scheduling problems considering time-dependent reliability of resources: A new immune genetic local search algorithm. *Kybernetes* **2026**, *55*, 2571–2606. [CrossRef]
49. Wu, Z.; Zhang, F.; Dong, W.; Zhu, Z.; Wang, J. A diffusion-enhanced reinforcement learning framework for dynamic hybrid flow shop scheduling with energy and tool constraints. *Expert Syst. Appl.* **2026**, *333*, 133819. [CrossRef]
50. Wang, X.; Zhang, Y.; Zhang, S. Dynamic order allocation in a duopoly hybrid workforce of competition: A machine learning approach. *Eur. J. Oper. Res.* **2024**, *315*, 668–690. [CrossRef]
51. Chen, X.; Yin, X.; Yuan, X.; Bouferguene, A.; Al-Hussein, M. Adaptive job scheduling and resource allocation for industrialized construction processes using digital twin and reinforcement learning. *Adv. Eng. Inform.* **2026**, *76*, 105166. [CrossRef]
52. Qiu, L.; Zhu, J.; Liu, Y.; Cui, J.-H. Task allocation in distributed multi-UUV: An adaptive fuzzy response threshold method with task-age awareness. *Ocean Eng.* **2026**, *363*, 126674. [CrossRef]
53. Moazzami, S.; Mirzaei, A.; Aminian, M.; Karimi, R.; Mikaeilvand, N. A hybrid fuzzy logic and deep reinforcement learning algorithm for adaptive task scheduling and resource allocation in heterogeneous Fog–Cloud environments. *Sustain. Comput. Inform. Syst.* **2026**, *49*, 101260. [CrossRef]
54. Trigo, A. Artefact-driven narrative literature review (ART-NLR): Supporting evidence synthesis for design science research. *J. Doc.* **2026**, *82*, 899–930. [CrossRef]
55. Mikkelsen, M.F.; Aaltonen, K. IT-enabled management of project complexity—An Action Design Research project. *Int. J. Manag. Proj. Bus.* **2022**, *16*, 141–164. [CrossRef]
56. Ghazinoory, S.; Zadegan, M.G.; Phaal, R. Research design unlocked! Roadmapping for integration of paradigms, strategies, and tools. *J. Open Innov. Technol. Mark. Complex.* **2025**, *11*, 100688. [CrossRef]
57. Neves, P.; Silva, F.J.G.; Ferreira, L.P.; Pereira, T.; Gouveia, A.; Pimentel, C. Implementing lean tools in the manufacturing process of trimmings products. *Procedia Manuf.* **2018**, *17*, 696–704. [CrossRef]
58. Silva, F.J.G.; Morgado, L.; Teixeira, A.; Sá, J.C.; Ferreira, L.P.; Ferreira, A.F. Analysis and development of a failure prediction model for electrical terminals used in the automotive industry. *Procedia Manuf.* **2020**, *51*, 207–214. [CrossRef]
59. Marnewick, A.L.; Marnewick, C. Preparing project managers for digitalisation: Identifying critical skills and learning pathways for the digital era. *Proj. Leadersh. Soc.* **2026**, *7*, 100240. [CrossRef]

60. Ali, M.U.; Tipu, J.A.K.; Arif, M.; Shaqour, N. Lean management for the sustainability of projects in construction sector. *Int. J. Lean Six Sigma* **2026**, *in press*. [CrossRef]
61. Meireles, M.A.C.; Rodrigues, E.; Lobão, L.; Oliveira Steinmacher, I.; Maldonado, J.C.; Conte, T. Applying design thinking in research and development environment: Insights from a case study in a Brazilian R&D institute. *J. Syst. Softw.* **2026**, *242*, 113029. [CrossRef]
62. Turner, J.R.; Ledwith, A. Project management in small to medium-sized enterprises: Fitting the practices to the needs of the firm to deliver benefit. *J. Small Bus. Manag.* **2018**, *56*, 475–493. [CrossRef]
63. Söderlund, J. Review of Reinventing Project Management: The Diamond Approach to Successful Growth and Innovation, by Aaron J. Shenhar and Dov Dvir. *R D Manag.* **2008**, *38*, 355–356. [CrossRef]
64. Sanchez, O.P.; Terlizzi, M.A.; Moraes, H.R.O.C. Cost and time project management success factors for information systems development projects. *Int. J. Proj. Manag.* **2017**, *35*, 1608–1626. [CrossRef]
65. Silva, F.J.G.; Kirytopoulos, K.; Ferreira, L.P.; Sá, J.C.; Santos, G.; Nogueira, M.C.C. The three pillars of sustainability and agile project management: How do they influence each other? *Corp. Soc. Responsib. Environ. Manag.* **2022**, *29*, 1495–1510. [CrossRef]
66. Sebbe, N.P.V.; Sá, J.C.V.; Pereira, M.T.; Pinto, I.M.; Baptista, A.; Viamonte, A.J. Implementation of Assembly and Balancing Line Aiming at Operational Excellence in Pre-Hospital Transport Equipment. *J. Mech. Eng. Manuf.* **2026**, *2*, 7. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.